

Motivation Modelling and Computation for Personalised Learning of People with Dyslexia



by
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Declaration of Authorship

The content of this submission was undertaken in the School of Computer Science and Informatics, De Montfort University, and supervised by Prof. Liming Chen, Prof. Aladdin Ayesh, and Dr. Ivar Solheim during the period of registration. I hereby declare that the materials of this submission have not previously been published for a degree or diploma at any other university or institute. All the materials submitted for assessment are from my own research, except the reference work in any format by other authors, which are properly acknowledged in the content. Part of the research work presented in this thesis is published or being prepared for publication in the following papers:

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Abstract

The increasing development of e-learning systems in recent decades has benefited ubiquitous computing and education by providing freedom of choice to satisfy various needs and preferences about learning places and paces. Automatic recognition of learners' states is necessary for personalised services or intervention to be provided in e-learning environments. In current literature, assessment of learners' motivation for personalised learning based on the motivational states is lacking. An effective learning environment needs to address learners' motivational needs, particularly, for those with dyslexia. Dyslexia or other learning difficulties can cause young people not to engage fully with the education system or to drop out due to complex reasons: in addition to the learning difficulties related to reading, writing or spelling, psychological difficulties are more likely to be ignored such as lower academic self-worth and lack of learning motivation caused by the unavoidable learning difficulties. Associated with both cognitive processes and emotional states, motivation is a multi-facet concept that consequences in the continued intention to use an e-learning system and thus a better chance of learning effectiveness and success. It consists of factors from intrinsic motivation driven by learners' inner feeling of interest or challenges and those from extrinsic motivation associated with external reward or compliments. These factors represent learners' various motivational needs; thus, understanding this requires a multidisciplinary approach.

Combining different perspectives of knowledge on psychological theories and technology acceptance models with the empirical findings from a qualitative study with dyslexic students conducted in the present research project, motivation modelling for people with dyslexia using a hybrid approach is the main focus of this thesis. Specifically, in addition to the contribution to the qualitative conceptual motivation model and ontology-based computational model that formally expresses the motivational factors affecting users' continued intention to use e-learning systems, this thesis also conceives a quantitative approach to motivation modelling. A multi-item motivation questionnaire is designed and employed in a quantitative study with dyslexic students, and structural equation modelling techniques are used to quantify the influences of the motivational factors on continued use intention and their interrelationships in the model.

In addition to the traditional approach to motivation computation that relies on learners'

self-reported data, this thesis also employs dynamic sensor data and develops classification models using logistic regression for real-time assessment of motivational states. The rule-based reasoning mechanism for personalising motivational strategies and a framework of motivationally personalised e-learning systems are introduced to apply the research findings to e-learning systems in real-world scenarios. The motivation model, sensor-based computation and rule-based personalisation have been applied to a practical scenario with an essential part incorporated in the prototype of a gaze-based learning application that can output personalised motivational strategies during the learning process according to the real-time assessment of learners' motivational states based on both the eye-tracking data in addition to users' self-reported data. Evaluation results have indicated the advantage of the application implemented compared to the traditional one without incorporating the present research findings for monitoring learners' motivation states with gaze data and generating personalised feedback.

In summary, the present research project has: 1) developed a conceptual motivation model for students with dyslexia defining the motivational factors that influence their continued intention to use e-learning systems based on both a qualitative empirical study and prior research and theories; 2) developed an ontology-based motivation model in which user profiles, factors in the motivation model and personalisation options are structured as a hierarchy of classes; 3) designed a multi-item questionnaire, conducted a quantitative empirical study, used structural equation modelling to further explore and confirm the quantified impacts of motivational factors on continued use intention and the quantified relationships between the factors; 4) conducted an experiment to exploit sensors for motivation computation, and developed classification models for real-time assessment of the motivational states pertaining to each factor in the motivation model based on empirical sensor data including eye gaze data and EEG data; 5) proposed a sensor-based motivation assessment system architecture with emphasis on the use of ontologies for a computational representation of the sensor features used for motivation assessment in addition to the representation of the motivation model, and described the semantic rule-based personalisation of motivational strategies; 6) proposed a framework of motivationally personalised e-learning systems based on the present research, with the prototype of a gaze-based learning application designed, implemented and evaluated to guide future work.

Table of Contents

Chapter 1 Introduction	1
1.1 Background	1
1.2 Research Questions	4
1.3 Aim and Objectives	5
1.4 Research Methodology	6
1.5 Contributions to Knowledge.....	10
1.6 Thesis Outline	12
Chapter 2 Related Work	14
2.1 Introduction.....	14
2.2 Learning Difficulty and Dyslexia	14
2.2.1 Learning Difficulty and Learning Disability	14
2.2.2 Assessment and Intervention Practice.....	15
2.2.3 Cognitive Difficulties of Dyslexia.....	18
2.2.4 Affective Difficulties of Dyslexia	19
2.3 Assistive Technology for People with Dyslexia	20
2.3.1 Design Considerations for People with Dyslexia.....	20
2.3.2 State of the Art of Assistive Technology	22
2.4 Motivation Modelling and Computation	26
2.4.1 Motivation Modelling from Psychological Perspective	26
2.4.2 Motivation Modelling from Technology Acceptance Perspective	28
2.4.3 Motivation Modelling from Computational Perspective.....	30
2.4.4 Motivation Computation and Assessment.....	35
2.5 Existing Motivation-based Personalisation for People with Dyslexia	38
2.5.1 Personalised Learning Process	39
2.5.2 Existing Personalisation for People with Dyslexia.....	41
2.5.3 Using Motivational Strategies in E-Learning Systems	42
Chapter 3 Motivation Modelling for People with Dyslexia in E-learning Environments ..	46
3.1 Introduction.....	46
3.2 Characterisation of E-learning Systems and Motivation	47
3.3 Conceptual Motivation Modelling	49
3.3.1 Initial Model Construction	49
3.3.2 Empirical Study for Motivational Factor Elicitation.....	52
3.3.3 Thematic Categorisation.....	59
3.3.4 Emerging Themes Discovery	63
3.3.5 Refined Motivation Model.....	65
3.4 Computational Motivation Modelling.....	69
3.4.1 An Overview of Ontology for People with Dyslexia	70
3.4.2 Ontology-based Motivation Modelling	71
3.5 Conclusion	76
Chapter 4 Quantitative Model Specification and Parameterisation.....	77

4.1 Introduction.....	77
4.2 Questionnaire Design and Data Collection.....	78
4.2.1 Multi-item Questionnaire Design	78
4.2.2 Sampling and Data Collection	80
4.3 Quantitative Motivation Model Analysis.....	81
4.3.1 Methodology	81
4.3.2 Dimension Reduction	82
4.3.3 Measurement Model.....	83
4.3.4 Structural Model	86
4.3.5 Mediation Analysis	94
4.4 Quantified Motivation Model and Factor Interrelationships.....	96
4.4.1 Key Findings	96
4.4.2 Theoretical Findings	98
4.4.3 Mediators	100
4.4.4 Limitations	102
4.5 Conclusion	103
<i>Chapter 5 Real-time Sensor-based Motivation Computation</i>	105
5.1 Introduction.....	105
5.2 A Novel Approach to Motivation Computation	106
5.3 Experiment Methodology.....	108
5.3.1 Participants and Learning Materials	108
5.3.2 System Setup	108
5.3.3 Procedure.....	111
5.4 EEG and Eye Tracking Feature Analysis and Experiment Results	112
5.4.1 Data Pre-processing	112
5.4.2 Feature Extraction.....	112
5.4.3 Individual Differences.....	114
5.4.4 Feature Selection	117
5.4.5 Prediction Results of Classification Models.....	120
5.4.6 Discussion.....	126
5.5 Different Approaches to Predicting Motivational Consequence	127
5.5.1 Towards an Integrated Motivation Model	127
5.5.2 Comparing the Different Approaches.....	130
5.6 Conclusion	133
<i>Chapter 6 Motivation-based Personalised Learning.....</i>	135
6.1 Introduction.....	135
6.2 Sensor-based Motivation Assessment Using Ontology and Classification Mechanism....	136
6.2.1 The Sensor-based Motivation Assessment System Architecture.....	137
6.2.2 Information Mapping and Raw-data Ontology.....	139
6.2.3 EEG-Eye-Motivation Ontology and Motivation Assessment.....	140
6.3 Motivation-based Personalisation through Motivational Strategies	142
6.3.1 Motivation Strategies Corresponding to the Motivation Model.....	142
6.3.2 Sensor-based Evaluation of Motivational Strategies	149
6.3.3 Rule-based Reasoning Mechanism.....	153
6.4 Conclusion	157

Chapter 7 A Framework of Motivationally Personalised E-learning Systems.....	158
7.1 Introduction.....	158
7.2 The Proposed System Framework	159
7.2.1 Diagnostic Input for Motivation Assessment	161
7.2.2 System Reactions from Repertoire of Motivational Strategies.....	162
7.3 A Prototype of Gaze-based Learning Application	163
7.3.1 Design and Implementation.....	164
7.3.2 GazeMotive Walkthrough.....	168
7.4 Evaluation Study	170
7.4.1 Heuristic Evaluation.....	171
7.4.2 Pre-defined Tasks.....	173
7.4.3 System Usability Scale	177
7.4.4 Interviews.....	177
7.5 Conclusion.....	180
Chapter 8 Discussions and Conclusions	182
8.1 Summary of Research	182
8.2 Summary of Contributions to Knowledge	183
8.3 Future Work	187
8.4 Conclusions	188
References	190
Appendices.....	213
Appendix 1 mYouTime Learning Materials in the Qualitative Study.....	213
Appendix 2 Interview Probing Questions in the Qualitative Study	214
Appendix 3 Measurement Scales	215
Appendix 4 The Significant EEG and Eye Tracking Features ($p < 0.05$) According to Spearman Correlation	220
Appendix 5 The Significant EEG and Eye Tracking Features ($p < 0.05$) According to One-way ANOVA/Kruskal Wallis Test	222
Appendix 6 Classification Tables.....	224

List of Figures

- Fig. 3.1 The proposed conceptual motivation model
- Fig. 3.2 On the left (a): an example interface with text and audio in mYouTime; on the right (b): an example interface with a quiz correctly answered in mYouTime
- Fig. 3.3 Mock-up prototype of alternative feedback
- Fig. 3.4 Two screenshots from the remote view showing a participant learning in mYouTime
- Fig. 3.5 A screenshot in NVivo10 showing part of the coding density with each node corresponding to the qualitative data on the left
- Fig. 3.6 The refined conceptual motivation model and new interrelationships
- Fig. 3.7 The result motivation model showing sources from different perspectives
- Fig. 3.8 The key relationships within the overall ontological model for dyslexic students
- Fig. 3.9 Example of class instances and property assertions
- Fig. 3.10 Ontological motivation model by OntoGraf
- Fig. 3.11 Hierarchy of the **MotivationState** class by OWLViz
- Fig. 3.12 The **Personalisation** class and **Student** class with their subclasses in Protégé
- Fig. 4.1 A screenshot of the online questionnaire
- Fig. 4.2 New hypothesis motivation model
- Fig. 4.3 CB-SEM result model of dyslexic users' motivation to engage in e-learning systems
- Fig. 4.4 PLS-SEM result model of dyslexic users' motivation to engage in e-learning systems
- Fig. 4.5 The quantified motivation model showing the grouping and sequencing of factors
- Fig. 5.1 The high-level structure of motivation model with incorporation of sensor data
- Fig. 5.2 On the left (a): the screenshot of an e-learning interface with the attention map in OGAMA; on the right (b): the multi-item motivation questionnaire in Google Form
- Fig. 5.3 The raw EEG interface in EmotivPro
- Fig. 5.4 On the left (a): the international 10-20 system with electrode positions corresponding to brain lobes; on the right (b): the experiment setup
- Fig. 5.5 The flow diagram of the experiment procedure
- Fig. 5.6 ROC curve for Visual Attractiveness
- Fig. 5.7 Specification of an integrated motivation model for people with dyslexia in e-learning environment
- Fig. 5.8 The logistic regression model predictors for Attitudes Toward School as an example for those shown in Fig. 5.7
- Fig. 5.9 Logistic regression model for predicting Continued Use Intention based on real-time sensor data
- Fig. 6.1 The architecture of the sensor-based motivation assessment system for motivation-based personalised learning
- Fig. 6.2 "Raw-data Ontology" without any data
- Fig. 6.3 "Raw-data Ontology" with EEG and eye-tracking data
- Fig. 6.4 The structure of the "EEG-Eye-Motivation Ontology"
- Fig. 6.5 Example motivational strategies corresponding to the factors in the motivation model
- Fig. 6.6 Screenshot showing part of the SWRL rules within Protégé

- Fig. 7.1 The framework of motivationally personalised e-learning systems
- Fig. 7.2 Use case diagram of GazeMotive
- Fig. 7.3 Class diagram of GazeMotive
- Fig. 7.4 Screenshots of expert interface for (a): login; and (b): adding a quiz
- Fig. 7.5 Screenshots of expert interface showing (a): the process of adding an AOI, and
(b) an example of the AOIs added
- Fig. 7.6 Screenshots of user interface showing the examples of personalised feedback to
provide motivational help

List of Tables

Table 3.1	Comparison of design between Group A and Group B
Table 3.2	An example of answers comparison between participants in Group A and Group B
Table 3.3	The themes identified (in bold) and number of participants that mentioned the themes in open-ended questions
Table 3.4	A comparison of learning experience between groups
Table 3.5	The new interrelationships in the refined motivation model
Table 4.1	Sample demographics (n=88)
Table 4.2	Reliability and convergent validity statistics
Table 4.3	Discriminant validity: AVEs versus cross-factor squared correlations
Table 4.4	Modification of relations between factors in CB-SEM
Table 4.5	Modification of relations between factors in PLS-SEM
Table 4.6	CB-SEM and PLS-SEM results comparison
Table 4.7	Standardised direct, indirect and total effect on Continued Use Intention
Table 5.1	The significant differences between diagnosed participants and the undiagnosed according to Mann-Whitney Test
Table 5.2	The significant differences between two groups of participants for Attitudes Toward School according to Mann-Whitney Test
Table 5.3	The significant differences between two groups of participants for Self-efficacy according to Mann-Whitney Test
Table 5.4	The significant EEG and eye tracking features ($p < 0.05$) according to Spearman Correlation Test
Table 5.5	The significant EEG and eye tracking features ($p < 0.05$) according to one-way ANOVA or Kruskal Wallis Test
Table 5.6	The features from direct independent factors
Table 5.7	Model coefficients and accuracy based on gaze features
Table 5.8	Part of coordinates of the ROC curve for Visual Attractiveness
Table 5.9	Omnibus tests of model coefficients using logistic regression
Table 5.10	Classification accuracies for the motivational factors with cut-off points and significant features
Table 5.11	AIC and BIC for the three models resulting from different approaches for predicting the motivational consequence
Table 6.1	Examples of SWRL rules
Table 7.1	Quiz performance
Table 7.2	Motivational strategies implemented in GazeMotive, times appearing and average ratings in the evaluation study

Chapter 1 Introduction

1.1 Background

Human-computer interaction (HCI) is a multidisciplinary research area in which psychology and other social sciences unite with computer science and related technical fields with the goal of making computing systems useful, usable and aesthetically pleasing. There are currently two major directions in HCI research. One is multimodal interactions, e.g. using audio, video, gesture, voice, pointing and eye gazing to facilitate user interaction with systems and devices. The second one is personalisation and adaptation of HCI, i.e., using user profiles such as the changing capabilities or behaviours to personalise and adapt user interfaces and/or the modality of interaction and/or formality of content, e.g. in video, audio or text. New technologies and applications, e.g. pervasive computing, smart technologies and healthcare assistive applications, continuously challenge HCI researchers with new options and requirements, as the emergence and advance of technologies presents a wide range of possibilities and the increasing diversity of users poses new demands. The rapid development of HCI technologies offers opportunities to help improve the quality of life for people with specific needs, for example, those who suffer from various learning difficulties such as dyslexia, by enhancing the usability and lower the barrier for them to use assistive technologies and applications.

Dyslexia is a common learning difficulty pertaining to reading, writing and spelling, causing young people not to engage fully with learning or drop out. Although prevalent estimates vary from region to region, it has been indicated that dyslexia accounts for 4%-8% of the UK population [1], [2]. In addition to the learning difficulties related to reading, writing and spelling, dyslexia can also bring with it many psychological effects like lack of academic self-worth or frustration. Evidence shows that students' high motivation is positively associated with their good learning performance [3], [4], [5]. This is of course true for all students, but for those with dyslexia, it is a more acute issue. Students with dyslexia usually struggle with more literacy difficulties and suffer from lower academic self-worth, and they are more likely to get demotivated and disengaged with learning compared with those without dyslexia, which reveals the necessity of applying

motivational strategies for dyslexic students to improve their learning motivation. Looking at motivation and learning more broadly, motivation, involving both cognition and emotion, is “a natural part of any learning process” that “explains the direction and magnitude of behaviour” [1]. In general, the factors that have been recognised to influence human motivation are internal states (e.g., thirst), potential outcomes (e.g., monetary gain), and the perceived probability of successful outcome [1]. The actual composition of motivation is more complicated than the aforementioned factors and is dependent on context. As a result, human motivation has been studied in various contexts, as motivation directly influences human behaviour and is defined as the arousal, direction, and persistence of behaviour [6]. In education, students’ high level of motivation to learn is associated with their learning success [4], [5]. Thus, it is vital to consider user motivation in the design and personalisation of technology to assist students with learning difficulties.

Compared with traditional classroom learning, mobile or web-based e-learning systems offer students a more personalised approach to learning as users can learn anytime and anywhere with access to a computer or smartphone in a self-paced manner. Recognition of the determinants of dyslexic users’ motivation to engage in e-learning systems is crucial to help developers improve the design of e-learning systems and educators direct their efforts to relevant factors to enhance dyslexic students’ motivation. Moreover, users with a high level of motivation are more likely to achieve a high level of engagement and better understanding [7]. E-learning systems allow users’ learning behaviour to be observed during the interaction process between users and systems for the detection of users’ motivational states in real time to enable personalised guidance or services to be provided to suit an individual user’s motivational needs for enhanced learning.

This research project hypothesised that, if learners’ motivational states can be identified, corresponding strategies can be personalised and applied to the learners’ interaction with e-learning systems to address their individual motivational needs. Establishing an explanatory model with interdisciplinary research and theories is necessary for users’ motivation including multiple dimensions. Motivation modelling in this context, as a subarea of user modelling, looks at user’s different mental factors that can determine their continued intention to use e-learning systems. However, existing research has rarely attempted to model dyslexic users’ motivation in e-learning context

from a comprehensive perspective, while few attempts only covered a specific aspect that may improve motivation such as gamification [1].

It is a truism that learners are likely to find educational games compelling and have “flow” experiences while learning, meaning the players are immersed in the feeling of full involvement and enjoyment in the process of an activity, and they are thus more likely to exhibit high levels of motivation to continue. It has been found that language learning fits well with the ethos of educational games, but in other domains such as writing skills there may be tension between the motivational effect of the game and its cognitive and metacognitive effects [8], [9]. Moreover, educational games may work well on dyslexic children, but dyslexic adults may find the games boring [10]. In contrast, with the proliferation of various e-learning systems, applying motivation modelling and personalised learning to e-learning systems as the context to fit user needs is believed to have a much wider range of user groups and application domains.

By modelling motivational factors, the e-learning environment can be personalised to improve learning experience and success based on the learner’s motivational states. This method seeks to consider the motivational factors to perform personalisation, thus foster learning success. This differs from other motivational design but overlaps with that, because motivation-modelling-based personalisation does not seek to influence motivation directly through a one-size-fits-all solution, but through the personalisation process the motivation will be influenced indirectly.

These factors identified through motivation modelling represent learners’ various motivational needs; thus, each factor should be assessed in order to design and implement personalised learning services such as personalised feedback output to user to address the motivational need corresponding to the factor. Important indicators of motivational factors include time spent on completing a learning task, quiz scores, and various sensor data. The identification of the specific indicators of motivational factors is still at its initial stage, though researchers have stated that through motivation-diagnostic input data, appropriate tactical and strategic pedagogic moves are applicable toward motivationally personalised systems [8].

In summary, a highly motivated user is more likely to learn, respond and interact effectively in an e-learning environment and vice versa. Each user has specific individual needs, and the same user also has changing motivational states when learning in an e-

learning system, thus the personalisation of motivational strategies in e-learning environments is imperative and necessary to respond to their individual motivational needs. For people with dyslexia, they usually suffer from negative psychological effects such as frustration and even learned helplessness due to the learning difficulties experienced, and thus the motivation modelling and the corresponding personalisation of strategies for them to be applied to e-learning systems are of more importance and urgency.

1.2 Research Questions

E-learning systems embedded with sensors allow learners' behaviour and physiological responses to be monitored and thus the motivational needs to be identified that influence their motivation to engage in the systems. This requires:

A) motivation modelling to identify the most relevant factors that represent multiple motivational dimensions and users' motivational needs;

B) investigation of the behavioural or physiological indicators and production of classification models for computing the motivational factors and classifying each factor into different levels. However, existing user models for dyslexics mostly considered dyslexia types and learning difficulties, and there is a distinct lack of empirical research investigating motivational determinants that are essential to users' learning behaviour and thus the learning effectiveness in e-learning environments. Due to such a lack of a model looking at dyslexic students' motivational factors, there is few guidance and support from the motivation model as a basis to design personalised e-learning systems that can respond to users' different motivational states. Accordingly, the main research questions this thesis will address are as follows.

A) How to develop a motivation model consisting of the most important factors that determine a dyslexic student's motivation to engage in an e-learning environment?

B) How to compute motivation to distinguish different levels of each motivational factor during a user's learning process in an e-learning system in real time?

C) How to apply the motivational factors and the computation method of motivation assessment and personalised learning to e-learning environments in a real-world application?

1.3 Aim and Objectives

The main aim of this research project is to propose a hybrid approach that models the multiple dimensions of motivation for people with dyslexia and computes the dynamic motivational states including the multiple dimensions. This will ultimately enable personalised motivational strategies to be applied to e-learning systems to address their specific motivational needs identified through real-time motivation computation.

Specifically, according to the main research questions, the objectives of this thesis are:

A) to identify factors related to key motivations and barriers that affect dyslexic users' continued intention of using e-learning systems (Section 3.3);

B) to construct a conceptual motivation model based on the identified factors combining different perspectives, namely from perspectives of psychological theories, technology acceptance and an empirical study with target users (Section 3.3), and to design a multi-item questionnaire to quantitatively specify the weights of the factors along with their interrelationships within the motivation model (Chapter 4);

C) instead of users' subjective self-reported data collected by the questionnaire, to capture objective dynamic data such as learning behaviour and physiological data collected by sensors and produce classification models for computing the motivational factors identified by previous steps (Chapter 5). This will enable real-time assessment of a user's motivational states during the learning process;

D) to create a computational motivation model using ontology-based user modelling technique to represent the motivational factors formally and explicitly (Section 3.4), and to propose a semantic rule-based reasoning mechanism for supporting motivation-based personalised learning (Chapter 6). This will allow data captured from users to be read, processed and understood by machines precisely and intelligently and facilitate personalised learning experience to be provided based on learners' motivational states in real time;

E) to propose a framework of motivationally personalised e-learning systems based on the previous steps that will guide the design of e-learning systems, and to implement a prototype that applies the developed motivation model, classification models, and personalised motivational strategies to a real-world scenario, and to conduct user studies

to evaluate the user experience compared to the traditional e-learning system that doesn't output the motivationally personalised strategies (Chapter 7).

1.4 Research Methodology

The research methodology in this thesis has employed a hybrid approach, namely combining the strengths of qualitative and quantitative analysis methods, to motivation modelling. This thesis examines a variety of factors representing different dimensions which affect dyslexic people's motivation to engage in e-learning systems from different perspectives and establishes their interrelationships.

After the motivation is modelled with various factors, the use of sensors including an eye tracker and an EEG sensor is explored for motivation computation to assess the level of the motivational factors for learners with dyslexia in real time. Afterwards, the motivational needs assessed by sensor data should be responded to by e-learning systems through personalisation. The thesis then proposes a semantic rule-based approach for supporting dynamic personalised learning based on the motivation model and sensor-based motivation computation.

Finally, a framework of motivationally personalised e-learning systems is proposed and implemented partially in a prototype to guide future design and development of motivationally personalised e-learning systems.

The project consists of five phases of research. These phases are planned and implemented in order to robustly develop the motivation model and enable real-time motivation computation for personalised learning.

To model motivation, the first question to be answered is: what makes a student with dyslexia motivated to continue to learn or not in an e-learning environment? We need to understand the factors behind the continued use intention. A main challenge is to integrate different research perspectives and theories into a compound model. To answer this question, extensive literature review is conducted on related work to combine perspectives of psychological theories, technology acceptance and dyslexics characteristics and construct the conceptual motivation model. A qualitative study is then used to collect first-hand data about dyslexic students' views empirically and to elicit the factors that should be taken into account to model the motivation for dyslexic students in

their use of e-learning systems. This allows coding and thematic analysis to take place, gathering together the different themes that define the motivations and barriers behind the continued use intention pertaining to both users themselves and users' perceptions about the system. Accordingly, the conceptual motivation model is refined combining the prior research theories, findings and the qualitative analysis of data collected from an empirical study with dyslexic students.

Having a conceptual motivation model with motivational factors and their interrelationships, it is essential to further specify the model quantitatively by exploring how these factors work together to impact on the motivational consequence, i.e., continued use intention, and how these factors relate to each other. This requires statistical modelling approach to parameter estimation. Structural Equation Modelling (SEM) is employed to achieve this goal, which results in a connected graph of the themes established with parameters for each connection. Specifically, each factor in the motivation model is represented by a latent variable, and a multi-item questionnaire is designed to measure each latent variable with multiple items. It is distributed amongst people with dyslexia to acquire empirical data. As the two different approaches of SEM, covariance-based analysis (CB-SEM) is primarily used for confirmatory research purpose, while variance-based analysis (PLS-SEM) is preferred for exploratory research purpose. More details of SEM including CB-SEM and PLS-SEM approaches will be introduced in Chapter 4. Because the purpose of analysis is not only to confirm the conceptual model built from the qualitative approach but also to explore the weight of each factor and the quantified relationships between the factors, both CB-SEM and PLS-SEM approaches are applied to determine the quantitative mapping between dyslexic people's continued use intention and motivational factors while allowing comparison between the results from the two approaches.

After the conceptual motivation model is developed from both the qualitative and quantitative approaches, the next question to be answered is: how to compute the motivational states of users with dyslexia dynamically during their learning process in e-learning environments?

Firstly, what motivational states should be computed? Motivational consequence has many possible causes. It is not enough simply to ascertain that the student is motivated or demotivated for the system to make right pedagogical move. It is essential to trace the

causes of the motivational consequence. The student might be demotivated because the system is hard to use or because they feel the system doesn't fit their learning needs. What needs to be done in these two cases is very different. The motivation model enables the explanation of how a user get into a current state of continued use intention. Each factor in the motivation model represents a cause of continued use intention, a motivational dimension, as well as one of users' motivational needs. Therefore, each factor in the motivation model should be computed to assess its current level when a user is learning in an e-learning system to identify the user's specific motivational need in real time.

Secondly, what data should be captured to compute the motivational states, and how? This thesis explores the possibility of using physiological and behavioural data captured by sensors including an eye tracker and a wearable EEG device for automatic motivation assessment in real time including multiple dimensions identified from motivation modelling. To achieve this goal, an experiment is conducted with participants with dyslexia to capture their sensor data including EEG data and eye-tracking data. The experiment also collects participants' self-reported motivation during the learning process to label data on different motivational factors identified in previous steps. Then after the feature extraction and selection process, a classification model is produced using logistic regression to compute each motivational dimension by predicting its high or low level. This information can be then consumed by systems to perform personalisation accordingly.

After motivational states are computed and the motivational needs are identified, the next question is: what personalisation should be applied to address the motivational needs identified? In other words, what system reaction, such as praising or providing suggestion, will positively influence a student's current motivational state? There are many aspects of learning that can be personalised, such as course quantity, reading and writing support, all of which aims at improving gains of knowledge and skills, but without motivation none of those can be achieved. Satisfying users' motivational needs is the prerequisite of any long-term engagement in e-learning systems and the learning effectiveness, so this thesis focuses on motivational aspects of dyslexic users' needs, investigates motivation modelling and applies personalised motivational strategies that adapt to their motivational states, which can be called motivation-based personalised learning. This reasoning about personalised strategies can be used by e-learning systems

to output appropriate feedback to respond to a specific motivational state and address the learner's corresponding needs.

This thesis proposes an approach using ontology and semantic rules to illustrate the process of sensor-based motivation assessment and rule-based personalisation of motivational strategies. Ontology is used for knowledge representation, specifically, to represent raw data and the extracted features about users' learning behaviour or physiological responses in a structured, machine-readable manner as well as to represent the concepts of motivational factors in the conceptual motivation model and the motivational strategies to be personalised to adapt to users' motivational states. The extracted features are selected and then used to infer the high or low level of each motivational factor from the logistic regression models. Representing each concept of motivation and features for computing motivation by a specific ontology facilitates an explicit expression, extensibility and reusability of the concepts, allowing data to be readable and understandable by machines.

The semantic rule-based reasoning mechanism is adopted using a set of rules to define the causal relationships between a user's motivational states and the system reactions of personalised motivational strategies. A reasoning engine is responsible for generating and feeding personalised motivational strategies back to users according to the motivational states identified. Semantic web rules language provides explicit and transparent definition of the personalisation rules in the system and encourages the reusability and modifiability of the rules. This approach makes it easy to modify a component of personalisation without having to reconfigure the whole system or amending the low-level implementation code. Additionally, to investigate the effectiveness of motivational strategies, this thesis exploits sensors capturing EEG and eye-tracking data and compares the sensor data before and after each strategy is applied while users are interacting with an e-learning system.

Finally, this thesis describes a framework of motivationally personalised e-learning systems to guide the future design and implementation of the systems that attempts to detect learners' motivational states and respond to them dynamically with personalised motivational strategies. The framework specifies the diagnostic input data for computing motivation including its multiple dimensions and the system reactions for outputting personalised strategies in real time. Additionally, a prototype of gaze-based learning

application is designed and implemented to apply the framework to the real-world scenario as an example, which employs an eye tracker to monitor dynamic eye gaze for motivation assessment and incorporates part of the motivation model, the classification models to assess the states of the motivational factors, i.e., high or low levels, as well as the personalised motivational strategies to respond to the motivational states detected in real time. Initial user studies are conducted to evaluate user experience, the effectiveness of the gaze-based motivation computation and personalised feedback in the prototype, compared to the traditional system that does not have gaze tracking for real-time motivation assessment and corresponding personalisation.

1.5 Contributions to Knowledge

The area of motivation modelling and computation for people with dyslexia has not obtained a comparable level of attention with a relatively low number of publications. This thesis presents a hybrid approach to motivation modelling for people with dyslexia and specifies the sensor-based motivation computation for real-time assessment of motivational states. A rule-based reasoning mechanism is described for personalisation of motivational strategies to be output to users to adapt to their motivational states detected during the learning process in e-learning systems.

The conducted research has led to the following contributions.

A) A conceptual motivation model is constructed for people with dyslexia in e-learning environments that specifies the motivational factors and their quantitative mappings in the model. It combines psychological theories, technology acceptance perspectives from prior research and dyslexics' views from both qualitative and quantitative empirical studies with dyslexic students. This model provides a comprehensive view and explanatory framework to deepen and broaden the understanding of motivational factors including both intrinsic and extrinsic ones behind dyslexic users' continued use intention in e-learning systems. It also produces insights in the relationship between system design and user experience, helping designers reprioritise design considerations as well as reveal potential undetected problems relating to system usability.

B) A multi-item questionnaire is designed to measure the motivational factors in e-learning context. This questionnaire is designed by adapting the items from the

acknowledged questionnaires to the present research context and operationalising the new factors in the motivation model that emerge from the modelling process. The reliability and validity of questionnaire have been tested; thus, the questionnaire is reusable in future.

C) A novel approach to motivation computation is introduced using dynamic sensor data that facilitates real-time motivation assessment compared to the traditional approach using self-reported data. This thesis exploits two sensors, an eye tracker and a wearable EEG device, and produces a classification model using logistic regression for computing each motivational factor by classifying it into high or low level based on an integrated set of features selected from sensor data including eye-tracking and EEG data.

D) The features extracted and selected from the raw sensor data progress the insights into the relationships between the sensor data, i.e., the brain activities captured by the EEG device and the eye movements captured by the eye tracker, and learners' motivational states. This contributes to the knowledge about the sensor features that can indicate the level of the motivational factors. The feature selection process of the EEG and eye-tracking data is inspiring and reusable for future research when other sensors are introduced to investigate and improve the prediction accuracy of the motivational states.

E) A sensor-based motivation assessment system architecture is proposed for motivation-based personalisation using ontology and the classification mechanism using logistic regression to support real-time motivation assessment, and semantic rule-based reasoning mechanism is used for personalisation of motivational strategies. This allows for explicit, formal knowledge representation of the motivational factors, sensor features, personalisation rules, and motivational strategies as well as better sharing and reusability of the knowledge.

F) The sensor-based evaluation of motivational strategies provides empirical evidence of the effect of the strategies, and the evaluation methods are reusable for evaluating other strategies and stimuli in e-learning environments.

G) A framework of motivationally personalised e-learning systems is introduced and implemented partly in a prototype of gaze-based learning application. The application prototype implements part of the proposed methods for outputting personalised motivational strategies based on real-time gaze-based motivation assessment. The proposed framework and implemented prototype will guide future design and

development of motivationally personalised e-learning systems.

H) A series of empirical user studies is conducted for evaluating the prototype of gaze-based learning application. Evaluation results from both learners and experts provide evidence on the advantage of the gaze-based learning application compared to a traditional e-learning application without incorporating the motivation model, computation method and personalised strategies, thus highlighting the strength and usability of the proposed model and methods for motivation-based personalised, enhanced learning in real world.

I) The motivation model, sensor features selected, classification mechanism using logistic regression algorithms for real-time sensor-based motivation computation, and rule-based reasoning mechanism for motivation-based personalisation are all reusable, producing great insights for both HCI researchers and practitioners to apply the knowledge and methodology to future research and applications in different domains.

1.6 Thesis Outline

This thesis is outlined as follows.

Chapter 2 Related Work

This chapter delineates the prior research work related to the target user group, present research context and the present research topics, including dyslexia as the most common learning difficulty, assistive technology for people with dyslexia, motivation modelling from different perspectives, approaches to motivation computation and assessment, personalised learning with the emphasis on motivation-based personalisation applied to e-learning environments.

Chapter 3 Motivation Modelling for People with Dyslexia in E-learning Environments

This chapter identifies the motivational factors that determine dyslexic users' continued intention to learn in e-learning environments from both prior theories and an empirical study directly with dyslexic students to combine different perspectives and develop a conceptual motivation model. Using the concepts and relationships identified in the conceptual modelling process, an ontology-based computational motivation model is developed to formalise the knowledge related to the conceptual motivation model and the

possible personalisation components in e-learning systems.

Chapter 4 Quantitative Model Specification and Parameterisation

This chapter further specifies the conceptual motivation model quantitatively with parameters estimating the relationships between factors in the motivation model based on a quantitative empirical study with dyslexic students. Furthermore, this chapter also applies two types of statistical modelling approaches to the collected data and compares the results from the two analysis approaches.

Chapter 5 Real-time Sensor-based Motivation Computation

This chapter explores the possibility of real-time motivation assessment based on sensor data combining both eye-tracking data and EEG data. A new approach that combines eye tracking and EEG along with other learning behaviour data is proposed for real-time motivation computation. The chapter delineates the approach, the experiment with dyslexic participants and the process of feature extraction and selection, and the results of the logistic regression models produced to predict the level of each motivational factor in the motivation model.

Chapter 6 Motivation-based Personalised Learning

In this chapter, based on the ontology-based motivation model and the classification mechanism using logistic regression algorithm for real-time motivation computation, a rule-based reasoning mechanism is proposed based on ontology and semantic rules for supporting dynamic personalised strategies to be provided during users' learning process in e-learning systems.

Chapter 7 A Framework of Motivationally Personalised E-learning Systems

In this chapter, a framework is proposed to guide the design of motivationally personalised e-learning systems. The framework takes users' motivational states including various motivational dimensions into account and respond to them dynamically, and an essential part of the framework is incorporated and implemented into a prototype of gaze-based learning application. Finally, the evaluation process is described in detail for the prototype via a series of user studies.

Chapter 8 Discussions and Conclusions

This chapter reflects on the entire thesis and recapitulate the contributions to knowledge made throughout the research project. Furthermore, potential future work provides new interesting challenges followed by a short conclusion of highlights in this research work.

Chapter 2 Related Work

2.1 Introduction

In this chapter, representative related work is presented and critically analysed. Specifically, this chapter presents and discusses prior research related to learning difficulty and dyslexia, assistive technology to support learning for people with dyslexia, existing theories and models from perspectives of psychology and technology acceptance that offer insights into the users' motivation to engage in e-learning systems. Moreover, the computational motivation modelling approaches and different data sources for motivation assessment are described. Furthermore, it summarises the personalised learning process, prior attempts on personalised learning of people with dyslexia as well as motivation-based personalisation through the use of motivational strategies in e-learning systems based on motivation models and assessment of users' motivational states. Finally, the chapter is concluded with emphasis on the research gap and the main aim of this thesis.

2.2 Learning Difficulty and Dyslexia

2.2.1 Learning Difficulty and Learning Disability

People's difficulties with learning can be split into two types: learning difficulty and learning disability. Learning difficulties are deficiencies with the ability of brain to receive, process, analyse or store information. Common learning difficulties include dyslexia, dyscalculia and dyspraxia. Dyslexia affects verbal functions, dyscalculia affects numerical functions, and dyspraxia affects coordination and balance. Learning difficulty differs from learning disability mainly in two aspects. Firstly, learning disability is usually more serious. It affects not only how people learn at school or college but also the rest of their lives, as they can find it difficult to understand new information or live independently, and common learning disabilities include autism spectrum disorder and dementia [11]. Secondly, learning difficulty relates to specific forms of learning obstacles and does not affect the overall IQ of an individual, while an individual with learning

disability is supposed to have an IQ scored less than 70 [11]. It should be noted that in the US, the terms are defined differently, where intellectual disability and mental retardation are used for what is called learning disability in the UK, and learning disability in the US covers what is regarded as learning difficulty in the UK [12]. The two terms along with learning disorders are sometimes interchangeable.

Learning difficulty can be classified according to the severity of impairment in learning [12]. The Special Educational Needs codes uses the terms “moderate learning difficulty”, “severe learning difficulty” and “profound and multiple learning difficulty” [13]. Moderate learning difficulty involves difficulties across all areas of the curriculum though pupils can remain in mainstream schools. Severe learning difficulty refers to significant impairments, which means they may have trouble with mobility, communication and self-help skills. Profound and multiple learning difficulty means that there are also other difficulties such as medical conditions or physical disabilities in addition to severe and complex learning difficulties. In UK, the term “learning difficulty” usually refers to Specific Learning Difficulty (SpLD), which affects a specific aspect of learning [12]. Dyslexia is the most common SpLD, accounting for approximately 4% of the population [14]. It has genetic origins as well as being neurological in nature. It is a deficiency of language which can be based on speech or written text resulting in issues with word recognition, writing, reading and spelling [14].

2.2.2 Assessment and Intervention Practice

There is a consensus that dyslexia predominately involves problems with the development of effective word-decoding strategies, low levels of reading fluency and poor spelling performance [15]. People with this problem often have difficulties with phonological processing skills given adequate working memory performance, and difficulties related to grapheme-phoneme correspondence resulting in poor decoding skills and unsatisfactory development of a “sight” vocabulary [16] and poor performance on tests of Rapid Automatised Naming (RAN) is highly diagnostic for the problem [17].

Based on the definition, the York Adult Assessment-Revised (YAA-R) is a recognised test battery for the assessment of dyslexia in university students comprising tests of reading, spelling, writing and phonological skills [18]. Furthermore, there are various

measures of reading ability such as the Neale Analysis of Reading Ability-Revised (NARA) and selected subtests from the Woodcock-Johnson Tests of Achievement-Revised (WJ-Ach); also, Peabody Picture Vocabulary Test-Third Edition (PPVT-III, a measure of verbal intelligence) can be highly helpful to diagnose learning difficulties like dyslexia, as research found that it is significantly correlated to verbal intelligence [19]. However, more cautious consideration is required for the choice of measurement tools and how test selection impacts on the diagnostic models used for dyslexia as there has been research questioning the reliability of certain measurements. For example, Ferrier et al. [20] examined factors affecting the free writing speed of 11-year-old students using the Group and Individual Assessment of Handwriting Speed, and concluded that vulnerability to teacher effects and other factors degraded the reliability of free writing as a method to measure writing speed.

Since learning disabilities may also have an influence on an individual's reading ability [15], it is necessary to consider assessments to identify it. Psychometric assessments are mainly used to assess intellectual functioning on the basis of normal distribution of general intelligence. For example, the Wechsler Intelligence Scale for Students Fourth Edition (WISC-IV) [21] is a commonly adopted one to assess students' intellectual functioning. Other assessments are supposed to be considered including formal assessments such as the Bayley Scales of Infant Development [22] and the Leiter International Performance Scale [23] as well as detailed observations of the child within various environments or play based assessments [24]. Another aspect worthy of attention is the understanding of a developmental history of the child being assessed such as the information with regard to important unusual events which happened during their lives and how that might impact their skills now [25]. Such information together with the formal assessments can help make a more accurate diagnosis. After a child is identified as a dyslexic, early intervention is crucial and has attracted much attention of both researchers and medical practitioners [10]. Research studies have supported that training and interventions designed to facilitate phonological awareness and letter-sound mapping have a positive effect on reading ability [26].

Research has compared different schools regarding treatment of dyslexia from psychological perspectives [10], [27]. Cognitive approaches indicate that individuals are able to monitor and control their internal processes according to the norms and rules of

objective methods such as the rules for grammar in language; however, the norms and rules are unavailable for the senses, and the student's intellectual skills risk being overtaxed if cognitive methods are used, making it difficult to integrate motivation in learning due to the differences between cognitive skills, and needs and drives [27]. A range of intervention programmes has been implemented involving structured, intensive phonic instruction, text reading fluency, vocabulary and comprehension. For example, phonological-based interventions are targeted at dyslexic spelling difficulties; "word study" intervention which helps students with dyslexia by teaching them phonic strategies regarding Grapheme-Phoneme Correspondence (GPC) to read monosyllabic words and effective strategies to read multi-syllabic words; Some students with reading difficulties may also need intervention that aims to improve oral language [10]. In addition, "word study" including syllabic and orthographic study as well as motivation are also key ingredients to be considered particularly for older readers in primary school for successful intervention [10]. There are a variety of variables influencing the efficacy of intervention programmes, mainly categorised as cognitive-linguistic variables including phonologic awareness and verbal memory and environmental factors such as personnel adopted in the programme [10].

As for the cognitive processes in spelling, the sub-lexical processes of the dual-route working of grapheme and phoneme and the conversion between them are identified crucial, so is the lexical-level working of semantic and orthographic system [10]. With regard to the environmental factors, the main variables examined are group size, duration of programme, length of intervention sessions and personnel fidelity. It is shown that intervention in small group size (1-3) and individual tutoring have similar effectiveness, though individual tutoring is more effective for severe dyslexia, and it is found that duration of 10 weeks and 20 weeks have similar effectiveness, maintaining for 11 months, also it is suggested that individual sessions not exceed 30 minutes; additionally, professional teachers and trained personnel are found to have similar effects on the efficacy of intervention [10].

These findings provide basic ideas and insights for the design and implementation of intervention programmes. As for the evaluation of the intervention efficacy, randomised controlled study is the most rigorous, and further longitudinal research studying looking

for the presence of persisting reading and spelling difficulties and the change of reading ability after the child has returned to regular literacy instruction in classrooms.

2.2.3 Cognitive Difficulties of Dyslexia

Dyslexics have differences in the neurobiology of the brain. In the brain of someone with dyslexia, the temporoparietal languages areas of the two sides of the brain are symmetrical instead of being left-side dominant, also there are differences in the development of the visual system in the brain [28]. Relatively low motion sensitivity, poor visual localisation and phonological problems are some of the features of the dyslexic brain, which affects the ability to use words and its constituents to make up speech, and studies also show that for an acoustic stimulus, the electroglottograph (EGG) amplitude modulation is lower [10]. These difficulties can lead to problems in the acquisition of certain language skills and affect reading, and there will be poor ability in oral reading skills, reading comprehension, reading fluency, phonological awareness and word spelling [10]. More specifically, reading abilities involve both decoding factors and comprehension factors, and the decoding factor affects reading individual words whereas the comprehension factor is more about understanding, memory and acquired knowledge [19]. It is these difficulties in reading and writing that affect a dyslexic's learning ability. This barrier to better comprehension can result in below normal skills for their age. The main reading problem is a failure to develop adequate phonological skills and memorisation difficulties [29]. Dyslexics have difficulties regarding the language-related components, or the visual components or the need for rapid cognitive processing [30], [31], and the three difficulties that students with dyslexia have can also be classified as visuo-spatial difficulties, speech sound difficulties and correlating difficulties [32], which require help in different areas.

Despite of writing, spelling and reading difficulties, dyslexics also have problems of incoordination, left-right confusions and poor sequencing in general both temporally and spatially [28]. Therefore, students with dyslexia have different learning styles from others and they need specific personalised teaching and instructions to help them avoid or overcome the weaknesses and play their strengths to the greatest extent. They are primarily picture-thinkers through mental or sensory images rather than using words,

sentences or internal dialogues in their minds, so they are poor with word-based sequential and step-by-step reasoning, but very good at creative endeavours and solving real-world problems [29]. Accordingly, current educationalists and psychologists have developed a variety of ways to improve both brain efficiency and reading related abilities.

2.2.4 Affective Difficulties of Dyslexia

In addition to the cognitive difficulties, dyslexia can bring with it many psychological effects like lack of self-worth or frustration. Singer [33] showed that there have been experiences of intense emotional distress due to dyslexia in school-aged students which is made worse due to bullying in school as well. Firth et al. [34] cited several papers that showed students can develop maladaptive coping strategies which can lead to learned helplessness, avoidance or social withdraw as well as frustration and anger that they were not better supported. Burden [35] summarised that although people with dyslexia might not necessary have decreased social self-worth, studies have shown that there is significantly lower level of academic self-worth among people with learning difficulties or dyslexia.

This lower level of academic self-worth or self-concept can affect their motivation especially due to learned helplessness, and the motivational aspect was addressed looking at self-efficacy, learning attributions and locus of control [36], [35]. It was found that those with an internal locus of control will have greater motivation and academic self-concepts leading to better academic success; furthermore, the paper shows that this reduced academic self-concept is malleable if the learning environment is tailored toward an ethos of success [35]. Firth et al. [34] demonstrated through a school-wide dyslexia programme that perceived control and adaptive coping can be improved. Burden [35] further stated that more research is necessary to explore the negative feelings and how they manifest as well as how best to improve the motivation and academic self-efficacy of the learner.

People with dyslexia should be assisted through interventions that address both their cognitive and affective difficulties to improve the learning and the lives of those affected. Assistive technology can help alleviate some of the issues, for example helping with

reading, writing and spelling which they might be behind their peers. This can potentially increase academic self-worth though more studies are necessary to examine how to improve the motivation and self-efficacy for the student, which is seen as an important factor leading to better academic success.

2.3 Assistive Technology for People with Dyslexia

Assistive technology, defined as "any item, piece of equipment, or product system, whether acquired commercially off the shelf, modified, or customised, that is used to increase, maintain, or improve the functional capabilities for individual with a disability" and can be beneficial for students with disabilities or difficulties as part of their Individualised Education Program (IEP) [37].

In an experiment investigating the effect of assistive technology on students with dyslexia, participants receive a recording device, text-to-speech software and concept mapping tools in addition to a standard computer system to help with their studies. The result shows that most participants are satisfied or very satisfied with the hardware and the software that they receive, including both the computer systems and the special purpose software [38]. Assistive technologies applied to dyslexics include those for reading evaluation and comprehension of texts, software and e-readers used to promote better reading performance in dyslexics [38].

2.3.1 Design Considerations for People with Dyslexia

Understanding the reason of difficulties of interaction with technology is of crucial importance to decisions on what support should be provided and how design can meet specific users' needs. Assistive technology can be very beneficial to those with learning difficulties if designed appropriately. Lots of recommendations and practice guidance in different aspects including usability or psychology have been provided for designers [39]. For example, it is suggested that users with specific needs be included into design process, and positive reinforcement should be adopted. Users with cognitive and learning difficulties can also benefit from scaffolding techniques which can be utilized to build support structure in training [39]. A majority of the considerations are about usability and

user experience of user interface, while concrete practices from psychological or educational perspectives to address individuals' specific needs are relatively insufficient.

Technology should be mapped to individuals' specific needs including both educational needs and psychological needs. It is suggested that the design of mobile assistive learning technology firstly aligns with the principles of universal design of learning providing multiple means of representation, engagement and expression, and then consider other users and context factors, in this case, to address the educational needs of students with dyslexia [30], [40]. For example, when reading documents, dyslexic readers can benefit from text-to-speech software or summariser software; when developing essays or presentations based on existing knowledge, dyslexic individuals can utilize concept mapping software to brainstorm ideas and their relationships using their creative thinking and basic knowledge, and can also help memorise data.

As for psychological aspects, students with dyslexia tend to have problems with short term memory for serial order, self-identity and academic self-concept, self-esteem, motivation, emotion, stress, social relationship, attention, thought, verbal intelligence and school refusal [41], [35], [19]. Serious dyslexia is associated with anxiety and depression and compulsive behaviours as well [42]. People with dyslexia are also found more comfortable learning in an environment they can control and adapt easily [34].

Correspondingly, technology is expected to help with these problems. For example, to improve communication skills, technology such as class web pages, course management systems and electronic discussion groups can be applied. Ease of use, motivation, self-paced online course and adaptable learning style as well as learning games can be helpful to develop the independence and confidence of students with dyslexia. Providing opportunities to use novel ways to work, present and think can also help students with dyslexia make good use of their creativity.

Technology should be designed in a way that engagement and interest can be improved, and skills learned can be retained by self-assessment tests. Necessary support for dyslexic learners such as instructional video can reduce their cognitive load and thus avoid frustration. Time emphasis, in-time reward and immediate feedback are found useful to improve motivation and positive emotion. To design technology for specific user groups such as students with dyslexia, user models to guide design and personalisation are crucial.

Before moving forward to modelling and personalisation, the categories of assistive technologies for students with dyslexia are introduced in the next section and the reason why e-learning systems are used as the context of the present research.

2.3.2 State of the Art of Assistive Technology

Assistive technology has developed along with the increase in technology, resulting in assistive technology available for all manners of difficulties. Assistive technology has varying levels of sophistication and can be hardware or software or a combination of both [38]. General-purpose hardware includes computers and personal digital assistants, while special-purpose hardware includes handheld spellcheckers, recording devices, scanning reading pens and portable note takers. General-purpose software includes word processing, speech recognition software and typing tutor programs, while special-purpose soft wares are talking dictionaries or concept mapping software and word prediction and word banks such as typing and word selection systems [38]. For software technologies, assistive software should be differentiated from literacy learning software and e-learning software. They are all designed to aid the learning process, substituting for any difficulties that a person may have. Assistive software includes text-to-speech software, speech-to-text software, typing correction software, satellite navigation systems (to provide real-time information or map), synthesis and summariser software, concept mapping software (to help brainstorm ideas and use creative thinking to develop presentations and essays/memorise data) and validation and proofreading software [43]. On the other hand, literacy learning software works on developing intrinsic skills (e.g. working memory) or literacy skills (e.g. phonological analysis skills) and e-learning contains both acquisition of knowledge and verification of learning [43]. Other assistive technology for dyslexics includes password management systems, desktop reminders such as post-its, time management systems, screen recording systems, on-screen magnifiers, screen sharing and video conferencing and data sharing systems. Moreover, training in assistive technology is helpful to effective usage including basic video guides for software use and on-screen demonstration. The author also indicates that blended learning combining technology-based learning and human support is key for all learners [43].

In general, the assistive technology available can be classified into the areas that the technology helps with reading, speech, writing, mathematics and organisation and self-management [44]. Specifically, for reading difficulties, text-to-speech uses computer-synthesised speech to read out digital text providing visual as well as audio to the user. This can be used on many different devices and allows customisation of parameters to suit the user's needs. Digital text in this way can also be processed or restructured for ease of understanding, like rewording, descriptions or definition checking [44]. Other assistive technology for reading difficulties include Accessible Text where a user has multiple choice of text format [45] and Supported e-Text where digital text is processed with various strategies such as rewording or highlighting [46]. For writing difficulties, commonplace tools used by students like the word processor can also be very beneficial to those with difficulties. The ease of editing and the presence of spell checking makes the writing process much easier. Speech recognition software like Dragon Naturally Speaking is also used to assist input where typing is a difficulty [43]. Technology helping with mathematical difficulties not only supports mathematical literacy but also helps with computational and problem-solving issues. In this category, calculators, especially those with multi-function and graphing functions are very valuable to increase conceptual understanding and lighten the cognitive load. Alternative to numerical data, physical or virtual objects can be used to represent mathematical concepts and manipulated to aid understanding [44]. Organisation and self-management software targets at the general learning or writing process and help with executive functions such as organisation and memory [47]. Assistive technology falling into this category is common technology that can be used by every user; for example, mobile devices or smart pens can be used to store information supporting memory difficulties or providing reminders and time planning capabilities. Graphical organisers can help students to visually represent their ideas [44].

With the proliferation of mobile technologies like smartphones, iPod, and tablet computers, they are being used not just for enjoyment but also for learning. The customisability can allow each student to be provided with a tailored set of applications to help their specific needs, a virtual technology toolkit, and the accessibility of material is also increased along with its interactivity providing an enhanced presentation of concepts [30]. Mobile devices are particularly useful for dyslexia as the ease of customisation can allow the devices to adapt to the dyslexics' different difficulties might

have as well as being highly portable. The traditional approaches to dyslexia are different depending on different theories, mobile applications can adopt one of the approaches to digitalise and implement the theory; for example, ensuring that the learning process is multisensory is crucial [48], and mobile apps can fulfil this role.

In summary, there is no off-the-shelf answer to dyslexia, but there are many key factors to be considered such as user profile, including dyslexia types, preferred learning styles, affective factors, etc. Assistive technology, ranging from a hardware device to a software plugin, can help dyslexic learners to overcome some of the difficulties that they face. There is now a wide range of different technologies available helping with many aspects of dyslexics' needs including reading, writing, mathematics and organisation. These technologies are becoming increasingly adaptive and more mobile.

However, there are still shortcomings. Compared with having tutors in the classroom, there is a lack of context-dependent feedback such as encouragement provided by assistive technology to explore ideas and solve problems, as well as the constant measurement of students' responses and the corresponding feedback. Furthermore, most products were developed from a well-intentioned concept; instead, they should involve wider user groups with diverse strengths and weaknesses and those supporting them in the design process. Moreover, the software may just help users learn the strategy to solve the tasks instead of targeting literacy skills [43]. There is also a shortage of independent measurement and evaluations specifically looking at how technology can support dyslexic individuals. Most research only involves the general population and thus gets positive results. Evaluations are also usually conducted by developers with unavoidable bias. In short, the technology needs to meet the needs of each individual dyslexic to help them best. Therefore, there is a lack of suitable methodology and empirical studies to ensure that the technology is designed and developed most appropriately for the specific needs of dyslexic individuals.

As researchers have pointed out that the role of "cognitive prosthesis" in which many assistive technologies have played, the availability, high cost and training needs are all barriers that prevent their adoption and use by students with difficulties or disabilities [49]. Therefore, there should be systems available and easily accessible to all students. On one hand, e-learning systems have been differentiated from assistive software that is

often designed to fulfil certain specific functions to provide cognitive assistance, as stated before; on the other hand, researchers have also stated that mobile apps, desktop apps and web apps or extensions can serve as assistive technology to support students with dyslexia and enable them to “learn and function independently” [43].

The increasing development of e-learning applications in recent decades have benefited ubiquitous computing and education by providing freedom of choice to satisfy various needs and preferences of learning places and paces. E-learning systems in computers and other mobile devices, including mobile applications mentioned before, can serve as the most common “assistive technology” that is able to provide personalised learning assistance in various aspects for all, no matter whether they have learning difficulties like dyslexia or not. In that way, students with dyslexia will feel more engaged in the generic education system with access to the full range of educational options as well as peers and mentors and thus benefit their academic self-worth.

Furthermore, e-learning systems have made it possible to observe users’ learning behaviour and capture data during the interaction process between users and systems to detect users’ mental states and individual needs in real time. Once users’ mental states and needs are detected, e-learning systems can respond to them dynamically by using personalised reactions to address their needs, encourage their continuous effort, and improve their experience to eventually enhance learning efficiency and effectiveness. Any intelligent tutoring systems, also known as personalised e-learning systems, are in nature e-learning systems which provide automated personalised guidance or services to suit an individual user’s cognitive or emotional states for enhanced learning. That’s why e-learning systems are used as the context of the present research of motivation modelling and computation and applying that for personalised learning.

Due to the absence of human experts’ intervention, learners’ motivational states in e-learning environments has gained more and more attention in HCI research field. The next section will explain in detail the motivation modelling and computation with existing research and approaches.

2.4 Motivation Modelling and Computation

Motivation, as an essential foundation of learning success [4], [5], has received relatively low level of attention in e-learning area. Associated with both cognitive processes and emotional states, motivation is a multi-dimensional concept that results in learners' continued intention of using an e-learning system, thus leading to better chance of learning success. As stated, e-learning systems provide an opportunity to track learners' behaviour and states while they are learning in the systems and thus provide personalised assistance. This thesis will put effort in modelling dyslexic learners' needs focusing on motivational factors and providing personalised learning based on motivation. The following sections will present motivation modelling from different perspectives, namely psychological, technology acceptance and computational perspective.

2.4.1 Motivation Modelling from Psychological Perspective

Motivation modelling in the present e-learning context for the target user group should be treated as a subdivision of HCI, which describes the process of establishing a conceptual understanding of the factors that determines a user's motivation to engage in an e-learning system.

Human motivation has drawn psychologists' attention for over a century. A variety of motivation theories and models have addressed the motivational factors from different perspectives to explain people's behaviour intention. Motivation is a multi-facet concept, considered by many to have multiple factors. Shroff et al. [50] have broken down motivation into several components: perceived competence, perceived challenge, feedback, perceived choice, perceived interest and perceived curiosity. The perceived competence can be further made up of self-efficacy, anxiety or emotion as used in Sun's study [51]. Perceived curiosity is also an important part of motivation which is discussed in more detail by Arnone et al. [52] with personal, contextual and situational conditions the main contributors to curiosity. Theory of Planned Behaviour assumes that intention immediately determines behaviour, which is shaped by attitudes toward the behaviour, subjective norms and perceived behaviour control [53]. Ryan and Deci [54] has distinguished extrinsic motivation as "doing something because it leads to a separable

outcome” from intrinsic motivation as “doing an activity for the inherent satisfaction of the activity itself”. In other words, extrinsically motivated behaviour is driven by the reward of the activity, while intrinsically motivated people are attracted by the activity that they find pleasant or challenging. Chan [55] has mentioned the importance of intrinsic motivation for high quality and performance, especially the importance of autonomy, choice and cognitive stimulation for this intrinsic motivation. The intrinsic motivation often accompanies increased attention and intrinsic goals. Researchers have also looked into factors contributing to intrinsic motivation, which are perceived challenge, feedback, perceived choice, perceived interest, curiosity and perceived competence consisting of self-efficacy, anxiety or emotion [50], [51]. Deci and Ryan’s self-determination theory supposes that people’s motivation is self-determined by the degree to which their innate psychological needs are satisfied, i.e. autonomy, competence and relatedness [54]. Self-determination perspective also involves Cognitive Evaluation Theory (CET) and Organismic Integration Theory (OIT). Specifically, CET is used to model the impact of psychological needs and social conditions, while OIT classifies extrinsic motivation with emphasis on contextual factors influencing internalisation of extrinsically motivated behaviours. Several other theories also make up this perspective. For example, Causality Orientations Theory (COT) and Basic Needs Theory (BNT) look at individual differences and autonomy, respectively [56]. Bandura’s social cognitive learning theory explains behavioural intention with one’s perception of control over outcome, external barriers and self-efficacy [57], [58]. Keller [59] has proposed ARCS model of motivation identifying its four components being attention, relatedness, confidence and satisfaction.

In contrast, there are much less theories or models targeting at behaviour motivation of people with dyslexia. Daki and Savage [60] has suggested that a short-term intervention improve dyslexic students’ beliefs about their reading skills and perceived social support for reading, whereas the intrinsic and extrinsic motivation is more stable without improvement. Glazzard [61] has found that early diagnosis and positive interaction with peers and teachers can contribute to the positive self-esteem of students with dyslexia. Burden and Burdett [62] has reported that the successful learning of pupils with dyslexia is associated with low levels of depression and learned helplessness and high levels of positive self-efficacy, locus of control and commitment to effort. Only a few factors such

as self-efficacy have been considered by prior research regarding the motivation of students with dyslexia with a lack of incorporation of multiple dimensions.

2.4.2 Motivation Modelling from Technology Acceptance Perspective

As an essential factor for learning performance, user motivation should be considered in the design of assistive learning technology to provide personalised services for people with dyslexia. In the context of technology use, people's motivation changes are reflected in the degree of their acceptance of the technology, where perceived ease of use and perceived usefulness are also important factors. Thus, user motivation can be contextualised as continued use intention in the context of interacting with e-learning systems. For example, expectation-confirmation theory in consumer behaviour regarding motivation continuance of technology use is worth mentioning. This dictates that if user experience matches the expectation, the users are more likely to continue using a product of e-learning system as they will perceive it to be more useful and satisfactory [63].

Assistive technologies including e-learning systems, as introduced before, play an important role in supporting dyslexic students, including spell checkers, text-to-speech functionality and speech recognition programs, mostly aiming at improving dyslexic users' literacy or knowledge skills. Lindeblad et al. [64] have found that using assistive technology as applications in smartphones and tablets could help reading-impaired children develop at the same rate as non-impaired ones and increase their school motivation. As a result, a growing part of research has attempted to predict continued intention of using e-learning systems, and motivational factors should be regarded as key determinants of the information system acceptance and usage [65].

From this perspective, Technology Acceptance Model (TAM) is the most widely adopted model to explain users' acceptance of technology by two drivers, perceived ease of use and perceived usefulness [66]. However, this model has been criticised for its overemphasis on extrinsic motivation, so there have been many attempts to extend the model with intrinsic motivation or other factors, as stated by Chang et al. [67] who has extended TAM with perceived convenience and playfulness that influence continued use intention for a mobile learning system. This is in particularly relevant to e-learning

systems where motivation could result from differing goals and interests resulting in different intrinsic and extrinsic motivations. For example, Larsen et al. [63] looked at the factors affecting teacher's use and continued use of an information system (IS) and proposed the extended post-acceptance model, where IS-continuance theory is used as a foundation to assess the likelihood of continuation. This model mainly uses two determinants, confirmation of their initial expectations and their perceived usefulness of this system, leading to an overall satisfaction. These together and with motivation, makes up the user's willingness to continue to use the system. The authors conclude that perceived usefulness is the most important factor, along with perceived competence and perceived autonomy. Venkatesh [68] proposed a model for ease of use consisting of control (internal and external), intrinsic motivation and emotion especially anxiety; the unified theory of acceptance and use of technology (UTAUT) model extended TAM and defined four determinants of technology use intention being performance expectancy, effort expectancy, social influence, and facilitating conditions [69]; however, contradictory results have been shown in recent research where the effect of effort expectancy on the adoption of e-learning systems became insignificant [70].

Increasing interest has been shown in recent research based on TAM. TAM provides good insight into whether people are likely to start using new technology. Ng's study [71] on motivation to learn computing among the elderly touches on both intrinsic factors like not wanting to be left behind society and extrinsic factors like family and peer support as well as good tuition. Other contexts are also considered, for example, Wong et al. [72] discussed the after-school clubs where students are exposed to technology outside the classroom setting. This has a lot of intrinsic motivation where students were motivated to spend much time on this even though there is no material reward. Singh et al. [73] developed a conceptual model and found that ease of use, usefulness, perceived risk, attitude had significant effect on user's intention and recommendation to use a mobile wallet service. Park et al. [74] recently extended TAM with perceived playfulness and perceived risk for the adoption of digital devices for children education in Korean cases where buyers and users are different entities. Tawafak et al. [75] have integrated academic performance, student satisfaction, support assessment and effectiveness with TAM to explain the continuance of intention to use the universities' learning management systems. Herrador-Alcaide et al. [76] targeted at students of financial accounting and revealed that

students' perception of both e-learning environment and their own skill have effect on their overall feelings of satisfaction. Hanif et al. [77] also extended TAM where subjective norm, perception of external control, system accessibility, enjoyment, and result demonstrability have a positive influence on undergraduate students' use of e-learning systems. Kimathi and Zhang [78] conducted a study in Tanzania and concluded that subjective norm, experience, enjoyment, computer anxiety are the factors positively influencing perceived usefulness or perceived ease of use that further determine the usage intention of e-learning, while computer anxiety negatively affects students' behavioural intention to use e-learning, found by Chang et al. [79]. Mehta et al. [80] and He and Li [81] also extended TAM with human values or cultural differences; the former found the value of achievement being an important predictor of e-learning adoption, and the latter emphasised the need for digital competence training and satisfactory user interface design.

It can be seen that researchers have focused on different aspects of technology acceptance, making conclusions regarding the factors that affect the adoption of technology in different contexts. Extending TAM with factors from other theories is still an open door for scholars, as pointed out by Al-Emran et al. [82].

In summary, motivation is a substantial factor for learning engagement and performance especially for dyslexic students, and motivation modelling provides a way to define the users' motivational needs as well as the relevant factors related to systems perceived by users that may influence their motivation. Motivation has been modelled from both the psychological perspective and technology acceptance perspectives. However, research grounded in motivation theories for people with dyslexia in e-learning environments has been scarce to date, and only a few motivation-related factors have been considered such as gamification and self-efficacy. Therefore, motivation modelling needs to be further studied looking at the way in which the model is built to best suit the needs of the dyslexics.

2.4.3 Motivation Modelling from Computational Perspective

From computational perspective, motivation modelling involves using the approaches to computational modelling, which “helps us to extract value from data and ask questions

about behaviours; and then use the answers to understand, design, manage and predict the workings of complex systems and processes, including robotic and autonomous systems” [83]. Motivation modelling can look at many different factors relevant to motivation in aspects of both a user and the system perceived by the user, such as user’s attitudes, learning experience, perceived usefulness of the system, etc. By classifying these concepts, a high-level view of the user’s motivation can be gained allowing easier reuse of the knowledge in different applications.

The techniques of computational motivation modelling can range from logics (to infer motivation through a set of logical statements) to probabilistic or machine learning techniques (using large amount of data to infer trends and predict outcomes of motivation). Logics-based modelling involves using general rules of mathematical proof for inference. Biswas et al. [84] have attempted this technique by adopting a sensor network that drives a set of rules with define the user model, in this case various visual styling changes. The disadvantage is its low ability of dealing with dynamic user data due to the set rules, and this sort of inference can be complex and daunting.

Probabilistic reasoning is used to analyse sensor data which is based on machine learning, such as using Bayes networks [85]. An example of probabilities being used for user modelling has been applied to city tours in the paper by Fink et al. [86]. This application looks at utilizing user’s usage of the application to learn their interests and preferences. This prediction looks at the likes of similar users and is based on heuristics. Another use of machine learning for user modelling has been practiced by Virvou et al. [87], where the authors used k-means clustering. The algorithm uses an initial set of stereotypical user profiles and then adapts the user profile based on the log of the user interacting with the system. The clustering is then used to place the users into the right categories. Gao et al. [88] have listed more algorithms that can be considered for the task of user modelling and classification. KNN and k-means clustering and classification are listed are important clustering algorithms whereas Naïve Bayes can be used for independent data and Bayesian networks for producing probabilistic dependencies. Decisions trees are discussed for drawing meaningful conclusions whereas neural networks and Support Vector Machine (SVM) are considered useful models but belong to a “black-box” solution. Frias-Martinez et al. [89] have investigated some techniques being applied to users and behaviour modelling, especially looking at fuzzy logic and

neural networks. One of the key points is that such soft computing techniques better handle uncertainty and allow flexibility. Neural network and fuzzy clustering are example of techniques that can be used to perform this analysis. Fuzzy logic and genetic/evolutionary methods are also discussed with the interpretability and the fact that no training data is required being the benefits.

Webb et al. [85] went into more detail and discussed the various limitations of machine learning and potential solutions to overcome the difficulties. The issues discussed are the need for a large amount of data for training, difficulty in labelling data, the changing nature of data and the complexity of the machine learning algorithms with regard to computational cost. The solutions that the authors came up with are using algorithms that do not need much training or using learning approaches that do not need much data. Labels can be inferred from user behaviour or inferring labels using a small dataset representation of the larger population. The changing nature of data can be addressed through weighing newer observations more compared with older observations. Finally, algorithms that work faster but less accurate can be chosen to alleviate complexity issues or alternatively heavy computation can be done offline.

Depending on the application, often the results do not need to be precise and many studies consider generalisations or stereotypes to make the models easier or faster to build and maintain. For example, Aghabozorgi and Wah [90] adopted a specific solution to the model complexity and computation problem by suggesting building the initial model offline allowing a great amount of processing to take place and then updating the model online which should now be less computationally extensive as it builds upon the offline data. Similarly, uncertainty reasoning and inferring based on incomplete data or partial computation is discussed by Jrad et al. [91].

As for modelling targeting at motivational aspects, Derbali and Frasson [92] has attempted to produce logistic regression models to predict learners' motivational states during serious gameplay based on physiological data, where learners' groups have been successfully classified into "above" or "below" based on the levels of the four motivational factors involved in the ARCS motivation model with the prediction success of between 65.5% and 79.3%. However, existing computational models of motivation mostly focused on specific emotional and cognitive aspects; also, they were all developed

for general people. Examples include the computational model for perceptual classification from Saggar et al. [93] that incorporates motivation using artificial neural network for general decision making behaviour when doing tasks, and more recently, the dynamic computational model of motivation (DCMM) from Chame et al. [94] which is built upon self-determination theory based on a recurrent neural network for general user groups across application fields, and Kasmarik's computational motivation model [95] to be used by artificial agents in goal-selection tasks.

The computational motivation modelling approaches above focus on the assessment of the user's current motivational state, and the use of this information to support immediate personalisation of system reactions according to the user's state. However, as the demands for system effectiveness and agent believability increase, motivation models will increasingly need to support not only immediate motivation assessment and personalisation, but also more extensive motivation understanding: a more in-depth understanding of the user's motivation profile, and the user's motivational needs addressed by factors in the model over longer periods of time. To this end, another approach of computational motivation modelling involves the use of ontology.

Ontologies provide a common understanding of the domain and facilitate knowledge sharing, and they are also very expressive through the use of the web ontology language and reusable across many different application platforms. Furthermore, in contrast to probabilistic reasoning, the ontology-based approach does not rely on the availability of large amounts of data. Ontologies can deal with ambiguous and uncertain data which can occur due to the imperfection of the sensor network or other information source, and the modular structure also allows the models to be easily reused and extended [85].

In ontology-based modelling, certain criteria are defined to identify a certain user and the relationships between the different criteria and their effects on each other [96]. For example, Biletskiy et al. [97] used ontology as a user modelling technique. Learner information is presented as many different categories contributing to the ontology model including their academic performance, interests and aspirations. Not only is this information fed into the system at the beginning, the learner can also view and edit any of the constituents of the model to correct or update information. The authors emphasised that for good user modelling, it is important for the user to provide accurate and truth

information or the model will be rendered useless. Earley [98] stated that even with good modelling, data and analysis techniques, the approaches “still require creative human input, judgement and expertise”. A similar method uses hierarchical relationships to depict the user model. Kim and Chan [99] discussed a user interest hierarchy which looks at user attributes but places in a general to specific hierarchy. The user’s behaviour on the website can then be used to populate the hierarchy and algorithm can be used to cluster the different hierarchy themes and levels together. Skillen et al. [96] discussed the importance of dynamic and adaptive user profiles, understanding context and providing the right amount of granularity. The different elements are then connected through “is or part relationships” demonstrating how the more specific attributes are connected with the more general ones. Another ontology that was developed to help with disability is the ADOOLES ontology [100]. This ontology looks at the different user abilities and assistive mechanisms available in the context and builds a profile of the user this way. The importance of context is further highlighted by Palmisano et al. [101], where for customer modelling, the context of a purchase is extremely important to the user model as much as the purchase itself.

The ontology-based approach to user modelling can not only utilize an “expert” to build the model but also use probabilistic techniques to define criteria and create the ontologies. For example, Javier et al. [102] have used logistic regression to produce the probability of correctness of the association between words and then performed the inference of lexical ontologies in other languages given the ontologies for one language and bilingual mapping resources.

In summary, existing attempts and research related to computational models of motivation mostly focused on emotion and cognition. Some were developed in a general context or another other than the e-learning context for personalised learning, while others developed in e-learning context were based on existing theories for generic people without dyslexia. Therefore, there is a lack of those targeting at people with dyslexia, and user studies with dyslexics should be incorporated into the process of model development. Ontology-based modelling has the advantage of being modular, easily extendable and not reliant on large amounts of data. Using this structured modelling approach will result in a highly adaptable yet reusable system that can be easily aligned to the needs of the learner [32]. Therefore, the present research will develop a computational representation of the

motivation model using ontology-based modelling approach and formal ontology language.

2.4.4 Motivation Computation and Assessment

As stated before, motivation consists of various factors from intrinsic motivation and extrinsic motivation. These factors represent learners' various motivational needs; thus, each factor should be assessed in order to design and implement personalised feedback to address the corresponding need. Important indicators of motivational factors include time spent on a completing a learning task, quiz scores, and various sensor data. The identification of the physiological or behavioural indicators of motivation is still at its initial stage, though researchers have stated that through motivation-diagnostic input data, appropriate tactical and strategic pedagogic moves are applicable toward motivationally intelligent systems [8]. This section puts emphasis on different data sources as input for motivation computation and assessment.

Pertaining to motivation computation for assessing the level of each motivational factor, this corresponds to two main questions: 1) what information and data is used to answer the question about a learner's dynamic motivational states? And How? 2) What kinds of personalisation should be applied to e-learning systems to address the learner's motivational needs? This section will review answers to the first question, and the second one will be discussed in the next section.

Motivation assessment, achieved through motivation computation using the computational modelling approaches mentioned before, can mainly be categorised into those based on explicit/static data collected from users' self inputs or implicit/dynamic data collected by systems or sensors during the interaction process. The static/explicit data is based on user input, whereas implicit/dynamic data is derived from the observation of user behaviour [91]. An example is if users remain uninterested in a promotion and do not interact with systems, then that promotion is removed from the user's interest list. Motivation is frequently measured using interviews such as the interview style adopted by Ng [71] or questionnaires exploring people's situation with regard to the factors above. The questionnaires can often use Likert-type scales to allow quantitative analysis to take

place. Also there are pre-defined scales that can be used such as the 8-point Computer Anxiety Scale from Althaus and Tewksbury [103]. Questionnaires, sliders or the use of emotion detection can be used to assess motivation, allowing personalisation of subsequent learning. This can also be linked with test or quiz results to indicate overall performance and flag any issues [55], [104].

Razmerita et al. [105] have pointed out two ways in which user information can be gathered to identify and adapt to the user, either using user-supplied data or through system-collected data. In addition to user-supplied data, i.e., explicit/static data described above, one example of using system-collected data is shown in Hatala and Wakkary's Ec(h)o System [106], the museum installation adapted to the type of museum visitor based on their interactions with the system allowing differentiation between visitors who want detailed information versus busier visitors who just want an overview. The interaction data collected by the system is a kind of implicit/dynamic data introduced above.

In addition to interaction data collected by systems, sensor measurements have been attempted as substitutes for users' self-reports to achieve real-time assessment of mental states including motivation. For example, it has been proved that the "attention ratio" called C_3 Theta/low-Beta in electroencephalogram (EEG) is a stronger predictor of learners' motivation compared with skin conductance and heart rate [92]. EEG is an electrophysiological technique to record the electrical activity generated by the human brain via electrodes placed on the scalp.

The main EEG metrics are from the non-overlapping waveform frequency bands, and the different predominant frequencies of human indicate different states (e.g., excitement, drowsiness, sleep). EEG waveform frequency bands are categorised into the followings: 1 to 4 Hertz (Hz) are delta, 4 to 8 Hz are theta, 8 to 12 Hz are alpha, and 12 Hz to about 25Hz are beta. Frequencies above 25 Hz are termed gamma [107]. The term "ripples" (generally >100 Hz) are thought to reflect epileptiform discharges [107]. Delta activation is usually detected in infants or associated with deep sleeping of older adults. Theta waves are related to a variety of cognitive processes such as memory and cognitive workload [108], and alpha activation is associated with an alert but relaxed mental state [109], while beta waves can indicate an active mental state such as anxious thinking

and/or active concentration [110] (usually with a low-amplitude) or any body movement [111]. Gamma is related to peak mental or physical performance or simultaneous processing of information from different brain areas [112].

The electrodes placement of EEG recording usually follows the 10-20 system which is based on the relationships between the locations of the electrodes and the corresponding areas of cerebral cortex. The activities recorded from different regions of the cortex can be interpreted differently. Occipital region is mainly responsible for visual processing, while parietal region is primarily associated with motor function. Temporal region is linked to function related to language and speech with inner regions more active during spatial navigation. Frontal region is responsible for executive function such as planning and control. In addition, EEG asymmetry is also associated with mental activity [113]. For example, the alpha-power asymmetry derived from the spectral differences between a symmetric electrode pair at the anterior brain regions is a common indicator of emotional states [114]. Alpha intra-hemispheric power asymmetry has been found to be an effective feature to distinguish patients with Parkinson's disease from normal control group during emotion information processing [115].

In addition to EEG, eye tracking can also provide insights into real-time motivation assessment, as a way of collecting data about human eye movements, which has been widely used for gaze analysis for evaluating purpose or as gaze input for interaction purpose. The principal eye-tracking metrics are fixations and saccades. Fixations are those times when our eyes hold the central foveal vision in place to process the information being looked at, while saccades are those when the fovea is moved rapidly from one point of interest to another to search information.

Multiple eye-tracking measures from fixations and saccades can reveal useful information about viewers' mental processing or states. For example, more fixation counts may imply less efficient web searching [116]; more fixations on a specific area may indicate more difficulty in information processing or purely more information to process, and to distinguish between the two situations, dividing the fixation counts by the number of words is necessary if there is only text to be processed in the specific area [117]. A longer fixation duration can mean a higher level of the engagement of viewers or the difficulty of information processing [118]. A high spatial density of fixations on a

small area can imply more concentrated viewers or efficient searching [119]. Longer saccade distances mean that viewers' attention is distracted by some cues that is more prominent or interesting to them [120], while regressive or backwards saccades mean that the information is less easy to understand [121]. A higher ratio of fixations to saccades means more information processing compared to information searching [122].

In addition to fixations and saccades, a lower blink rate or a larger pupil size may indicate a higher level of cognitive effort, whereas a higher blink rate may indicate viewers' fatigue [123], [124], while they are less commonly used as both indices can be subject to other factors such as light levels [125].

In summary, motivation can be assessed through computation based on explicit/static which can take the form of registration forms, questionnaires and user provided feedback or implicit/dynamic data sources which in computer system can take the form of logs, databases, cookies or information from user choices, selections and browsing habits as well as sensor measurements. Especially, EEG and eye tracking have provided great insights into assessment of motivational factors. Further studies are required to look at how motivation is best assessed using different data sources.

2.5 Existing Motivation-based Personalisation for People with Dyslexia

Ideally, every user should be regarded as a unique individual, so technology should provide the right service for the right user, so called personalisation, to meet the different needs and preferences of different users on the basis of their different characteristics. User modelling has been proved to be a good way to perform personalisation for users. Motivation modelling works in the same way in the present context for people with dyslexia to better personalise the learning for different users with different motivational needs. Only if e-learning systems have users' information on motivational factors, the human-computer collaboration can be improved and thus users can be assisted according to their various motivational needs. A student with insufficient learning motivation is more likely to fail in learning tasks. Especially for those with dyslexia, they probably feel more frustration and have lower dignity. Personalisation of learning focusing on users'

motivational needs for those with dyslexia, and any other learning difficulties in a bigger picture, is becoming increasingly necessary and attractive to researchers and designers.

2.5.1 Personalised Learning Process

User modelling is central to service personalisation. In this way, a user profile is represented as a data structure encompassing the characteristic attributes of a specific group of users. User modelling, while beneficial for designing applications, are often used for real-time personalisation of services. This process will often require an input of data, a method of algorithmically processing the data and then a final conclusion or decision that can be used by the system to tailor the experience, configuration, behaviour or output to the user. User models will need to be representative of the users that are being modelled. The data can be from a range of different inputs, which can all contribute to the model. Data can either be implicit/dynamic or explicit/static, as introduced before. The context of the data is important when considering the data as input though [126]. Palmisano et al. [101] have provided an example where the purchase data input is wrongly attributed to the customer when it was bought from a friend. To provide better data as input for analysis and modelling, a combination of both implicit and explicit data should be used to gauge accuracy and provide the best input.

Many studies have investigated user modelling for the application of personalisation. Kurkovsky and Harihar [126] discussed monitoring shopping habits to change marketing preferences and adjust promotions. This can be based on user location or user selection. As with all mass data collection system, there are privacy issues that need to be considered. Vassileva [127] looked at adjusting the incentives that a user received based on their interests. This means that users would be rewarded appropriately and would be more motivated to complete the tasks and to complete them well. An example of such system given in the article is a user-contributed question and answer website. Apart from marketing uses, Nganji et al. [100] examined the use of personalisation for e-learning depending on the users' disabilities. It is specified that this will give the user control and freedom in the learning experience. A further application of personalisation was tourism in Fink and Kobsa's study [86] where user interest and preferences were taken into account to determine what parts of the city tour should be given higher weighting.

In the personalisation process, a user model needs to be constructed that can then be consumed by the system for personalisation. This user model can potentially be used universally by many different systems. Niederée et al. [128] have considered this as a “passport” which allows that user model to move across different applications. This user model will need to consider the cognitive aspects of the user, the task, relationships between the different elements and the overall environment. Gao et al. [88] looked at the user profile in more depth populating the domains of personal data, cognitive style, device information, context, history, interests, intention, interaction experience and domain knowledge. The context and domain knowledge are seen to be important to determine the user’s intentions and reduce ambiguity. An example in the article is the search for Apple which can mean the fruit or the company. The user model is constructed using an ontology-based approach in the article. Overall, a comprehensive model is seen to be cross-platform and able to deliver optimum personalisation.

Once the input data is collected or made available, the data will need to be passed through an algorithm that will provide the conclusions and predictions that will make its way into the model. In order to customise data and features being delivered to the user or to provide helpful recommendations, the system can perform filtering of the whole data or functionality set. The filtering can be rule-based, content-based, collaborative or a combination of them [91]. Specifically, the rule-based approach requires that pre-defined rules are used to customise data. This however can be inflexible and difficult to update. The content-based approach looks at text data but is not supported for multimedia. The collaborative approach uses interest detection of many people but does not give satisfy results for new users or items. Often a hybrid approach combining all these approaches can give better results but it complicated and difficult to implement [91].

In order for the data to be converted into a user model which can then be used repeatedly and by different users for personalisation, automated modelling and classification will need to be performed. As described before for motivation modelling from computational perspectives, this can be achieved using various computational modelling techniques including ontology-based or machine learning approaches. The application of different techniques to build user models along with the inputs for such a model, possible parameters and examples of personalisation using the output. These techniques can be adapted and build upon for investigating users with dyslexia and e-

learning systems by leveraging learner inputs to feed a computational algorithm and model and producing output that can help personalise the learning environment and tools.

2.5.2 Existing Personalisation for People with Dyslexia

Existing personalisation of assistive technology systems helps to separate out the needs of different type of dyslexia. Dyslexia is classified into several different types with the three main categories being visuo-spatial difficulties, speech sound difficulties and correlating difficulties. The visuo-spatial difficulties refer to difficulties in distinguishing between letter, syllables and phrase order, relying on shapes to identify the letters. This may cause issues with identifying the letters and confuse the order of the letters. The speech sound difficulties refer more to difficulties in spoken language, the forming of sentences and the separation of words into component syllabi. The correlating difficulties concerns more with writing difficulties where they are not able to link letters to speech sounds. Although these types are defined separately, they often occur in combination with an individual possibly having two or three of these types [32].

Alsobhi et al. [129] have attempted to linking dyslexia types and symptoms to the available assistive technologies by summarising the different current assistive technologies that exist and how they correlate with the different combinations of the types of dyslexia. The information from the correlation can start to be used to adapt the assistive technology to the needs of the individual dyslexic depending on the type or combination of types of difficulties that they have. They also considered using an ontology approach to address the dyslexia type personalisation issue, where an ontology web language which handles the content and the presentation of the content separately to allow different presentations of the same content to be show depending on the learning difficulties of the individual. The ontology approach involves splitting up the learning system into classes with dependences on each other, and the classes model the students, their individual dyslexia types and learning styles as well as the learning systems and the hardware and software personalisation that can be employed. The learning style is determined using a questionnaire and results in scores for five areas: reflective, visual, sensory, sequential, and auditory. This is then used to determine the personalisation of assistive technology

that are required. Users can also select preferences that are stored as settings for system features that will benefit their learning experience [32].

2.5.3 Using Motivational Strategies in E-Learning Systems

Compared to traditional classroom learning, students learning in e-learning systems usually feel less restrictions from tutors or peers, and students can take greater control for their learning experiences and outcome, which meanwhile makes it necessary and imperative to design and apply strategies in e-learning systems addressing users' motivational needs [92]. Learning requires learners to be motivated and engaged, and motivation is strongly related to the cognitive and emotional aspects, as mentioned before. Motivated learners are the prerequisite for the effectiveness of other personalised services and assistance offered to learners in e-learning system. However, much of the research pertaining to personalised learning has focused on emotion and cognition of learners such as inducing higher positive emotions or re-attracting learners' attention or providing personalised assistance in development of learners' cognitive skills, in contrast, educators and e-learning system designers have neglected to apply modelling and personalisation techniques to e-learning systems that aims at improvements in exactly motivational states.

Hundreds of motivational strategies have been defined to be adopted by teachers in the language classroom to maintain and increase motivation [130]. However, most e-learning systems have only aimed at improving users' knowledge and skills. Recently, there has been increasingly more attention drawn to applying motivational strategies in e-learning systems. Several studies have proposed e-learning systems with personalised emotional or cognitive strategies to reduce users' negative states. For example, Barolli et al. [131] have proposed an interactive web-based e-learning system trying to stimulate learning motivation by incorporating several system functions such as display of learning history, ranking, encouragement and self-determination of learning materials. Alias [132] has designed a Malaysian e-learning environment to scaffold motivation by applying the strategies such as confidence elicitation and effort encouragement. Arroyo et al. [133] have shown that the non-invasive interventions using meta-cognitive strategies to promote self-reflection can re-engage users and enhance learning in a tutoring system.

However, those strategies to improve users' motivation lack the support of motivation models or theories.

There have also been a few attempts to design or tailor strategies in e-learning systems based on motivation models or related theories. Hurley [134] has designed an online learning environment with interventions to support users' self-efficacy and motivation, where the intervention rules were from experts constructed on the basis of Bandura's social cognitive theory and users' learning behaviour. More adaptive motivational strategies were designed according to Keller's ARCS model. For example, Chang et al. [135] have embedded motivational strategies in a mobile inquiry-based language learning setting (M-IBL) corresponding to elements of ARCS model, showing the experiment group with the motivational strategies have a higher level of learning motivation. Derbali and Frasson [92] has attempted to assess the effect of motivational strategies embedded in a serious gameplay. The strategies included alarm trigger, informative feedback, displaying score to address the factors in ARCS model, and their study also demonstrated the possibility to use physiological measurements to assess learner's motivation. Going further from that, we can also see the possibility of automating personalised feedback output to a learner based on the learner's motivational states detected by a prediction model in real time.

However, the theory and model that their studies have used to apply motivational strategies were not constructed in e-learning context, thus failing to include crucial factors, and this research is even more scarce for people with dyslexia. One of the very few papers addressing motivational issues for students with dyslexia is an adaptive e-learning framework proposed by Alsobhi et al. [136] involving different dimensions of e-learning support based on TAM and dyslexia types but without consideration of motivation theories. The most motivation-related approach applied to e-learning systems for dyslexia is gamification. For example, Gooch et al. [1] have examined the use of gamification to motivate children with dyslexia, showing that gamification can enhance dyslexic children's learning motivation. However, their study fails to address more aspects of motivation for dyslexic students in a big picture; additionally, educational games have been found to work less effectively for adults with dyslexia compared to dyslexic children [10], [137], and also e-learning systems are more widely available than educational games. Therefore, research on e-learning systems based on users' motivation model to provide

personalised motivational support has a wider range of users, which is in fact applicable to generic users certainly including dyslexic users. There have been a lot of studies exploring the recognition of learners' emotional factors such as stress and boredom or cognitive factors such as concentration whose purpose is generally to arouse more positive emotion or improve attention of a learner during the learning process. (e.g., [138]).

In summary, interview and rating scales collecting self-reported data as well as sensors capturing physiological and behavioural data provide information input of motivation assessment which can be used further to personalise learning services. The personalisation for people with dyslexia to address their different needs to occur in an automated fashion especially in the big data age to ensure that the data available can be used to benefit everyone and provide the best personalisation.

However, assessment of learners' motivation including its multiple dimensions with a personalised feedback output by an e-learning system in real time is lacking in current literature, especially for those with dyslexia. There have been very few attempts of applying motivational strategies in e-learning systems for people with dyslexia to adapt to their motivational states; the design of motivational strategies for students with dyslexia also lack the fundamental basis or guidance from empirically tested motivation model in e-learning context. Motivation with specific links to people with dyslexia and e-learning systems should be further explored to gain an understanding of the personalisation required to improve their learning experience, engagement and eventually learning success.

The main aim of this thesis is to develop a motivation model for students with dyslexia and to develop sensor measurements for real-time motivation computation. The present research project brings together the aspects of motivation theories and technology acceptance along with dyslexics' characteristics as the ground for conceptual motivation modelling in e-learning context. The motivation model also incorporates the empirically tested factors from real dyslexic people's views about continued intention to use e-learning systems. In addition to traditional motivation assessment based on self-reported data, the present research employs sensor data for motivation computation in real time. A computational representation of the motivation model is developed using ontology-based

modelling approach, which is later enriched with semantic rules as the reasoning mechanism to support motivation-based personalised learning. The next section will explain in detail how different perspectives are integrated into the motivation modelling process for people with dyslexia in e-learning environments.

Chapter 3 Motivation Modelling for People with Dyslexia in E-learning Environments

3.1 Introduction

E-learning system design based on the motivation modelling addresses users' specific motivational needs including different dimensions and thus can enhance users' learning experience, and in long term, learning effectiveness. However, there has been a distinct lack of empirical research investigating the motivational determinants of dyslexic users' continued use intention in e-learning systems. Establishing such an explanatory model will provide great insights for deep understanding of dyslexic users' motivation in e-learning environments to help designers and educators to prioritise their considerations.

This chapter provides a comprehensive view of motivation modelling for dyslexic students in e-learning environments from interdisciplinary efforts to bring different perspectives together, namely psychology, technology acceptance and dyslexics characteristics. After the conceptual motivation model is constructed, a computational motivation model is developed accordingly using ontologies to represent the knowledge about the motivational factors in the conceptual model and the possible personalisation options in e-learning environments for the target user group: 1) to enable machines to use the knowledge base; and, 2) to allow the rule-based reasoning mechanism to be applied to e-learning systems in future to infer personalisation, which will be explained in detail in Chapter 6. Ontologies are the most suitable means of knowledge representation with the advantage of a high level of flexibility and extensibility in designing concepts and their interrelationships [139]. An ontology is a formal, explicit specification of a conceptualisation in a knowledge domain [140], and the conceptualisation provided by ontologies enables personalisation components to be defined with higher reusability. This will allow the components to be modified and maintained without changing the system implementation as a whole.

The main objective of this chapter is to develop a motivation model for people with dyslexia in e-learning environments. It improves existing models for people with dyslexia by combining existing research from perspectives of psychology and technology acceptance and factors identified from an empirical study with the target user group.

Specifically, the motivation model is firstly constructed by integrating the prior theories from the different theoretical perspectives with adjustment to the dyslexic user group and e-learning context and incorporation of both intrinsic and extrinsic motivational factors. The empirical study is designed and carried out with four controlled learning tasks based on real-world learning scenarios using a mobile learning application with small, highly concentrated learning sessions. Individual interviews are conducted with dyslexic students to gain direct, first-hand data about the key factors affecting their learning experience. Using coding and thematic analysis methods along with qualitative data analysis software, the main themes regarding motivational factors are identified along with their interrelationships. Based on these findings and prior theories, the conceptual motivation model is further refined by incorporating the dyslexic users' motivational needs identified from the empirical study. Using the concepts and their relationships in the conceptual model, then a computational motivation model is developed in which the factors in the conceptual model are structured as a hierarchy of classes with their interrelationships using ontology-based modelling technique and the formal ontology language. The motivation model for people with dyslexia in e-learning context will benefit both design and personalisation of e-learning systems in the future.

The remaining of the chapter is organised as follows. Firstly, the opportunities brought by e-learning systems are discussed for real-time monitoring of motivational states and dynamic provision of personalised strategies during users' learning process. Secondly, the process of motivation modelling is described in detail. Specifically, it is firstly explained how the model is initially constructed according to prior theories and the research context, and then an empirical study with dyslexic learners is presented with its methodological design and results to further refine the conceptual model. Following that, the process of ontology-based motivation modelling is illustrated for future application to personalised e-learning systems, before the chapter is finally concluded.

3.2 Characterisation of E-learning Systems and Motivation

With the wide availability of e-learning platforms, there is a great opportunity to apply motivation modelling and provide the corresponding personalised assistance for dyslexic users in their daily lives. Users can learn more independently with access to a computer or a mobile device. Unlike traditional classroom learning, users learning in e-learning

systems takes much more responsibility and control of their own learning progress. Highly motivated users are more likely to interact effectively with e-learning systems and thus learn more effectively. It is necessary and imperative to design and apply strategies in e-learning systems addressing users' motivational needs [92].

E-learning systems can support real-time monitoring of users' behavioural and physiological responses that indicate learning desires, effects and various mental processes or states, thus offering opportunities for enhanced learning through dynamic provision of personalised learning assistance. In mobile or web-based e-learning systems, it is possible for users' motivational states to be detected in real time and thus the personalised motivational strategies to be applied during the interaction process between users and systems. Once the motivational needs of a user are detected in an e-learning system, personalised reactions using motivational strategies can be output to the user to address the corresponding motivational needs dynamically to sustain or improve motivation and experience.

However, as pointed out in Chapter 2, most e-learning systems still focus on improving users' knowledge and skills, and the few attempts to provide motivational strategies lack the fundamental basis and guidance of empirically tested motivation model in e-learning context. Motivation is fundamental for long-term engagement in learning and it is a more acute issue for people with dyslexia due to the learning difficulties they usually experience leading to potential frustration and learned helplessness. Only when an e-learning system has information of different users' individual motivational needs, the motivational strategies applied can then support different users in a more personalised and thus more effective way.

A learner's motivational consequence is contextualised as continued use intention in the context of interacting with an e-learning system. The determinants of the motivational consequence includes multiple dimensions of learners' motivational needs, and thus motivation should be modelled to enable deep understanding by revealing how the various aspects of motivation work together to determine learners' continued intention to engage in e-learning environments and to facilitate further personalisation of motivational stimuli to be designed to address the corresponding motivational needs and eventually applied to e-learning systems.

Therefore, the first step of providing personalised motivational strategies in e-learning systems is to model the factors that reflect different aspects of users' motivation to engage in e-learning systems. However, there is little work on motivation modelling in e-learning context, and only a few motivation-related factors have been considered such as gamification and self-efficacy, not to mention research attempting to model the factors that influence dyslexic students' motivation in e-learning environments. Given the lack of the motivation modelling in e-learning context for dyslexic users, the motivation model in the present research draws insights from technology acceptance, motivation theories and dyslexics characteristics to fill this gap.

3.3 Conceptual Motivation Modelling

3.3.1 Initial Model Construction

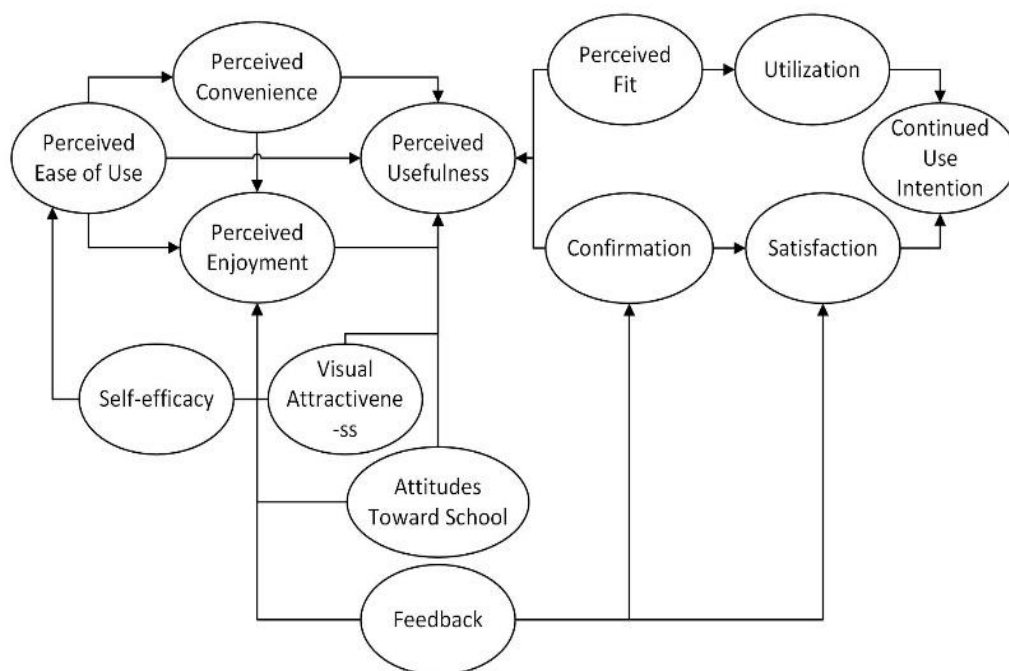


Fig. 3.1 The proposed conceptual motivation model

The conceptual motivation model with the factor interrelationships constructed initially in the present study is demonstrated in Fig. 3.1, which is built by integrating the extended post-acceptance model with the extended TAM along with the incorporation of the additional inspirations of the motivational factors whose relationships with each other in the model are also determined with reference to the existing motivation theories to better fit motivational characteristics of students with dyslexia in their use of e-learning systems.

As a starting point, the motivation model is constructed by integrating the factors related to the present context from different perspectives in current literature. From the perspective of technology acceptance, learners usually get a first perception of an e-learning tool after an initial trial of use and then intends to continue or discontinue to use it. As described in Chapter 2, Chang et al.'s extended TAM [67] has introduced perceived convenience and playfulness that brings about e-learning characteristics and compensate for the overemphasis of TAM on extrinsic motivation. Similar to the work-related factors proposed by Larsen et al [63], dyslexic users also need to perceive that the e-learning system fit their daily learning needs and tasks, because their first goal of engaging in e-learning systems is to satisfy their learning needs, thus the starting point of the present model are the extended TAM proposed by Chang et al. [67] and the extended post-acceptance model proposed by Larsen et al. [63]. Although the abovementioned two models were believed to be the most relevant to the present research context and target users, factors that determine technology acceptance are likely to change with the target users and context [141], [142]. Many other factors still need to be investigated to verify the effectiveness of their roles to extend TAM [82]. Therefore, the present model also benefits from psychology in addition to the perspective of technology acceptance.

The motivation model is then extended with factors from prior research on psychological theories with consideration of dyslexic students' specific characteristics, including technology self-efficacy (also referred to as self-efficacy in the following text), visual attractiveness of e-learning systems, attitudes toward school and feedback. Except that visual attractiveness is mostly regarded an extrinsic factor reflecting system features, the other three factors all reflect intrinsic motivation to compensate for the lack of intrinsic factors in the two models. The positions of the factors in the model can be seen in Fig. 3.1. In Venkatesh's model [68], both computer self-efficacy and computer playfulness are included as a factor of the general beliefs about computer and computer

usage to “anchor” the system-specific perceived ease of use. Also, perceived enjoyment has been confirmed as a surrogate construct for intrinsic motivation, and technology self-efficacy contributes to self-confidence, which plays a part in intrinsic motivation, and users can be intrinsically motivated through curiosity, enjoyment, or self-efficacy [29]. Moreover, self-efficacy contributes to perceived competence, which is also a construct of intrinsic motivation and can influence perceived ease of use and perceived enjoyment [38]. Therefore, two arrows are directed from self-efficacy to perceived ease of use and perceived enjoyment, respectively. In the motivation model proposed by Verhagen et al. [65], visual attractiveness reflects how much a person believes that an information system is aesthetically attractive [10]. In addition, perceived visual attractiveness can reinforce the perceived usefulness and entertainment value of a system, which is also applicable to dyslexics’ motivation in e-learning systems in the present model [47]. Therefore, two arrows are made from visual attractiveness to perceived usefulness and perceived enjoyment, respectively. To adjust the model better to the characteristics of students with dyslexia, attitudes toward school is taken into account as a construct of the model, which might intrinsically regulate the dyslexics’ learning behaviour with e-learning tools, as dyslexic students are more likely to have lower level of academic self-worth and more coping problems which might lead to further issues like learned helplessness or social withdraw compared to other students [33], [34], thus attitudes toward school can influence their motivation of interacting with e-learning systems to a great extent; also, researchers have found that attitudes toward school has contributed significantly to their regression model for prediction of information seeking behaviour. Regarding the relationship of attitudes toward school with other components in the model, it has shown that perceived enjoyment and perceived usefulness are significantly correlated to attitudes with the former being more strongly correlated than the latter [33]. Therefore, two arrows are created from attitudes toward school to perceived enjoyment and perceived usefulness, respectively. In addition, feedback is also one of the constructs of intrinsic motivation [50], which is output by system during the interaction process. Various kinds of feedback, informative or entertaining, contributes to user involvement in and interaction with the system, which might play an important part in perceived enjoyment and confirmation of expectation-experience match and thus the overall satisfaction. Therefore, three arrows

are created from feedback to perceived enjoyment, confirmation, and satisfaction, respectively.

3.3.2 Empirical Study for Motivational Factor Elicitation

While insights were drawn from different perspectives in literature, it is worth noting that the target user group in the current research is students with dyslexia. However, existing research has rarely employed empirical studies with dyslexic people to elicit the most relevant factors associated with their motivation to engage in e-learning systems. From this view, an empirical study is designed to validate the initial motivation model with the target audience to see whether the model is accurate and complete. In other words, the study in this section examines whether the model matches the target users and to elicit more relevant motivational factors directly in the real-world use scenario. This study has been approved by Norwegian Centre for Research Data (NSD). All data related to the present research project were anonymised before they were translated back into English, and no personal data was made available for the present research.

3.3.2.1 *Learning Materials*

The present study provides a clear real-world context by showing them a prototype of mobile learning application called mYouTime. The learning application is from another project called Personal Mobile Learning Arena (PLA) in Norwegian Computing Centre that aims to develop a personal, adaptive mobile learning arena that is targeted at students in school and adults that, for different reasons, are in danger of dropping out of education. Focusing on a practical application of existing e-learning technology allows the interviewees' usage to be observed, giving a fuller picture and understanding of their adoption of e-learning technology and why they continue to use them.

The application is designed to be used in smartphones for “micro-learning” with 10-to-20-minute lessons that can be downloaded or made by users using the application or a web browser. Splitting learning contents into small pieces in e-learning tools may help reduce learners' cognitive load compared with traditional learning in classroom. One lesson can contain a combination of text, pictures, audio, videos and quizzes in between.

The learning contents in mYouTime were designed and created by experienced science teachers. Twenty-one lessons were developed and made available for the study. Each lesson addressed a specific goal in the science curriculum for the level of participants, i.e., between 14 and 16. More information about participants is introduced in the next section. To limit the duration of the study to be less than one hour, nine lessons were selected according to this time criterion. Each was a learning task under 15 minutes with several pages of plain text with the “read aloud” button, videos and quizzes in between, and then the other version of these nine lessons that did not have the “read aloud” function was created. Furthermore, three control lessons made with videos and quizzes but without text pages were selected and used in both groups. The list of these twelve lessons is displayed in Appendix 1. Finally, three out of the nine lessons were selected randomly as experiment tasks and one from the three control lessons at random as a control task. The two important features in mYouTime, i.e., read aloud and feedback, are introduced below.

Read Aloud

Since the study is targeted at students with dyslexia, it may be beneficial to them if the text of the lessons is made available as sound that could be read out loud. People using mYouTime can control the sound by pressing a button in the interface, shown in Fig. 3.2(a), where the button is at the bottom of the interface and its text is in English (the rest of the content is in Norwegian). The idea is to examine how much the function contributes to their reading experience and to see if there is a difference between students that have the text read aloud and those that do not, and the between-subjects design is explained in detail in the next section.

Feedback

All the lessons have multiple-choice questions as quizzes in between along with the quiz feedback (Fig. 3.2(b)). Once an answer is selected, feedback is provided immediately regarding if it is correct. If the answer is wrong, the correct answer is not shown. To see if other forms of feedback can help motivate students to learn more, in the present research, an alternative version of feedback is prototyped with levels and badges showing their task performance (Fig. 3.3). It is translated into Norwegian for the study and presented to participants in both groups to compare with the current version (Fig. 3.2(b)).

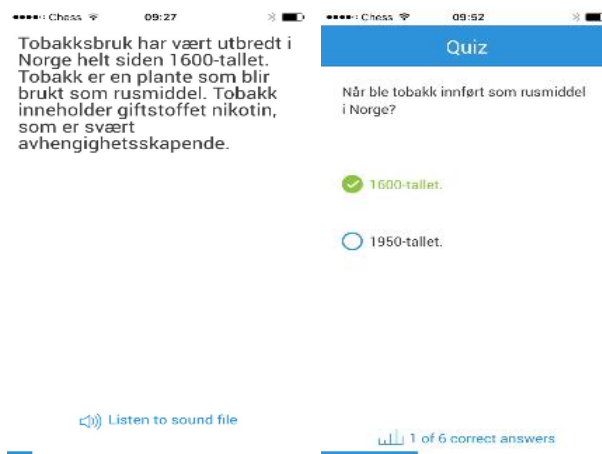


Fig. 3.2 On the left (a): an example interface with text and audio in mYouTime; on the right (b): an example interface with a quiz correctly answered in mYouTime



Fig. 3.3 Mock-up prototype of alternative feedback

3.3.2.2 Design and Participants

A between-subject design is adopted in the present study. In short, as shown in Table 3.1, each participant in Group A and Group B has four learning tasks in total with three being experiment tasks and one being the control task. The only difference between the two groups is whether the text of learning materials can be read aloud with audio or not: the three tasks in Group A have the text that can be read aloud while the three in Group B have the alternative version that cannot be read aloud.

Table 3.1 Comparison of design between Group A and Group B

	Learning tasks	Individual interviews	
	Read aloud	Follow-up open-ended questions	Feedback comparison
Group A	✓	✓	✓
Group B	X	✓	✓

The study consists of three stages. This is to allow the participants to experience the learning application through the lessons before being interviewed for thematic analysis to further elicit the motivational themes and refine the motivation model. Firstly, the participants are divided into two groups randomly. Each participant is asked to take the four learning tasks in either Group A or Group B. Secondly, in-depth interviews for all participants are conducted individually with open-ended questions to elicit the key factors affecting their motivation when they are doing tasks in the learning application. An alternative version of feedback is compared with the current version used in the learning tasks for all participants. The interviews allow coding and thematic analysis to take place, gathering together the different themes that define the users' motivational needs. The last stage involves refining the conceptual motivation model when necessary, according to themes identified in the previous stages of the empirical study with consideration of prior research related to dyslexia and motivation theories.

The participants were recruited among young members of the Norwegian dyslexic association, i.e., Dyslexia Norway or Dysleksi Norge, an organisation founded in 1976 that works for people with reading and writing difficulties, language difficulties and math problems. The inclusion criteria were:

- A) age between 14 and 16 from 8th grade to 10th grade at school;
- B) a dyslexic diagnosis confirmed;
- C) both genders equally represented approximately;
- D) geographical limitation due to practical concerns: eastern part of Norway, the larger Oslo area.

After some time and follow up from staff in Dyslexia Norway, more than twelve eligible students were confirmed. The students live in different towns scattered about the

larger Oslo area or the southeast part of Norway. Only eleven of them participated due to the scheduling issues, six in Group A and five in Group B.

3.3.2.3 Procedure

The participant arrives at the reserved room in a school for the study. The test leader greets the participant and helps them move to the testing area. Small talk with the participant is given to help create a relaxing environment, but details are not explained about the following process. After the participant sits in the testing area, the test leader describes the objectives of the study.

The participant is given time to ask questions. After the participant is done with questions, the researchers make sure that the informed consent form is signed. The test leader has to get this from the parents as they are less than 18 years old. Once this form is signed, the actual study can begin.

At the beginning, general demographic questions are given about age, gender, school information, dyslexia diagnosis, digital abilities; then the participant is helped with the setup for learning in mYouTime and researchers' observation.

After that, the participant goes through the four learning tasks. The participant can choose how to complete them but needs a little information from the researcher before that:

“Imagine you are a student that wants to review some science lessons. Your teacher informed you about a learning application called mYouTime that has some lessons tailored for you. You’ve downloaded mYouTime on your smartphone and are ready to start reviewing the lessons using the login information provided for you. There are four lessons, also called four mYouTimes, to go through. Please complete each one and let me know when you have done all of them. Then, we’ll have some questions afterwards.”

The participant is then left alone to work through the mYouTimes. The test leader follows along using the remote viewer, a screenshot of the process is shown in Fig. 3.4.



Fig. 3.4 Two screenshots from the remote view showing a participant learning in mYouTime

After all the mYouTimes are completed, follow-up interviews are conducted. Questions are designed to see how well the information was understood as well as other questions regarding their general learning experience in their life and actual experience using the application. For example, “What do you think are the good points of this learning application that would mean you would use it?” The probing questions are presented in Appendix 2.

Finally, the alternative version of the feedback was shown to the participants with an example of how it would work for a wrong answer, and then questions about their preferences and opinions were asked. The audio of the individual interviews was recorded. In addition, a stand-alone Tobii eye tracker and Morae are used during the process of the participants completing learning tasks, which allow for unobtrusive observation, as researchers can follow the progress from other screens or look at it later without making participants feel being observed. After the procedure above is completed, each participant is given a gift worth 500 Norwegian kroner as compensation.

3.3.2.4 Data Analysis

Data analysis is undertaken in three stages. Firstly, the interviews are transcribed and translated by the researchers in Norway from Norwegian into English; then the answers are extracted regarding the read aloud and quiz feedback and videos as well which are the key features of mYouTime, so that the answers from the two groups can be compared about the difference of their learning experience, and the two versions of feedback are also compared for all the participants. For example, the answers to the question about the text learning experience between one participant in Group A and one in Group B are compared in Table 3.2.

Table 3.2 An example of answers comparison between participants in Group A and Group B

One participant in	Answers about text learning experience
Group A	“Ok for me to read them, no problem”
Group B	“Difficult, must have them read aloud”

Then the second stage consists of two steps. Firstly, motivations and problems of using the e-learning software are identified and extracted from the transcripts, and participants’ reactions to each problem and good points are grouped. Using paper coding and a thematic approach, user motivations revealed for each participant are then associated with corresponding motivational factors extracted from literature in the context of e-learning systems. If no match can be identified in the literature, a new theme is put forward. Secondly, the interviews are coded and analysed using the qualitative data analysis software (NVivo10) [143], to reinforce the methodological rigour and reliability of the results. Nodes are created for the themes identified in the first step. Fig. 3.5 is a screenshot in NVivo10 showing part of the coding density and identified themes in the process of data analysis. Interviews are looked through individually and references to each theme are examined. A new node is created for any emerging theme. The second stage is adopted to refine the results and improve the objectivity of the analysis and results. The similar approach using paper coding and qualitative software has also been adopted by prior researchers [144].

The last stage involves reflecting on the conceptual motivation model according to the results of data analysis and refining the model as well if necessary.

relate to their experience and motivation, for example, “How did the text pages affect your learning experience?” and “What do you think about the change of feedback?” belong to this category. One important point worth mentioning is that all the specific aspects in the questions such as “read aloud” and “feedback” are also proposed by at least one participant actively, when the purely open-ended questions were given to elicit the good points and problems that they found would affect their further use of the application. Therefore, the following part displays the results with thematic categorisation.

Largely following the grounded theory [145], the interview data regarding their thoughts about the application in relation to their motivations are categorised, grouped and regrouped until saturated so that no further regrouping of the themes is necessary. By comparing the themes with those in previous literature, ten motivational themes are confirmed at the end, which are Feedback, Perceived Ease of Use, Perceived Fit, Perceived Usefulness, Perceived Enjoyment and Perceived Convenience, Learning Experience, Reading Experience, Perceived Control and Perceived Privacy.

Table 3.3 The themes identified (in bold) and number of participants that mentioned the themes in open-ended questions*

F			LE				PCv	PEU	PE	PF	PP	PU	PCt
			RE		VE	GU							
ImF	InF	MF	RA	TL									
2	3	7	7	3	7	6	4	2	3	3	1	7	2

* *F=feedback, ImF=immediate feedback, InF=informative feedback, MF=motivating feedback,*

LE=learning experience, RE=reading experience, RA=read aloud, TL=text length, VE=video experience, GU=general understanding, PCv=perceived convenience, PEU=perceived ease of use,

PE=perceived enjoyment, PF=perceived fit, PP=perceived privacy, PU=perceived usefulness, and

PCt=perceived control

Table 3.3 shows the identified themes and the number of participants from whom the themes are obtained in the purely open-ended questions. It shows that Feedback, Learning Experience, Reading Experience and Perceived Usefulness are the most important themes to the participants. In particular, motivating feedback is mentioned the most frequently compared to other types of feedback, and read aloud and video are the key features related

to reading experience and learning experience, respectively. The themes identified from the empirical study are explained below in detail.

Among the motivational themes identified from the empirical study, six of them are in line with the factors in the initial motivation model constructed in the previous section built upon the motivation theories and the technology acceptance, which will be described below in this section. The other four themes that newly emerged from the present study are Learning Experience, Reading Experience, Perceived Control and Perceived Privacy, which will be defined in detail in the next section.

Feedback

In a learning context, students need to have “clear and realistic” learning goals and they need to receive positive informative feedback to inform them about their progress to improve intrinsic motivation [50]. In the study, the feedback is categorised into those with three types: immediate, informative and motivating feedback. Two participants like the feature that they could get responses once they chose an answer. For example, “It’s good that I can see at once when answers are wrong”. Though the current feedback can provide the information about whether an answer is correct, it cannot show the correct answer if a user chooses a wrong one. Three participants mentioned they wanted to know the correct answer when they answered incorrectly to learn from their mistakes.

It can be seen that there are overlaps between immediate feedback and informative one, as the immediate feedback in mYouTime is also informative to users. In other e-learning systems, all kinds of feedback can be immediately output to a user once the user takes certain actions or achieves certain goals in the system.

All the participants stated that they preferred the alternative version of feedback. Some felt that it would motivate students to try harder on the quizzes “to attain a high level” and might keep their interest longer in a subject they usually don’t like. Most participants felt that the alternative would be more encouraging. For example, “I like the new one better because it is more fun, and you can climb to higher levels”; “It was motivating. If I used this I would have worked more”. Only one felt that it might “also be a bit demotivating” if lower points were got. Another felt that the current quiz feedback in mYouTime was fine for subjects in which a student was interested, but probably wouldn’t hold students’ interest in a subject in which they weren’t interested.

Perceived Usefulness

Perceived usefulness, as a factor in TAM, has been mentioned frequently by prior research. The study also confirmed its importance in the present research context. Dyslexic students also formulate their perception about the usefulness of the e-learning tools when they are using them. The participants commented on it positively; for example, “It’s a good help in preparations for tests”.

Perceived Ease of Use

Similarly, as the other construct of TAM, perceived ease of use is also confirmed in the present study, participants perceived mYouTime easy to use and understand when they commented on their user experience compared to their previous experience in daily life. For example, “It seems easy to use, compared to what I am used to”.

Perceived Fit

Perceived fit is included in the motivation model based on the extended post-acceptance model [63] and the task-technology fit theory [146]. In the present research context, perceived fit refers to students’ perception about whether the e-learning tool fits their learning tasks and needs well. As an independent variable of perceived usefulness, over half of the participants commented on it positively. For example, “Homework can be done when it suits me best, when idle time or when I wait for something.”

Perceived Enjoyment

Perceived enjoyment, as a construct of intrinsic motivation [147], is also identified as a theme from the interviews. All the comments are positive mainly regarding the videos and the alternative version of feedback. For example, “The videos, for example, the car belt video was fun”; “It makes the schoolwork a bit more exciting.”

Perceived Convenience

As a construct of the extended TAM [67], perceived convenience is also identified from the thematic analysis. Since the study is based on mYouTime on smartphones, all the comments on this are positive, praising it as an advantage of the tool. For example, “It is an easier way to learn than from a book, much more accessible.”

3.3.4 Emerging Themes Discovery

Learning Experience

Learning experience is an emerging theme in the study that is not mentioned by prior research on motivation modelling. Learning experience, in the present research context, can be classified into three main categories: reading experience that is discussed in the next section, general understanding and video experience.

Amongst the comments on general understanding of the learning materials, around half of them are positive. Several participants commented the presentation way of the learning materials and the micro-learning idea positively. For example, “I like that there were questions in between so I did not have to wait until the end.” However, there are also some participants expressing their difficulties of understanding with their recommendations. For example, “Some terms could have been explained better.”

All participants love the videos provided in mYouTime. Most comments are positive, stating that the videos are entertaining and helpful to their learning. For example, “I learned more from the videos than from the text parts”; “Videos are fun.” Meanwhile, several of them also point out problems. For example, “Some videos are too long and could have been split.” One of the explanations is that students with dyslexia experiencing reading difficulties can benefit from video materials, but the prerequisite is the appropriate design to make sure that videos are not only entertaining but also fit students’ learning needs well.

Table 3.4 A comparison of learning experience between groups

Group	Number of participants having:		
	Read aloud	Learning experience	
		Positive (e.g. “Easier way to learn than from a book”)	Negative (e.g. “I had to read several times again, difficult”)
A	6	6	0
B	0	2	3

The participants’ learning experience in Group A and Group B are compared from the

analysis of open-ended questions regarding learning experience such as “what do you think is good with the application and has led you to use it further in your schoolwork”. Table 3.4 shows the number of participants that have positive or negative learning experience in the two groups, respectively. All participants in Group A and 3 of the 5 in Group B have positive learning experience. Therefore, it can be seen that having text being read aloud or not influences learning experience to a great extent. Not all the participants in Group B have negative experience, which is probably because that text is not the only presentation way of learning contents; instead, all participants have the learning tasks with videos and other elements provided in the application, which are praised by most participants.

Reading Experience

One of the main characteristics of students with dyslexia is their reading difficulties compared with the other students, thus reading experience is particularly essential for them, which integrates the experience of reading in different aspects or from different information channels during the learning process and can be affected by the task characteristics such as sensory interests and controllability of the reading progress. That’s why reading experience is regarded as a separate emerging theme though strictly it should be part of learning experience.

Two features, “read aloud” and text length, are examined in mYouTime regarding reading experience. It is found that having text read aloud or not plays an important role in users’ reading experience, as the participants in Group B who couldn’t have text read aloud did not have a positive reading experience; for example, “I had to read several times again, it was difficult”, and two of them mentioned that they thought it would be very helpful if the lessons could be read aloud, while those having text read aloud in Group A liked the text being read aloud, which is “particularly important” to them. Only one person in Group A did not discover the function, indicating that the design of the button should be improved in the future to make it more apparent.

Regarding text length, most data is negative. Four participants hope that the text could be longer, whereas the other one finds it good that “reading aloud had not too long paragraphs”. In addition, there is one participant finding “line spacing too narrow”. Meanwhile four participants state that they like the short lessons, so the questions about how long the text should be should not have the same answer for all students; instead, this

needs to be personalised to meet individuals' needs.

Perceived Control

Perceived control is another emerging theme that was not considered initially in the proposed conceptual motivation model. It refers to users' freedom to control the learning progress or their self-choice capability in the interaction process. For example, one commented that "to me, it is important that I can control when I listen and repeat when needed" regarding the feature of "read aloud", emphasising the importance of perceived control.

There is also an issue regarding external control related to the system design identified from the remote observation, which is that there is only one chance to pick an answer to a quiz. If participants accidentally tap the screen and select an answer, the answer cannot be changed. This happened a couple of times during the study, making participants feel frustrated even though they have been told that their answers in this study do not matter.

Perceived Privacy

The last emerging theme, perceived privacy, is a very interesting one identified from the study, though it was only stated by one participant, saying that "it is a good thing that you don't have to use a large computer screen where everyone can see what you have written", which makes the participant feel much better to use a smartphone. This can be explained by dyslexic students' high possibility of falling behind others, which can lead to subsequent, profound frustration [53], [148]. Therefore, they need more personal space for learning to avoid comparison with peers without dyslexia and thus minimise the possibility of feeling frustrated.

3.3.5 Refined Motivation Model

The four emerging themes are then incorporated into the conceptual motivation model at appropriate nodes. To this end, their interrelationships and the relationships between these themes and other factors in the conceptual motivation model need to be examined based on prior research with the consideration of the characteristics of students with dyslexia and the present e-learning context.

Learning experience is identified as a motivation theme, as it was found that the participants' answers to the questions regarding missing points that negatively affect their

continued use intention are all related to learning experience including reading experience. For example, one participant commented that “Some concepts could have been explained better, for example, in the lesson about cells”. Therefore, learning experience is supposed to be a necessary factor in the motivation model.

As improving learning success is the ultimate goal of e-learning tools, learning experience is a crucial part in dyslexic students’ user experience, good learning experience would thus improve their perceived usefulness of the tools and their acceptance and use intention. Moreover, when asked about the entertaining points in the interaction process, most participants pointed out that they liked video best and they found videos were “fun”; also, regarding the good points they thought leading to their further use, three of them mentioned again that they liked the videos making learning easier, for example, one said “I like to see a video first and then questions afterwards, make you understand the subject better”; thus, it can be inferred that good learning experience contributes to perceived enjoyment. Therefore, learning experience is expected to affect continued use intention through perceived usefulness and perceived enjoyment.

As discussed in the previous section, reading experience plays an important part of the learning experience of students with dyslexia. Also, when participants were asked about good points of the application that would lead to their further use, several participants mentioned that they liked “read aloud” making their learning easier; for example, one participant commented that “very good to read aloud, also nice with short lessons”, which is a good point affecting further use; furthermore, regarding the answer to missing points in the application that negatively affect their use, two participants in Group B mentioned that “read aloud” could have been used, which demonstrates that reading experience is one of the essential themes in relation to learning experience that affects dyslexics’ motivation to use e-learning tools.

Perceived control, as an emerging theme, is elicited from participants answers to questions, overlapping to some extent with the perceived behavioural control in the theory of planned behaviour [53] and control as part of ease of use in the model proposed by Venkatesh [68]. For example, one commented that “I can work in my own pace”, as a good point leading to continued use intention. Perceived control is related to both intrinsic factors like self-efficacy and extrinsic factors like perceived ease of use, as the belief on one’s abilities can apparently influence perceived control, determining the degree to

which additional help is needed during the learning process. That's why perceived control is expected to affect continued use intention through self-efficacy and perceived ease of use.

As discussed before, personal space helps ensure a private learning environment for students with dyslexia by isolating them from external pressure from peers, parents or tutors during the learning process. Therefore, perceived privacy is another motivational factor emerging from the study, contributing to users' continued use intention. The participant who proposed this also emphasised the portability and accessibility of smartphones, resulting relationships between perceived privacy and perceived convenience in the refined model. The refined conceptual motivation model is displayed in the next section in detail.

The motivation model is refined by integrating the four new themes that emerge in this study, shown in Fig. 3.6. Emerging themes are added to the motivation model at certain points along with six new interrelationships that are listed in Table 3.5, which have been explained above based on prior research into the concerns about dyslexia and motivation theories as well as the e-learning context. As the main objective of the interviews is to elicit more motivational factors for students with dyslexia in their use of e-learning technology rather than test each factor in the motivation model, and also due to the small number of participants, it is not reasonable to imprudently remove the factors from the model that did not involve in the themes identified from the empirical study, and also factors like self-efficacy were not examined in the study. Therefore, they are remained in the model with dashed circles for further validation.

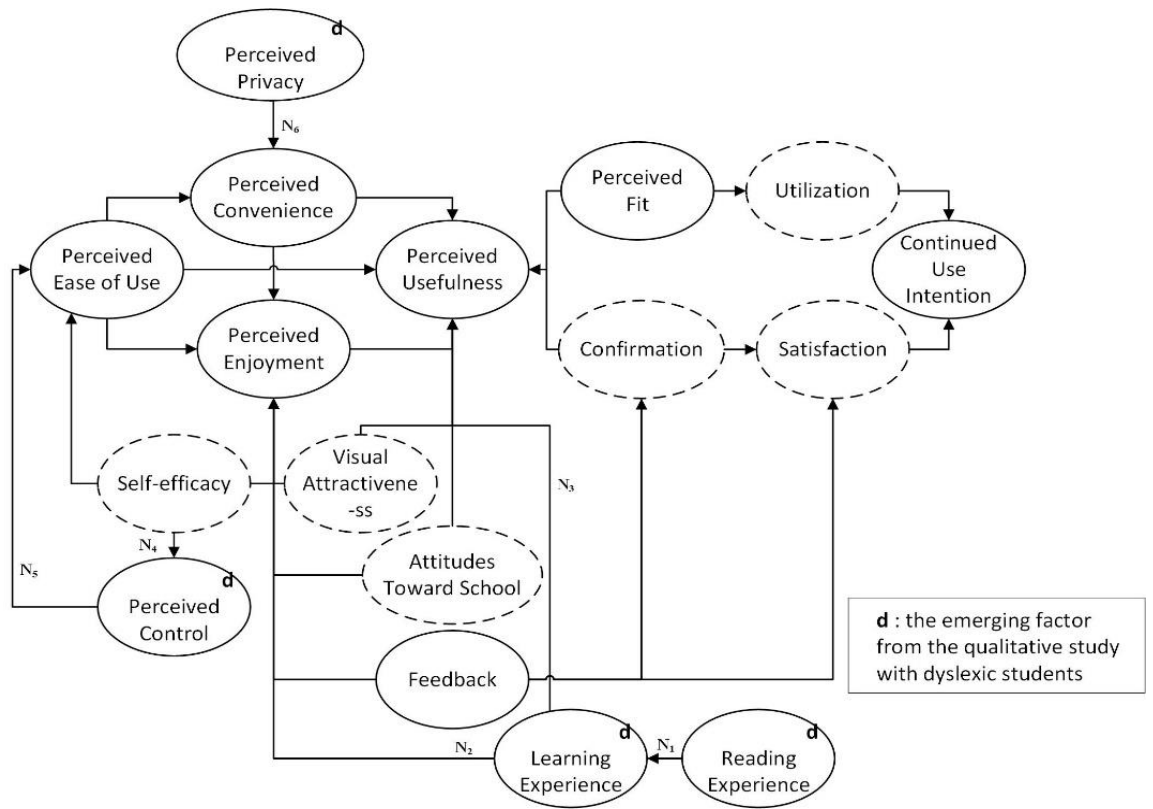


Fig. 3.6 The refined conceptual motivation model and new interrelationships

Table 3.5 The new interrelationships in the refined motivation model

N₁	Reading Experience positively influences Learning Experience
N₂&N₃	Learning Experience positively influences Perceived Enjoyment (N ₂) and Perceived Usefulness (N ₃)
N₄&N₅	Perceived Control is positively influenced by Self-efficacy (N ₄), and Perceived Control positively influences Perceived Ease of Use (N ₅)
N₆	Perceived Privacy positively influences Perceived Convenience

In summary, the conceptual motivation model brings together different perspectives from psychology and technology acceptance for people with dyslexia in e-learning context. The refined conceptual motivation model constructed showing different perspectives as the ground of the model is presented here in Fig. 3.7. In short, starting from the extended TAM [67] and the extended post-acceptance model [63], the motivation model is developed and refined by integrating both intrinsic factors and

extrinsic factors from existing theories together with emerging factors identified from the qualitative empirical study with real dyslexic users.

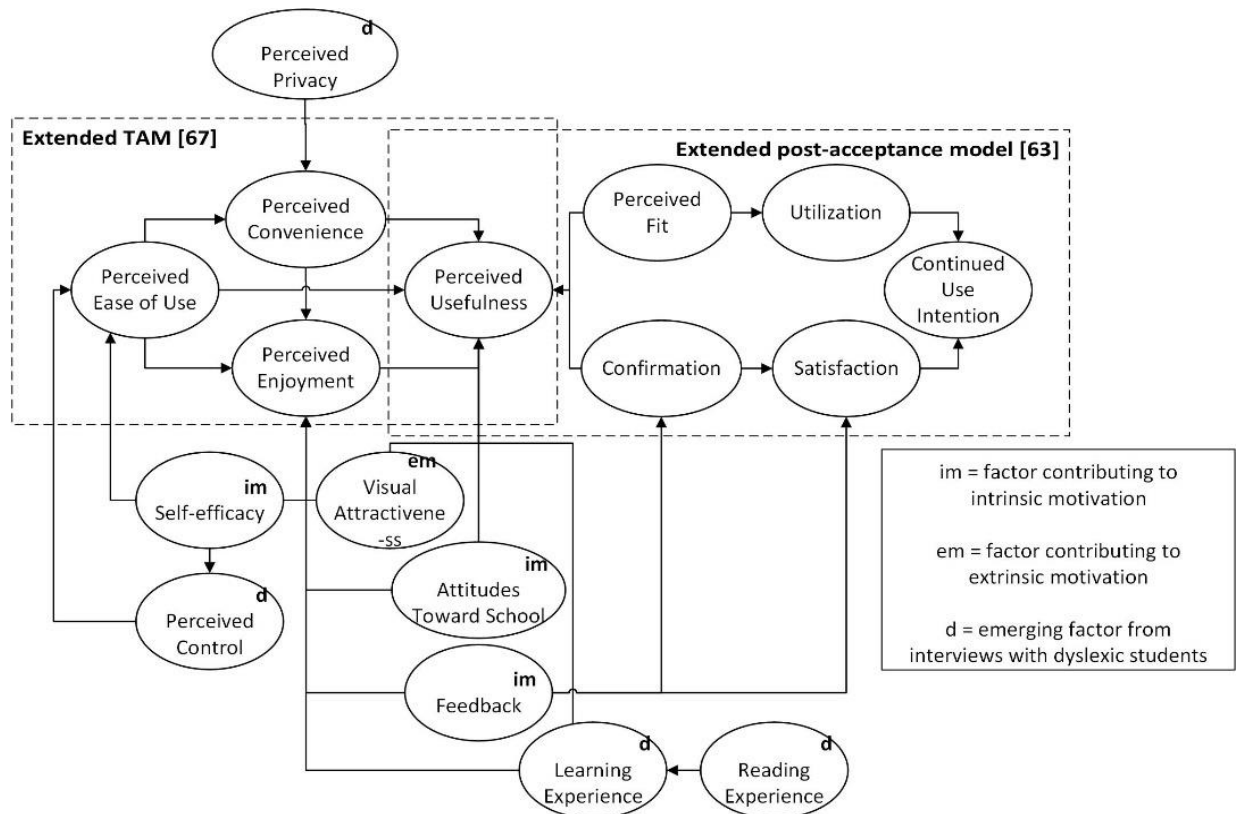


Fig. 3.7 The result motivation model showing sources from different perspectives

3.4 Computational Motivation Modelling

As stated in Chapter 2 for motivation modelling from computational perspective, ontology-based modelling has the advantage of being modular and easily extendable and reusable across different application domains. This section aims to model a user's motivational needs computationally using ontological modelling approach based on the conceptual motivation model to be used by e-learning systems for personalising services to adapt to the user's motivational needs. Existing ontological user models that have been applied to personalised e-learning systems are mostly restricted to taxonomies of user interests, requests or preferences. The ontology-based modelling approach adopted in this section provides high level of modelling capabilities to computationally represent the components of learners' motivation showing the motivational factors and those of

personalisation showing aspects e-learning systems that can be personalised. Ontologies facilitate organising the metadata about complex information that are encoded as instances in the ontology [149], and ontologies can represent the conceptual motivation model formally and explicitly by describing the main concepts (i.e., the factors in the conceptual motivation model) and their interrelationships. The following sections firstly introduce ontological motivation model in the big picture for dyslexic students in personalised e-learning systems and then detail the process of the ontology-based motivation modelling, which puts emphasis on the **MotivationState** class including factors that can determine learners' motivation in e-learning context and the **Personalisation** class including options for e-learning systems to be personalised based on the motivational states of dyslexic users.

3.4.1 An Overview of Ontology for People with Dyslexia

This section introduces the graphical representation of an overall ontological model for dyslexic students and the position of the motivation model in a big picture to illustrate how the motivation model extends the existing ontology.

An overview of ontology for users with dyslexia in a personalised assistive learning system is shown in Fig. 3.8, where the class “Course Materials and Feedback” represents the learning contents and other course elements such as quizzes and feedback in between. The *hasObjectives* property refers to the objectives of the learning course studied by a user. The classes, “Dyslexia Type” and “Learning Style” have been introduced in prior research to be used for personalised learning for dyslexic learners [150], [151], [32], in which “Learning Style” was built on Felder and Silverman’s Learning Style Model (FSLSM) and each type of dyslexia was matched with the dimensions of FSLSM [32], [152]. “Dyslexia Type” reflects the learning difficulties of dyslexia including five properties: reading, writing, speaking, mathematics, memory. “Dyslexia Type” class is matched with “Learning Style” with the *hasLearningStyle* object property. Furthermore, “Learning Style” is composed of the FSLSM components of learning styles including reflective, visual, sensory, sequential, and auditory styles. The same approach to link dyslexia types to learning styles has been employed by previous research [32].

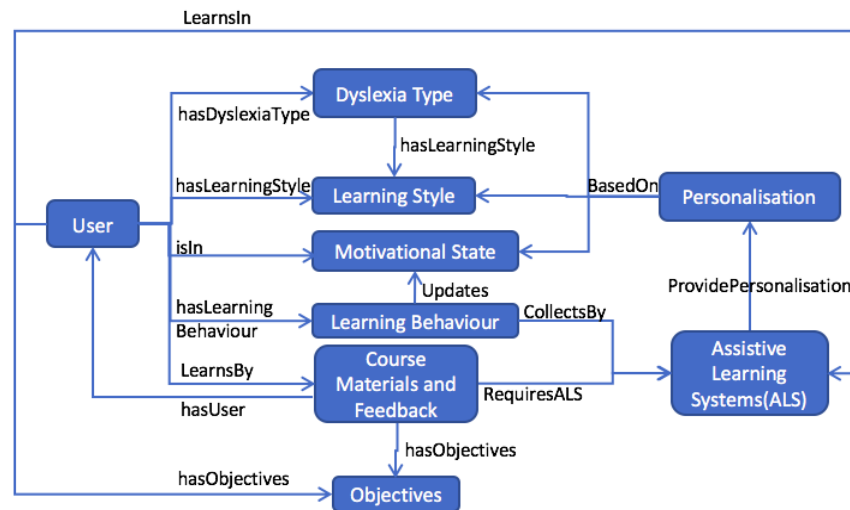


Fig. 3.8 The key relationships within the overall ontological model for dyslexic students

As shown in Fig. 3.8, the class “Motivational State” is integrated into the overall ontological model to allow for the motivation assessment and motivation-based personalisation for dyslexic learners. The present research work focuses on modelling factors that have impact on the dyslexic learners’ motivation to engage in the e-learning systems. The ontological motivation model in the present research will extend the existing ontologies by incorporating the motivational factors to make future personalisation of the e-learning environments not only adapt to factors like dyslexics’ learning styles and dyslexia types but also adapt to their motivation states. The next section will detail the process of ontological modelling process of dyslexic learners’ motivation and personalisation options in e-learning environments with the emphasis on the motivational strategies to be personalised based on motivation.

3.4.2 Ontology-based Motivation Modelling

The overview of the ontology introduced above for students with dyslexia provides a holistic picture of the context of the ontology-based motivation model. Ontological modelling involves defining a number of concepts related to a user in a domain along with the properties and relationships associated with those concepts. Ontological motivation model contains information about the learners’ motivation. The e-learning systems use this information in order to assess the learner’s motivational state and then

adapt to the learner's individual motivational needs. The system gradually updates the motivation model during users' learning process, in order to detect their specific motivational needs and then guide the learner accordingly through personalisation of the learning environment.

Ontology Web Language (OWL) is an extension of the Resource Description Framework (RDF) for resource description and information representation in the web with more expressivity and reasoning power based on description logic. An OWL-based design is adopted to build the computational model. Protégé 5.2 [153] is employed to edit and update contents.

The process of ontological motivation modelling to can be summarised as follows. User's characteristics related to motivation and their interrelationships in the context of e-learning environments have been identified through the conceptual motivation modelling process described in Section 3.3. The key concepts and properties are classified into a hierarchical structure that can represent the conceptual motivation model. Specifically, the **MotivationState** class is built by encoding the factors and their interrelationships identified in the conceptual motivation model. Each student will have a profile with a specific motivational state to be used for personalising the learning services, the student and his or her motivation state is connected by **isIn** object property. As shown in Fig. 3.9, an instance of **Student** class called "Student1" has a specific motivational state represented as "StudMotiv1" which is an instance of **MotivationState** class, and they are connected by **isIn** Object property. "Studmotiv1" has a value of Level 5 as its data property. Fig. 3.10 shows the motivation model produced by a Protégé 5.2 plugin called OntoGraf, where the classes are connected by properties representing causal relationships between continued use intention and the factors in the conceptual motivation model. Finally, they are encoded in a formal ontology language in Protégé. **MotivationState** class of the ontology reflects the factors that should be included in the motivation model, incorporating different aspects of motivational needs. Fig. 3.11 shows the class hierarchy generated by a Protégé plugin named OWLViz.

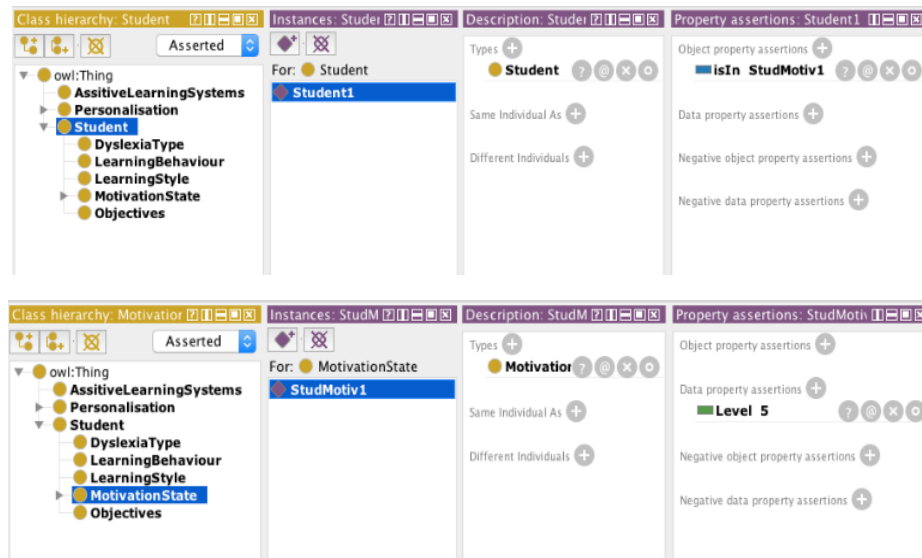


Fig. 3.9 Example of class instances and property assertions

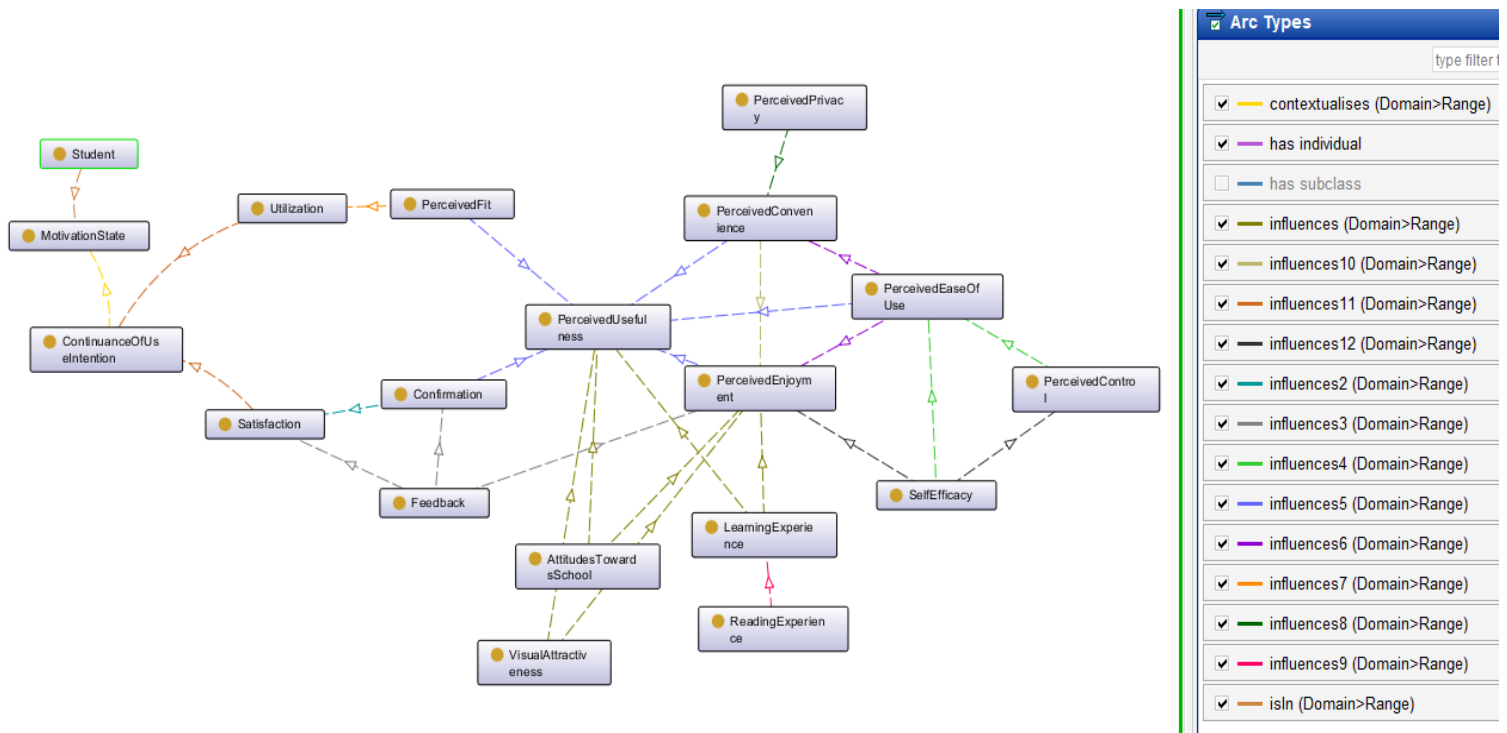


Fig. 3.10 Ontological motivation model by OntoGraf

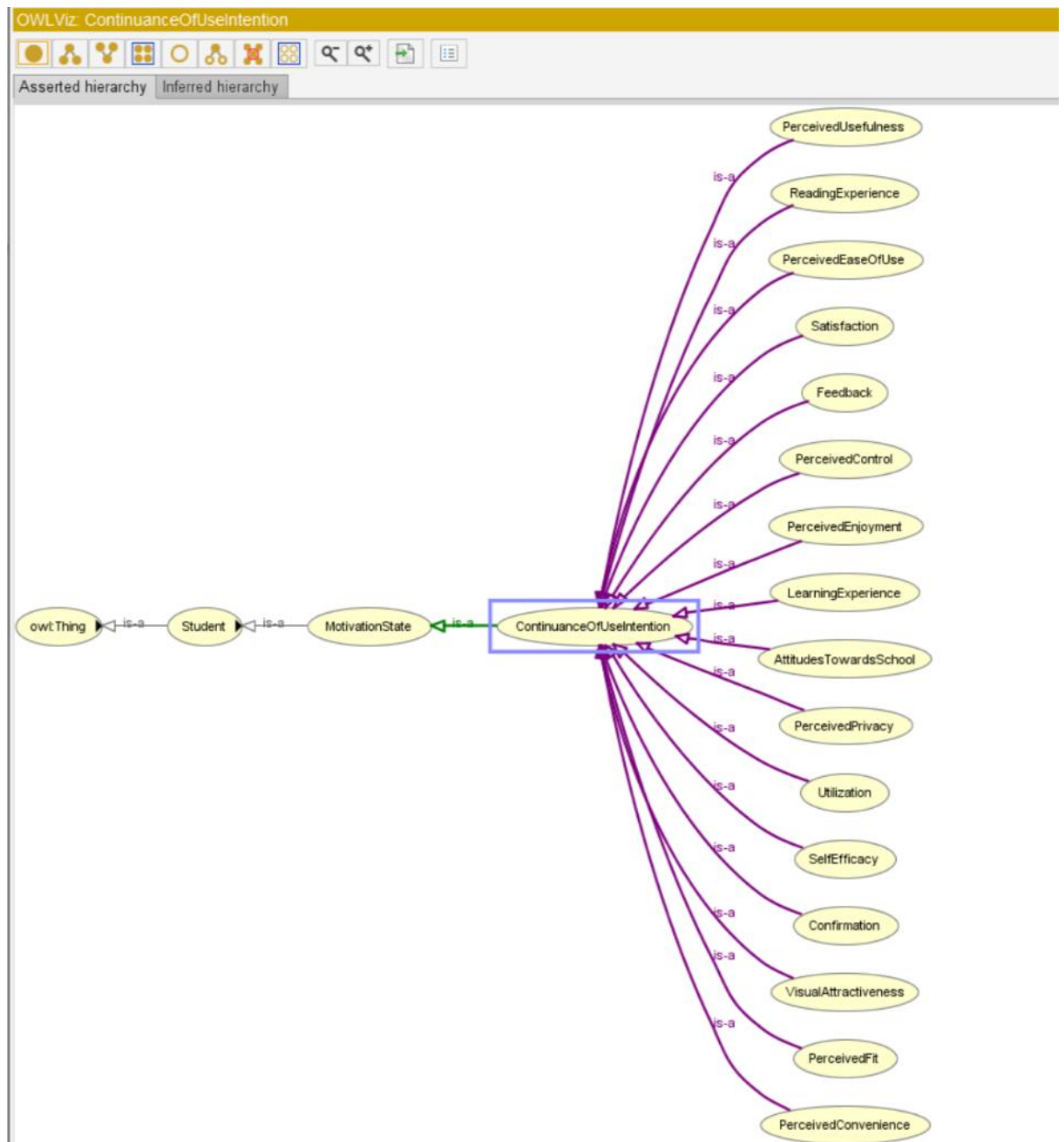


Fig. 3.11 Hierarchy of the **MotivationState** class by OWLViz

The **Personalisation** class shown in Fig. 3.12 is a semantic class to provide a range of personalisation options that allow the system to be adapted to the user’s motivational state and other dyslexic needs. The **Personalisation** class categorises the various solutions and applications available into semantic classes.” For instance, the first level of the class classifies the solutions into ten generic classes: **Reading, Writing, Communication, Hearing, Vision, Mobility, ShortMemory, Organisation, CourseFeedback** and

CourseQuantity related to the difficulties of students with dyslexia and can be personalised based on user's motivational needs and preferences. Specifically, motivation has been suggested to be considered in the quantity of course materials and feedback presented to the student [154], [155]. For example, students with higher level of motivation are more likely to learn faster and learn bigger quantities of the course materials; also, positive feedback can change user's motivational state, as studies have shown the positive correlation between the feedback of the learning progress (“which makes ability perception”) and learning engagement [154].

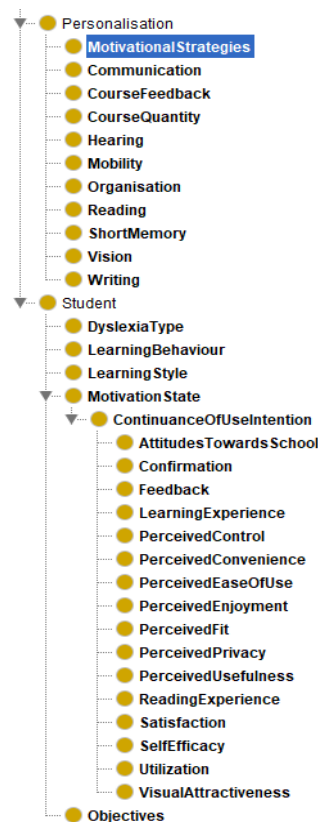


Fig. 3.12 The **Personalisation** class and **Student** class with their subclasses in Protégé

More important to motivation, e-learning systems can use motivational strategies such as probing a problem or output an attention alarm to stimulate learners to address their motivational needs in order to make learning easier, more enjoyable, more efficient and more effective. Though all the subclasses of **Personalisation** can be applied to personalised learning based on motivation, **MotivationalStrategies** is the most relevant

one to be personalised to fit different users' motivational needs, while the other aspects of personalisation such as course quantity, reading and writing are usually better executed upon users' direct requests instead of the assessment of motivational states. Therefore, the motivation-based personalisation in the present research will focus on personalising motivational strategies to address different motivational needs implied by the factors in the motivation model. The details regarding which strategies should be used during the learning process and whether they are effective will be described in Chapter 6. The more the classes in the ontological model is drilled down, the more the system is personalised.

3.5 Conclusion

In this chapter, dyslexic users' motivational factors are modelled in order to better adapt e-learning environments to their specific motivational needs accordingly in the future. Based on prior research on psychological theories, technology acceptance and dyslexics characteristics, and the empirical study with dyslexic students, a conceptual motivation model is constructed for people with dyslexia. The present empirical study provides invaluable first-hand data in the e-learning context on the views of dyslexic students, where ten themes are identified regarding dyslexic students' motivational factors in their use of e-learning tools. The present research has led to a novel motivation model with new factors, i.e., Learning Experience, Reading Experience, Perceived Control and Perceived Privacy. This chapter also describes an ontology-based computational motivation model for people with dyslexia to be embedded in a personalised e-learning system for providing personalised services based on the motivational needs represented in the motivation model. The construction process of the ontological motivation model is illustrated using the motivational factors and connections between them.

As the present motivation model along with the interrelationships between factors in the model is developed using a qualitative approach, the next chapter will apply a quantitative approach to motivation modelling to quantitatively validate the model and specify the interrelationships between the factors, including the ones built upon prior research but did not occur in the qualitative empirical study.

Chapter 4 Quantitative Model Specification and Parameterisation

4.1 Introduction

User modelling has been widely used for the personalisation of various context-aware applications including adaptive user interfaces, user recommendation systems and e-learning systems. The first step of applying personalised motivational strategies to e-learning systems is to model the factors that reflect different dimensions of users' motivation to learn in e-learning systems. Chapter 3 has described the motivation model developed using a qualitative approach detailing the factors that influence dyslexic students' motivation to engage in e-learning systems. The motivation model is developed combining the perspectives of technology acceptance, psychological theories and dyslexics characteristics. Starting with the qualitative motivation model, the objective of the quantitative motivation modelling in this chapter is to further investigate how the factors in the model function together to impact on the motivational consequence in the present e-learning context, i.e., users' continued use intention. The relationships between factors in the qualitatively constructed motivation model (Fig. 3.7) were inferred based on prior research and theories, but the drawback is that we can hardly confirm or identify the causal relationships between the factors in the model without quantitative data analysis, as the existing models have either a different target group rather than students with dyslexia or a different research context rather than e-learning context; Therefore, it is also expected the relationships between the factors will be modified and refined with the guidance from quantitative data analysis, given the shortage of theoretical references.

Therefore, this chapter will further quantitatively specify the conceptual motivation model with parameters that indicate the quantified relationships between the factors in the model, which can be in future used by e-learning systems to analyse a learner's motivational states and offer motivation-based personalised strategies. In this chapter, the process of the model specification and parameterisation will be explained which refers to revealing the motivational factors with statistically significant impact on continued use intention and quantifying the relationships between the factors in the model. To achieve that, each factor in the motivation model is represented by a latent variable, and a multi-item questionnaire is designed to measure each latent variable with multiple items. It is

distributed amongst people with dyslexia to empirically calculate the influence and weights of the motivational factors. Structural Equation Modelling (SEM) is employed as the approach of data analysis to validate the factors in the motivation model and modify the relationships between them based on the results of the study along with the reference to prior research and theories. SEM represents a set of statistical techniques including Confirmatory Factor Analysis (CFA) and path modelling [156], [157]. SEM is superior to tradition regression analysis for it analyses measurement model and structural model together as an integral part of the model [158] and models relationships among multiple independent and dependent variables systematically [159]. SEM can be either a covariance-based analysis (CB-SEM) or a variance-based approach, known as partial least squares (PLS-SEM). CB-SEM has the assumption of multivariate normal distribution aiming at reproducing theoretical covariance matrix, while PLS-SEM, aiming at maximising the explained variance of the dependent variables, is advantageous in the case of small sample size as well as when the data set does not meet the assumption of CB-SEM [159], [160].

The remaining of the chapter is organised as follows. Section 4.2 describes the process of multi-item questionnaire design and data collection, and section 4.3 explains the data analysis using both CB-SEM and PLS-SEM to quantitatively uncover how each factor work on the motivational consequence and how the factors relate to each other in the motivation model, followed by discussions on findings in Section 4.4 and a conclusion in Section 4.5.

4.2 Questionnaire Design and Data Collection

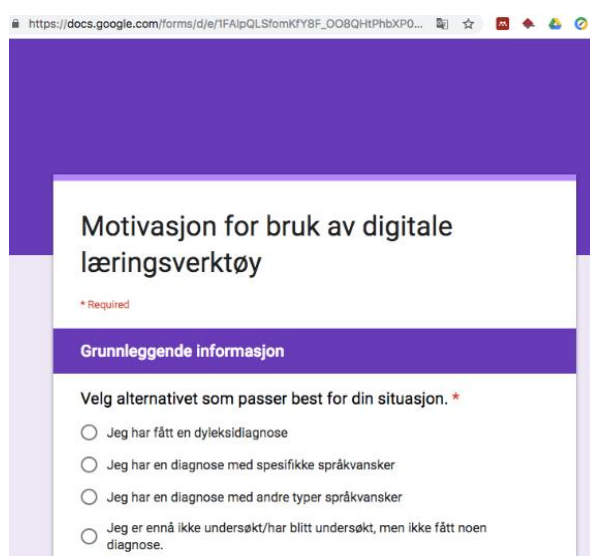
To quantitatively examine the reliability of the factors in the motivation model and how the different factors relate to each other, the first step is the questionnaire design for measuring the motivational factors to enable their quantitative interrelationships to be established and modified through SEM combined with theoretical backbones.

4.2.1 Multi-item Questionnaire Design

All the questionnaire items use a 5-point Likert-type scale, ranging from “strongly disagree” (i.e., “1”) to “strongly agree” (i.e., “5”). The questionnaire consists of multiple

items measuring each motivational factor. Extensive literature review is carried out to identify the reliable measurement instruments that has been used by acknowledged literature to measure the motivational factors. In terms of the present use scenario, the most relevant items and instrument is selected in case of more than one instrument or more than seven items found for that factor. Slight changes are made when necessary to reflect the present e-learning research context. Finally, in terms of the four motivational factors (i.e., Learning Experience, Reading Experience, Perceived Control and Perceived Privacy) that emerged from the qualitative empirical study described in Chapter 3, the concept for each of the four factors is operationalised to design the items to measure it according to the definitions explained before and the present e-learning context for dyslexic users. All the items are detailed in Appendix 3.

The questionnaire is then translated into Norwegian and several items are removed to avoid redundancy and confusion after expert review. Finally, a pretest is conducted to assess the wording and interpretability of the questionnaire with four Norwegian students from Dyslexia Norway. As suggested, optional fields are added for open comments under each question.



https://docs.google.com/forms/d/e/1FAIpQLStomKY9F_OO8QHtPhbXP0...

Motivasjon for bruk av digitale læringsverktøy

* Required

Grunnleggende informasjon

Velg alternativet som passer best for din situasjon. *

- ☐ Jeg har fått en dyleksidiagnose
- ☐ Jeg har en diagnose med spesifikke språkvanser
- ☐ Jeg har en diagnose med andre typer språkvanser
- ☐ Jeg er ennå ikke undersøkt/har blitt undersøkt, men ikke fått noen diagnose.

Fig. 4.1 A screenshot of the online questionnaire

4.2.2 Sampling and Data Collection

This online questionnaire study has got the ethical approval in the Faculty of Computing, Engineering and Media at De Montfort University. The sample was from young Norwegian student members of Dyslexia Norway. Eventually eighty-eight young respondents filled in the online questionnaire. Table 4.1 displays the sample demographics.

Table 4.1 Sample demographics (n=88)

Measure	Items	Frequency	Percent
Gender	Male	26	29.5%
	Female	62	70.5%
Age	13-16	42	47.7%
	17-19	4	4.5%
	> 19	42	47.7%
Diagnosis	Dyslexia	82	93.2%
	Other specific language difficulties	5	5.7%
	Not tested	1	1.1%
E-learning systems used	Reading and writing programs (e.g. LingDys, CD-ord) *	88	100%
	Learning management systems (e.g. Itslearning, Blackboard) *	79	89.8%
Usage	Every day *	52	59.1%
	In all classes *	27	30.7%
	At home doing homework *	45	51.1%
	At home in leisure time *	25	28.4%
Training and Support	have been trained *	32	36.4%
	have teacher's help *	16	18.2%

** Items are not exclusive of each other.*

The online survey using Google Forms was distributed through email circulated by Dyslexia Norway to the student members. They were invited to participate voluntarily in an online questionnaire (see Fig. 4.1 for a screenshot). The respondents were asked to

click on the link in the email leading to the questionnaire, and it takes ten to 20 minutes to complete all the questionnaire items.

4.3 Quantitative Motivation Model Analysis

4.3.1 Methodology

SEM has been suggested to be treated more as CFA rather than Exploratory Factor Analysis (EFA) with multiple regression, as it is more a theory-driven confirmatory technique, but it can also be used for exploratory purposes [161]. In the present study starting with the model in Fig. 3.7, SEM is used not only for confirmatory purposes but also combined with exploratory purposes, because the motivation model developed using the qualitative approach needs more evidence or re-exploration of the relationships between the motivational factors with the guidance of quantitative data analysis. While CB-SEM is primarily a confirmatory method, PLS-SEM is preferred to be used for exploratory research [162]. Therefore, to address both purposes, both CB-SEM and PLS-SEM are applied in the present research to enable deep understanding of the factors in the motivation model and their interrelationships, with the comparison between CB-SEM and PLS-SEM to ensure the methodological robustness.

The dimension reduction is necessary for the items used in the 5-point multi-item questionnaire in the case of redundancy to reduce the data to a smaller set of more representative summary variables, so EFA is employed to assess the sampling adequacy for each factor in the motivation model, i.e., each subscale of the questionnaire measuring one motivational factor. Furthermore, due to the qualitative nature of the starting model in Fig. 3.7, specifically the quantitative modelling aims to collect the multi-item questionnaire data to test the significance of the impact of the factors and to further explore and confirm the quantitative relations between factors in the motivation model.

Therefore, SEM analysis is performed to estimate the measurement model, i.e. to specify the reliability of the measured factors in the model, and the structural model, i.e. to show the interrelationships between the factors as a succession of structural equations. As CB-SEM requires the assumption of multivariate normality, the normality of the data of each scale that measures one factor is tested using Shapiro-Wilk tests of normality.

The score of each factor is calculated by averaging the scores of the questionnaire items measuring the factor. Results suggest that the data were non-normally distributed using Shapiro-Wilk test except data for the factor Utilization ($p=0.072$). Given that the data set does not meet the normality assumption, PLS-SEM is also used which does not require normal distribution in addition to applying bootstrapping procedure in CB-CEM. Furthermore, given the limitation of the small sample size of eighty-eight participants, PLS-SEM has always larger or equal statistical power [163]. Therefore, SEM techniques are employed including both CB-SEM in AMOS 22.0 [164] and PLS-SEM in SmartPLS 3.2 [165], which allows for examining if there are noteworthy different findings.

The objectives of the analysis are: 1) to ensure the reliability and validity of the measurement model; and, 2) to examine the statistical significance of the paths in the structural model. The objectives are identical no matter which statistical technique is used [166]. In CB-CEM approach, the overall model fit is reflected by the Chi-square test. A non-significant Chi-square indicates an acceptable model fit. However, as Chi-square statistic is prone to sample size [167], the fit indices used in the present research also include CMIN/DF (Chi-square divided by degree of freedom), the comparative fit index (CFI) as the supplementary incremental fit index to examine the covariance structures and the root mean-square error of approximation (RMSEA) as a measure of absolute fit index. In contrast, the classic measures for CB-SEM are not applicable in PLS-SEM approach [168], and the most commonly used measures are R^2 (explained variance), f^2 (effect size) and Q^2 (predictive relevance) [160].

4.3.2 Dimension Reduction

EFA was run using the principle components analysis in SPSS 22.0. The data passed the thresholds for sampling adequacy (KMO MSA 0.745, Bartlett's test of sphericity 6080.583, $P<0.001$). The items underlying factors Perceived Enjoyment, Perceived Convenience and Satisfaction were removed, since they demonstrated high cross-loadings in another factor Perceived Ease of Use. The three factors also had a very high correlation with each other (r bigger than 0.8); Confirmation and Perceived Fit were combined into one factor as Confirmed Fit representing users' confirmation of expected fit between systems and users, because the items of Confirmation loaded high in Perceived Fit and vice versa, and there was also a high correlation between the two factors

(r bigger than 0.8). A possible explanation is that the enjoyment was introduced from gaming environment which is not very applicable in the current e-learning context, and perceived convenience, confirmation, satisfaction, perceived fit and perceived ease of use were so highly correlated with each other that they cannot be well differentiated from each other using the questionnaire items in the context of e-learning systems.

After eliminating or combining the factors mentioned above, the rest twelve factors explained 61.3% of the variance in “continued use intention”. As such, preliminary evidence for convergent validity and discriminant validity was provided. The rest twelve factors were then used to run the CB-SEM and PLS-SEM.

4.3.3 Measurement Model

In both CB-SEM and PLS-SEM, the measurement model is assessed with indicator reliability (i.e., items’ factor loadings), internal consistency reliability, convergent validity and discriminant validity. Therefore, the results from both approaches are presented and compared in Table 4.2. the internal consistency is evaluated by computing the Cronbach’s alpha and composite reliability. In case that the alpha value of a factor is less than the recommended threshold 0.7 [169], the items are removed underlying the factor which were uncorrelated with the factor score, and the score for the factor is recalculated. All Cronbach’s alpha’s are bigger than 0.7 after the items are removed. The convergent validity is assessed with Average Variance Extracted (AVE) values. Another two items are removed under “learning experience” whose AVE values are less than the threshold 0.5 [170], and its score is recalculated, and an item is also removed under Utilization whose factor loading was less than 0.5 [169] (see Appendix 3). Afterwards, all factor loadings (the minimum one for each motivational factor shown in Table 4.2), AVEs, Cronbach’s alpha’s and composite reliabilities exceed the threshold values, reconfirming the validity and reliability of the measures.

Table 4.2 Reliability and convergent validity statistics

Factors ^a		PU	PE	CF	F	VA	UT	SE	AS	PC	PP	LE	RE	UI	Recommended
Cronbach's Alpha	CB-SEM	0.922	0.899	0.95	0.865	0.763	0.716	0.821	0.367 * 0.844 **	0.468 * 0.760 **	0.549 * 0.709 **	0.7	0.931	0.818	> 0.7
	PLS-SEM	0.922	0.902	0.971	0.866	0.764	0.726	0.822	0.459 * 0.846 **	0.463 * 0.765 **	0.557 * 0.708 **	0.728	0.932	0.819	
Composite Reliability	CB-SEM	0.945	0.933	0.961	0.909	0.864	0.835	0.871	0.907	0.895	0.837	0.810 * 0.863 **	0.952	0.893	> 0.7
	PLS-SEM	0.945	0.931	0.975	0.909	0.86	0.824	0.869	0.906	0.895	0.825	0.814 * 0.897 **	0.951	0.892	
AVE	CB-SEM	0.813	0.779	0.803	0.716	0.681	0.587	0.532	0.765	0.81	0.632	0.419 * 0.676 **	0.831	0.715	> 0.5
	PLS-SEM	0.813	0.772	0.813	0.714	0.673	0.584	0.528	0.763	0.809	0.617	0.414 * 0.686 **	0.831	0.734	
Minimum Factor Loading	CB-SEM	0.803	0.716	0.84	0.767	0.789	0.294 * 0.712 **	0.701	0.836	0.9	0.752	0.798	0.877	0.823	> 0.5
	PLS-SEM	0.798	0.787	0.842	0.758	0.708	0.197 * 0.823 **	0.63	0.807	0.887	0.615	0.805	0.872	0.825	

* The value before removing the item(s); ** the value after removing the item(s).

^aF = Feedback, LE = Learning Experience, RE = Reading Experience, Utilization = UT, SE = Technology Self-efficacy, PE = Perceived Ease of Use, CF = Confirmed Fit, PP = Perceived Privacy, PU = Perceived Usefulness, PC = Perceived Control, VA = Visual Attractiveness, AS = Attitudes Toward School, and UI = Continued Use Intention.

Then, the individual AVEs are examined and compared with the squared correlations among the factors, see Table 4.3. Each factor's individual AVE surpasses the values of the squared correlations between the factor and the other factors, so discriminant validity is reconfirmed according to Fornell-Larcker criterion [170]. CB-SEM and PLS-SEM have generated very similar values shown in Table 4.2 and Table 4.3, leading to the consistent results.

Finally, common method bias is tested by conducting Harman's single-factor test. Firstly, all measurement items are loaded into one EFA principle component analysis, and the number of factors to be extracted is fixed as one. The result shows that the factor has only explained 33.521% of the variance rather than a majority, so no indication for common method bias is found. Secondly, a CFA is conducted in AMOS 22.0 to assess the fit of a single factor model by loading all items on one factor. The single factor model has very poor fit (CMIN/DF=45.002; RMSEA=0.711), which again indicates that common method bias is unlikely to be an issue. For PLS-SEM, a full Collinearity test is an effective approach to the identification of common method bias, which is indicated by the occurrence of VIF values greater than the 3.3 threshold [171]. The VIF values generated for all latent variables are checked in SmartPLS with the biggest VIF value being 1.541, reconfirming no contamination of common method bias.

Table 4.3 Discriminant validity: AVEs versus cross-factor squared correlations

CB-SEM													
	PU	PE	CF	F	VA	UT	SE	AS	PC	PP	LE	RE	UI
PU	0.813												
PE	0.524	0.779											
CF	0.531	0.659	0.803										
F	0.139	0.091	0.130	0.716									
VA	0.074	0.081	0.149	0.305	0.681								
UT	0.040	0.030	0.022	0.079	0.241	0.587							
SE	0.058	0.083	0.104	0.043	0.092	0.104	0.532						
AS	0.078	0.060	0.053	0.029	0.035	0.061	0.050	0.765					
PC	0.106	0.194	0.219	0.130	0.147	0.130	0.226	0.036	0.810				
PP	0.022	0.010	0.038	0.100	0.057	0.071	0.070	0.071	0.038	0.632			
LE	0.026	0.047	0.070	0.085	0.110	0.049	0.071	0.203	0.095	0.166	0.676		
RE	0.303	0.288	0.389	0.143	0.255	0.151	0.154	0.052	0.202	0.104	0.198	0.831	
UI	0.118	0.051	0.097	0.154	0.399	0.286	0.120	0.149	0.078	0.075	0.154	0.350	0.715
PLS-SEM													
	PU	PE	CF	F	VA	UT	SE	AS	PC	PP	LE	RE	UI
PU	0.813												
PE	0.588	0.772											
CF	0.593	0.717	0.813										
F	0.127	0.093	0.116	0.714									
VA	0.095	0.094	0.166	0.288	0.673								
UT	0.105	0.044	0.069	0.094	0.281	0.760							
SE	0.070	0.132	0.181	0.074	0.194	0.183	0.528						
AS	0.048	0.065	0.092	0.061	0.116	0.108	0.167	0.763					
PC	0.130	0.182	0.248	0.135	0.181	0.176	0.299	0.103	0.809				
PP	0.023	0.016	0.054	0.068	0.078	0.136	0.148	0.135	0.063	0.617			
LE	0.052	0.079	0.123	0.048	0.203	0.118	0.268	0.381	0.168	0.255	0.686		
RE	0.323	0.288	0.382	0.149	0.095	0.256	0.224	0.100	0.236	0.112	0.283	0.831	
UI	0.136	0.076	0.104	0.158	0.445	0.332	0.190	0.187	0.101	0.080	0.264	0.406	0.734

Bold scores (diagonal) are the AVEs of the individual factors; of the diagonal are the squared correlations between the factors; refer to Table 4.2 for the short names.

4.3.4 Structural Model

As twelve factors are left from the modification described in Section 4.3.2, the motivation model resulting from research in Chapter 3 is further adjusted by redirecting the arrows

which pointed to the removed factors and pointing them to the corresponding factors in which the removed factors have demonstrated high cross-loadings. The modified model is displayed in Fig. 4.2.

It was claimed in prior research that learning experience in ICT use should be optimised without intruding on learners' privacy [172], [173], [174], so it is hypothesised that privacy perception has an impact on learning experience. Feedback was initially hypothesised to have associations with overall satisfaction and perceived enjoyment, but the two factors were removed as they had high correlations with perceived ease of use, and it has been found that emotional feedback had a significant influence on perceived ease of use when the use intention for computer based assessment was studied [175], so it is expected that feedback has an impact on perceived ease of use. Finally, the general learning experience with the e-learning system is hypothesised to impact on continued use intention in addition to perceived usefulness.

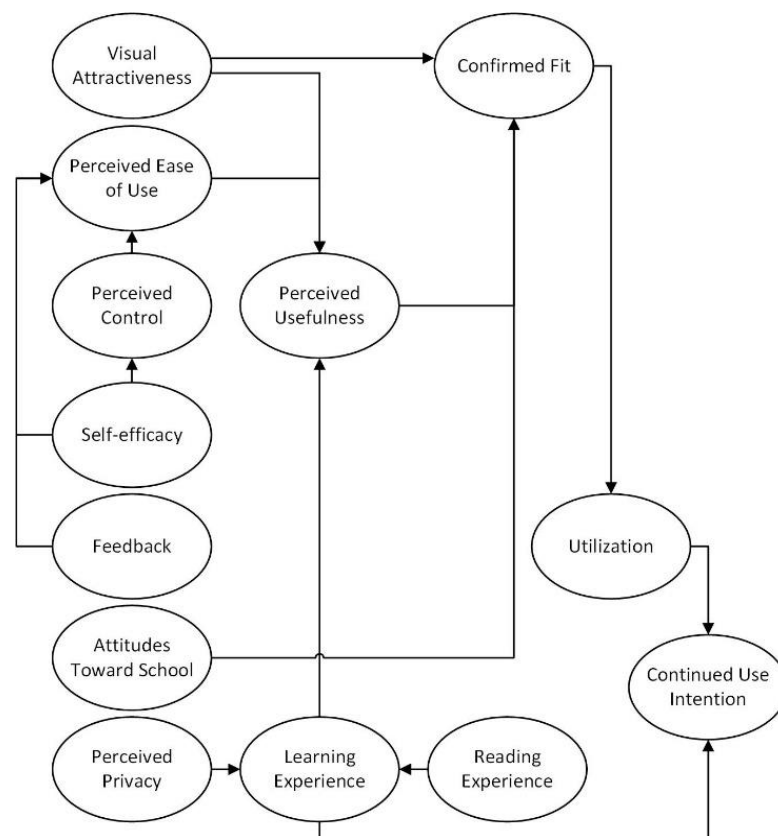


Fig. 4.2 New hypothesis motivation model

The structural model is assessed via SEM. PLS-SEM approach depends on the bootstrap procedure to evaluate the significance of the path estimates, and 1000 bootstrap replication samples are drawn with replacement from the data set. As the data are not normally distributed, the bootstrapping techniques with 1000 replication samples are also employed in CB-CEM, so that bias can be corrected and the fit indices can be referred to, though the hypothesis of normal distribution is not met, as suggested by prior research [156]. In CB-SEM, it was suggested that a CMIN/DF ratio of approximately 5 or less be used as an indicator of reasonable fit [176], while another researcher claimed that the ratio should be less than 3 to be acceptable [177]. CFI values close to 0.95 was suggested to be an acceptable fit between the model and the data, and RMSEA values close to 0.06 was suggested to be a good fit [178]. Therefore, it is implied that the fit of the model is poor (DF=61, Chi-square=326.292, $p < 0.001$, CMIN/DF=5.349, CFI=0.516, RMSEA=0.223), suggesting modifications to the model. In PLS-SEM, R^2 measures the overall effect size and variance explained in the endogenous variable for the structural model, with a value of 0.75 considered as substantial and of 0.26 considered as weak [179], [180]. Stone-Geisser Q^2 (also called Q^2) greater than 0 indicates predictive relevance [181], [182]. Q^2 value of 0.02 means small effect size, and 0.35 means good effect size [180]. The motivational consequence that is cared for was explained 44.4% variance in the hypothesis structural model in Fig. 4.2 and the Q^2 value is 0.287, so both R^2 and Q^2 have a medium value indicating the potential for improvement. The modification for the structural model might be different according to the results from the two approaches, so the following steps are shown separately for CB-SEM and PLS-SEM before comparing them.

In CB-SEM, based on the bias-corrected regressions, some causal relations are not significant, so their connections are deleted, while some paths are added as suggested by the modification indices and the results of Spearman's correlation test as well as the interpretability of the causal relationships (details displayed in Table 4.4).

Table 4.4 Modification of relations between factors in CB-SEM

Action	Relations	According to
Deleted	Perceived Ease of Use \leftarrow Technology Self-efficacy	Bias-corrected standardised regression weights (i.e., path coefficients) and p values (not significant at 95% confidence level)
	Perceived Usefulness \leftarrow Visual Attractiveness	
	Confirmed Fit \leftarrow Attitudes Toward School	
	Perceived Ease of use \leftarrow Feedback	
	Continued Use intention \leftarrow Learning Experience	
	Utilization \leftarrow Confirmed Fit	
Added	Perceived Usefulness \leftarrow Learning Experience	Modification indices; Interpretability
	Perceived Ease of Use \rightarrow Confirmed Fit	
	Visual Attractiveness \rightarrow Utilization	
	Attitudes Toward School \rightarrow Learning Experience	
	Perceived Control \rightarrow Utilization	
	Perceived Privacy \rightarrow Utilization	
	Reading Experience \rightarrow Continued Use Intention	
	Feedback \rightarrow Visual Attractiveness	
	Feedback \rightarrow Perceived Control	
	Technology Self-efficacy \rightarrow Visual Attractiveness	
	Utilization \rightarrow Reading Experience	
	Confirmed Fit \rightarrow Reading Experience	
	Visual Attractiveness \rightarrow Continued Use Intention	
	Attitudes Toward School \rightarrow Continued Use Intention	
Added	Technology Self-efficacy \leftrightarrow Perceived Privacy	Spearman's correlation test (significant at 95% confidence level); Interpretability
	Attitudes Toward School \leftrightarrow Perceived Privacy	
	Technology Self-efficacy \leftrightarrow Attitudes Toward School	

In summary, Perceived Ease of Use has an impact on Confirmed Fit; Visual Attractiveness has an effect on Utilization; Learning Experience is affected by Attitudes Toward School; Perceived Control of the system influences the Utilization of system functions; Perceived Privacy affects the Utilization of system functions, as it may generate discomfort about privacy concern of users; Reading experience, Attitudes Toward School and Visual Attractiveness directly affect dyslexic users' Continued Use Intention; Feedback affects Visual Attractiveness of systems and users' Perceived Control during interaction process; a system tends to be perceived less attractive by users with low confidence in using the system, consistent with the case of top-bottom information processing; the Utilization of system functions and Confirmed Fit, i.e., confirmed

expectation of the system-user fit, help bring about positive Reading Experience; also, based on Spearman's correlation test, correlations are added between three intrinsic factors, indicating technology Self-efficacy, Attitudes Toward School and Perceived Privacy are inter-correlated.

In addition, as mentioned before, reading experience is crucial to dyslexic students, so it is separated from learning experience. The original relation between them is reversed given the bias-corrected regression estimates in AMOS. Comparing two possible causal relations, it is found that learning experience has a bigger effect on reading experience (unstandardised $\beta=0.421$, $p<0.001$) compared to the other reverse way (unstandardised $\beta=0.221$, $p<0.001$), this may be because that learning need is directly related to the eventual purpose of the usage; therefore, as users' learning expectation is fulfilled, the reading is also likely to be recalled as a positive experience. An examination of the indices of fit suggests that the modified model adequately fits the data (Chi-square=73.522; DF=54; probability level=0.04; CMIN/DF=1.362; CFI=0.964; RMSEA=0.064), the standardised version of the final model is displayed in Fig. 4.3.

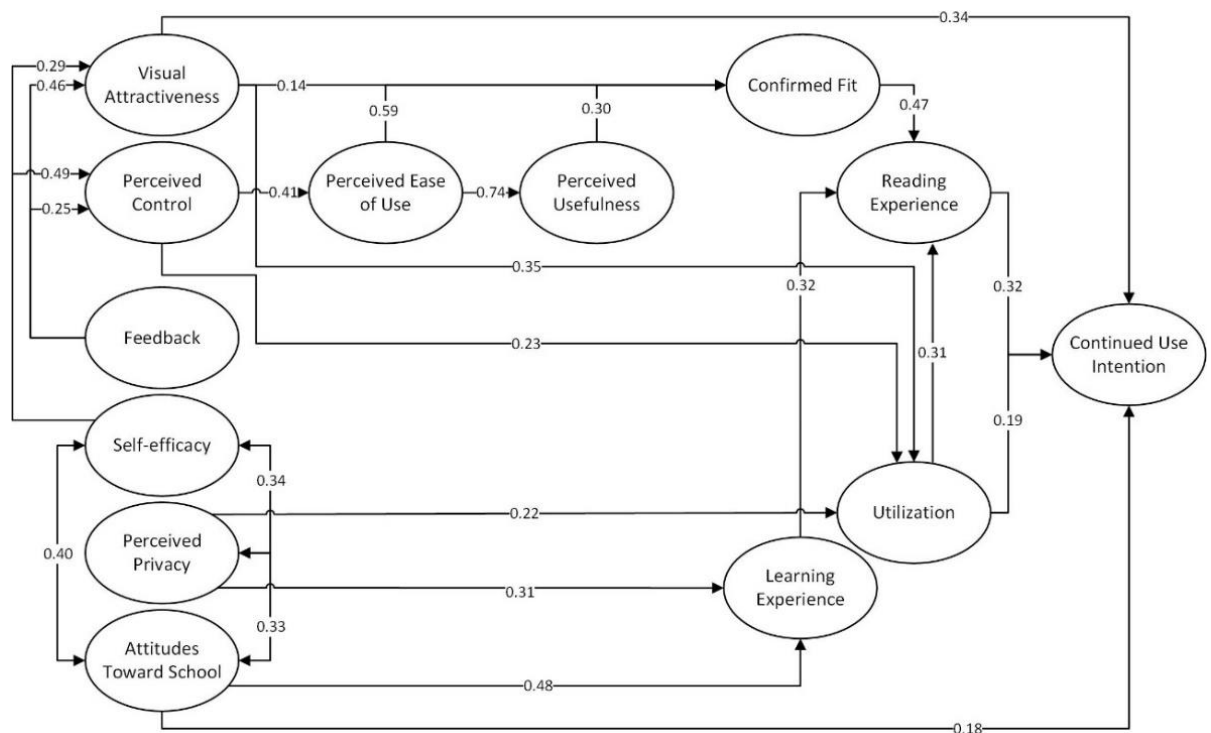


Fig. 4.3 CB-SEM result model of dyslexic users' motivation to engage in e-learning systems

All paths are significant, i.e., $p<0.05$, standardised β is shown in the diagram.

In PLS-SEM, firstly the insignificant paths between factors were removed according to the path coefficients and its significance level through the T-statistics test using the bootstrapping procedure mentioned above. The removed paths and the statistics are detailed in Table 4.5. Meanwhile, adding paths to or from the removed factors are necessary to remain the factors with the predictive relevance through direct or indirect connection to continued use intention in the model for further analysis instead of removing them imprudently, the paths added were also supported by Spearman's correlation test and interpretability; each time a path was added, it was tested in PLS-SEM and might be removed in case an added path was found as insignificant in terms of the path coefficients in PLS-SEM. The final modifications are detailed in Table 4.5.

Table 4.5 Modification of relations between factors in PLS-SEM

Action	Relations	According to
Deleted	Perceived Ease of Use \leftarrow Technology Self-efficacy	Standardised path coefficients and t values/p values (not significant at 95% confidence level)
	Perceived Usefulness \leftarrow Visual Attractiveness	
	Confirmed Fit \leftarrow Attitudes Toward School	
	Perceived Ease of use \leftarrow Feedback	
	Continued Use intention \leftarrow Learning Experience	
	Utilization \leftarrow Confirmed Fit	
	Perceived Usefulness \leftarrow Learning Experience	
	Continued Use Intention \leftarrow Utilization	
Added	Perceived Ease of Use \rightarrow Confirmed Fit	Spearman's correlation test (significant at 95% confidence level); Interpretability
	Visual Attractiveness \rightarrow Utilization	
	Attitudes Toward School \rightarrow Learning Experience	
	Perceived Control \rightarrow Utilization	
	Perceived Privacy \rightarrow Utilization	
	Reading Experience \rightarrow Continued Use Intention	
	Feedback \rightarrow Visual Attractiveness	
	Feedback \rightarrow Perceived Control	
	Self-efficacy \rightarrow Visual Attractiveness	
	Utilization \rightarrow Reading Experience	
	Confirmed Fit \rightarrow Reading Experience	
	Visual Attractiveness \rightarrow Continued Use Intention	

Same as that in CB-SEM, the path from reading experience to learning experience was reversed to ensure that both factors have a predictive relevance on continued use intention through a direct or indirect effect, since the effect of learning experience on continued use intention was found insignificant and thus removed.

Compared with CB-SEM, the differences of the results are twofold:

A) two paths (i.e., Attitudes Toward School \rightarrow Continued Use Intention; Utilization \rightarrow Continued Use Intention) are only significant in the model resulted from CB-SEM, whereas they do not exist in the model resulting from the PLS-SEM analysis due to insignificance;

B) the arrows in PLS-SEM are always single headed and it cannot model undirected correlations [183], so the three correlations in CB-SEM approach between the factors, namely Attitudes Toward School, Self-efficacy and Perceived Privacy were not re-examined in PLS-SEM approach. What is worth mentioning is that the two paths that were significant in CB-SEM approach were not very insignificant though they were removed from the model in PLS-SEM approach; instead, they were insignificant but close to the significance threshold at 0.05 level (p value is 0.073 and $p=0.052$ for the effect of Attitudes Toward School and Utilization on Continued Use Intention, respectively).

As already mentioned, the common measures in PLS-SEM to evaluate a model are different from those in CB-SEM. R^2 value for continued use intention as the motivational consequence in the model is 0.543, indicating 54.3% of the variance in continued use intention is explained by the model, which is pretty good as values above 0.33 are considered as moderate [184]. Q^2 value for continued use intention is 0.359, indicating the predictive relevance in the model is high [180]. The standardised version of the final model from PLS-SEM is displayed in Fig. 4.4. The path coefficients and significance levels from both approaches are listed in Table 4.6. In particular, f^2 for each path is shown for PLS-SEM, which measures the effect size by calculating the change in R^2 when a factor is removed from the model. According to Cohen [185], where 0.02, 0.15 and 0.35 represents a weak, moderate and strong effect size, respectively, the f^2 values show the effect size in the model is generally moderate or high.

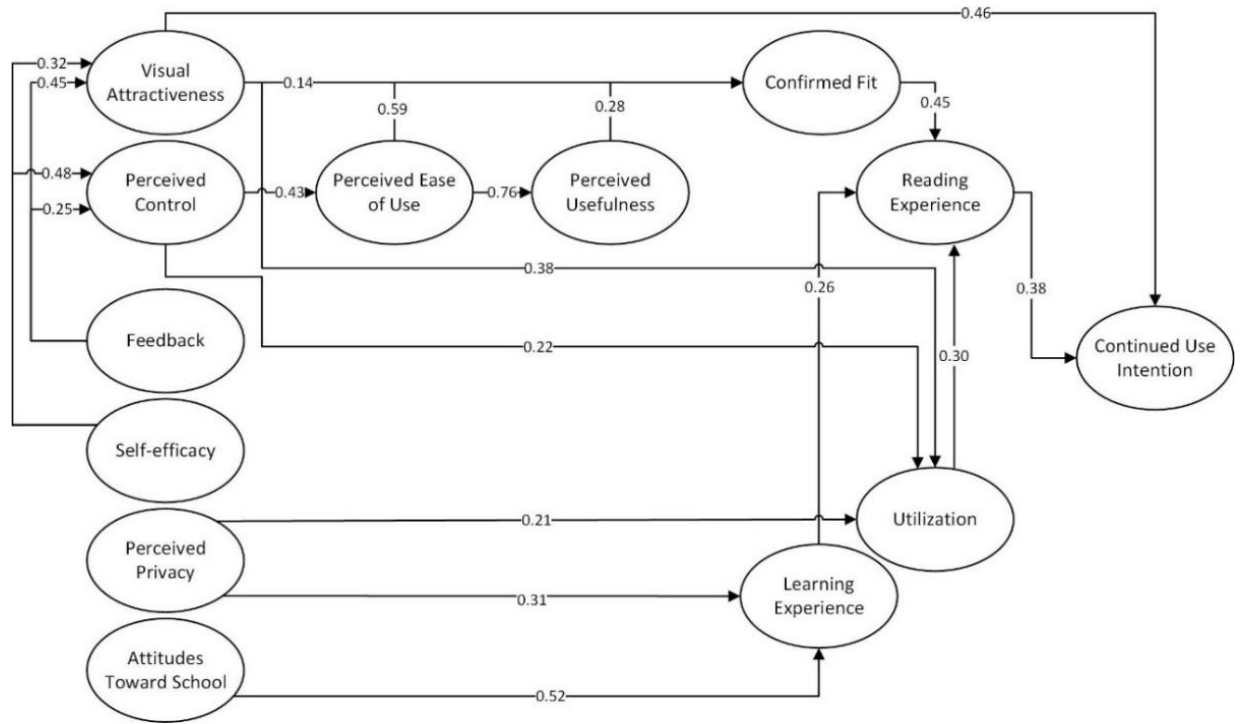


Fig. 4.4 PLS-SEM result model of dyslexic users' motivation to engage in e-learning systems

All paths are significant, i.e., $p < 0.05$, standardised β is shown in the diagram.

Table 4.6 CB-SEM and PLS-SEM results comparison

Relations	CB-SEM	PLS-SEM	
	Path Coefficients β	Path Coefficients β	Effect Size r^2
Attitudes Toward School \rightarrow Learning Experience	0.481**	0.520**	0.459
Confirmed Fit \rightarrow Reading Experience	0.470**	0.452**	0.402
Feedback \rightarrow Perceived Control	0.254*	0.246*	0.086
Feedback \rightarrow Visual Attractiveness	0.464**	0.449**	0.302
Learning Experience \rightarrow Reading Experience	0.320**	0.255*	0.122
Perceived Control \rightarrow Perceived Ease of Use	0.409**	0.425**	0.221
Perceived Control \rightarrow Utilization	0.231*	0.217*	0.060
Perceived Ease of Use \rightarrow Confirmed Fit	0.594**	0.588**	0.638
Perceived Ease of Use \rightarrow Perceived Usefulness	0.740**	0.755**	1.325
Perceived Privacy \rightarrow Learning Experience	0.305**	0.314**	0.168
Perceived Privacy \rightarrow Utilization	0.217*	0.211*	0.064
Perceived Usefulness \rightarrow Confirmed Fit	0.302**	0.283*	0.147
Reading Experience \rightarrow Continued Use Intention	0.315**	0.375**	0.209
Self-efficacy \rightarrow Perceived Control	0.489**	0.478**	0.326
Self-efficacy \rightarrow Visual Attractiveness	0.294*	0.321*	0.155
Utilization \rightarrow Reading Experience	0.312**	0.304**	0.183
Visual Attractiveness \rightarrow Confirmed Fit	0.142*	0.142*	0.078
Visual Attractiveness \rightarrow Continued Use Intention	0.344**	0.457**	0.310
Visual Attractiveness \rightarrow Utilization	0.354**	0.377*	0.177
^a Attitudes Toward School \rightarrow Continued Use Intention	0.176*	Non-existing due to insignificance	
^a Utilization \rightarrow Continued Use Intention	0.190*	Non-existing due to insignificance	
^a Self-efficacy \leftrightarrow Attitudes Toward School	^b 0.397**	Not Applicable	
^a Perceived Privacy \leftrightarrow Attitudes Toward School	^b 0.333*	Not Applicable	
^a Self-efficacy \leftrightarrow Perceived Privacy	^b 0.340*	Not Applicable	

All path coefficients are standardised; ^apaths only existing in the model resulted from CB-SEM;

^bcorrelation estimates; *significant at 0.05 level; ** significant at 0.001 level.

4.3.5 Mediation Analysis

The path diagrams of both Fig. 4.3 and Fig. 4.4, from CB-SEM and PLS-SEM analyses, respectively, include the standardised estimates of the causal relations for the indirect and direct effects. Following the mediation analysis procedure [186], the direct, indirect and

total effects of the motivational factors on the consequence along with the mediation type and mediators, if applicable, are listed in Table 4.7.

Table 4.7 Standardised direct, indirect and total effect on Continued Use Intention

	Direct Effect		Indirect Effect		Mediators		Mediation Type		Total Effect	
	CB-SEM	PLS-SEM	CB-SEM	PLS-SEM	CB-SEM	PLS-SEM	CB-SEM	PLS-SEM	CB-SEM	PLS-SEM
Attitudes Toward School	0.176	indirect only	0.048	0.05	RE, LE		partial	full	0.225	0.05
Confirmed Fit	indirect only		0.148	0.169	RE		full		0.148	0.169
Feedback	indirect only		0.246	0.255	RE, CF, UT, PE, PC, PU, VA		full		0.246	0.255
Learning Experience	indirect only		0.101	0.096	RE		full		0.101	0.096
Perceived Control	indirect only		0.116	0.082	RE, CF, UT, PE, PU		full		0.116	0.082
Perceived Ease of Use	indirect only		0.121	0.136	RE, CF, PU		full		0.121	0.136
Perceived Privacy	indirect only		0.093	0.054	RE, LE, UT		full		0.093	0.054
Perceived Usefulness	indirect only		0.045	0.048	RE, CF		full		0.045	0.048
Reading Experience	0.315	0.375	direct only		no mediation		no mediation		0.315	0.375
Self-efficacy	indirect only		0.194	0.208	RE, CF, UT, PE, PC, PU, VA		full		0.194	0.208
Utilization	0.19	indirect only	0.098	0.114	RE		partial	full	0.288	0.114
Visual Attractiveness	0.344	0.456	0.123	0.067	RE, CF		partial		0.467	0.523

All effects are significant at 0.05 level; refer to Table 4.2 for the short names.

Except Reading Experience that only has a direct effect on Continued Use Intention, all the other motivational factors influence the consequence through either full or partial mediation. While Visual Attractiveness and Reading Experience (and Attitudes Toward School and Utilization from CB-SEM) have both a direct effect and an indirect effect through partial mediation on Continued Use Intention, all the other motivational factors

influence Continued Use Intention only indirectly through full mediation. More details are discussed in Section 4.4.3.

4.4 Quantified Motivation Model and Factor Interrelationships

In the present study, a multi-item questionnaire is designed, a quantitative empirical questionnaire study is conducted, and both PLS-SEM and CB-SEM techniques are used to explore and confirm the factors and their interrelationship in the initial motivation model developed and described in Chapter 3. The quantitative motivation model developed in this chapter will progress the insight into the motivational processes of students with dyslexia that account for varying levels of motivation to engage in e-learning systems, i.e. continued use intention for e-learning systems. Most factors in the qualitative motivation model including the four factors emerging from the qualitative study with dyslexic students [3] are supported by the analysis results of the quantitative study, except that several factors (Perceived Enjoyment, Perceived Convenience and Satisfaction) are removed and two factors (Confirmation and Perceived Fit) are combined due to high cross-loadings, while the interrelationships are altered in the model based on the results from CB-SEM and PLS-SEM with references to prior research or theories.

4.4.1 Key Findings

From the qualitative empirical study, four factors (i.e., Learning Experience, Reading Experience, Perceived Control and Perceived Privacy) have been identified and incorporated into the motivation model. Consistent with the qualitatively constructed model, it has also been found in the quantitative study that Perceived Usefulness is influenced by Perceived Ease of Use; Perceived Ease of Use is influenced by Perceived Control, and Perceived Control is affected by Self-efficacy.

The present research has also yielded new findings: the quantitative study reveals direct effects of Visual Attractiveness and Reading Experience on Continued Use Intention from both CB-SEM and PLS-SEM analyses consistently, while CB-SEM also results in the significant direct effects of Attitudes Toward School and Utilization on Continued use intention, which is the only difference between the two structural models in terms of causal relations from the two approaches. Both approaches have implied the importance

of Visual Attractiveness, Reading Experience and Feedback with respect to their total effects on Continued Use Intention. It is found that Feedback has an influence on both Perceived Control and Visual Attractiveness. Positive and informative feedback appearing usually in visual form works as a kind of positive reinforcement for users, which improves users' sense of control during interaction process and the perceived visual appeal of the system. Visual Attractiveness and Reading Experience are found to be the strongest predictors, probably because that the respondents are young students with dyslexia, and they are more likely to be sensitive to visually attractive interface and put more value on reading experience than those without dyslexia. The influence of Visual Attractiveness is also mediated by Utilization. Utilization explains the acceptance of the functions of e-learning systems instead of systems per se, and Visual Attractiveness is related to the curiosity which can trigger the interest and engagement in technology according to prior research [63]. That may explain the effect of Visual Attractiveness on Utilization. In other words, if an e-learning system is more visually attractive, more possibly the user will fully utilize the system functions; therefore, the user will be more likely to have the intention of continued use.

The influences of Learning Experience and Confirmed Fit on Continued Use Intention were found to be fully mediated by Reading Experience, meaning the two factors will hardly exert their impact on use intention if a user's need for good reading experience is not fulfilled. The influences of Perceived Control and Perceived Privacy were fully mediated by Utilization; that is, a user's improved sense of control and perceived protection for privacy issue will positively impact the utilization of the system functions, thereby improving the user's intention of continued use. Confirmed Fit is influenced by the system-related extrinsic factors, Perceived Usefulness, Perceived Ease of Use, and Visual Attractiveness; that is, if a user perceives the e-learning system to be useful, easy to use, and visually attractive, more possibly the user will confirm the fit of the system to his or her own needs. Compared with recent research that found a positive effect of relatedness on perceived ease of use, in which relatedness was from the self-determination theory, meaning that it was completely in intrinsic level [187], Confirmed Fit in the present study is similar with relatedness but goes further by incorporating users' confirmed expectation after the usage, so the order of occurrence is different from that of relatedness, and confirmed fit involves both intrinsic-level and extrinsic-level motivation.

Users' technology Self-efficacy also has an impact on the Visual Attractiveness of the system, and Learning Experience is influenced by Attitudes Toward School and Perceived Privacy, which emphasises the importance of intrinsic motivation. Attitudes Toward School intrinsically regulates learning behaviour and has been found to be a predictor of information seeking behaviour [130], thus, if someone has a negative attitude toward school, he or she will tend to have a negative intention of learning behaviour, that may explain why the general learning experience is also affected in this case.

4.4.2 Theoretical Findings

The factors in the result motivation model integrating multidisciplinary perspectives can be grouped into different tiers: intrinsic factors (i.e., Self-efficacy; Feedback; Attitudes Toward School; Perceived Privacy), extrinsic factors (i.e., Perceived Usefulness; Perceived Ease of Use; Perceived Control; Visual Attractiveness) and motivation mediators (i.e., Confirmed Fit; Learning Experience; Reading Experience; Utilization), which all work on the consequence tier (i.e., Continued Use Intention). This does not mean the factors in the three tiers function in a complete sequenced order; instead, their associations are heavily intertwined. Overall, it reveals an apparent path that intrinsic factors and extrinsic factors influence together the consequence directly or indirectly through the motivation mediators in the final motivation model. Detailed grouping and sequence of the motivational factors is shown in Fig. 4.5.

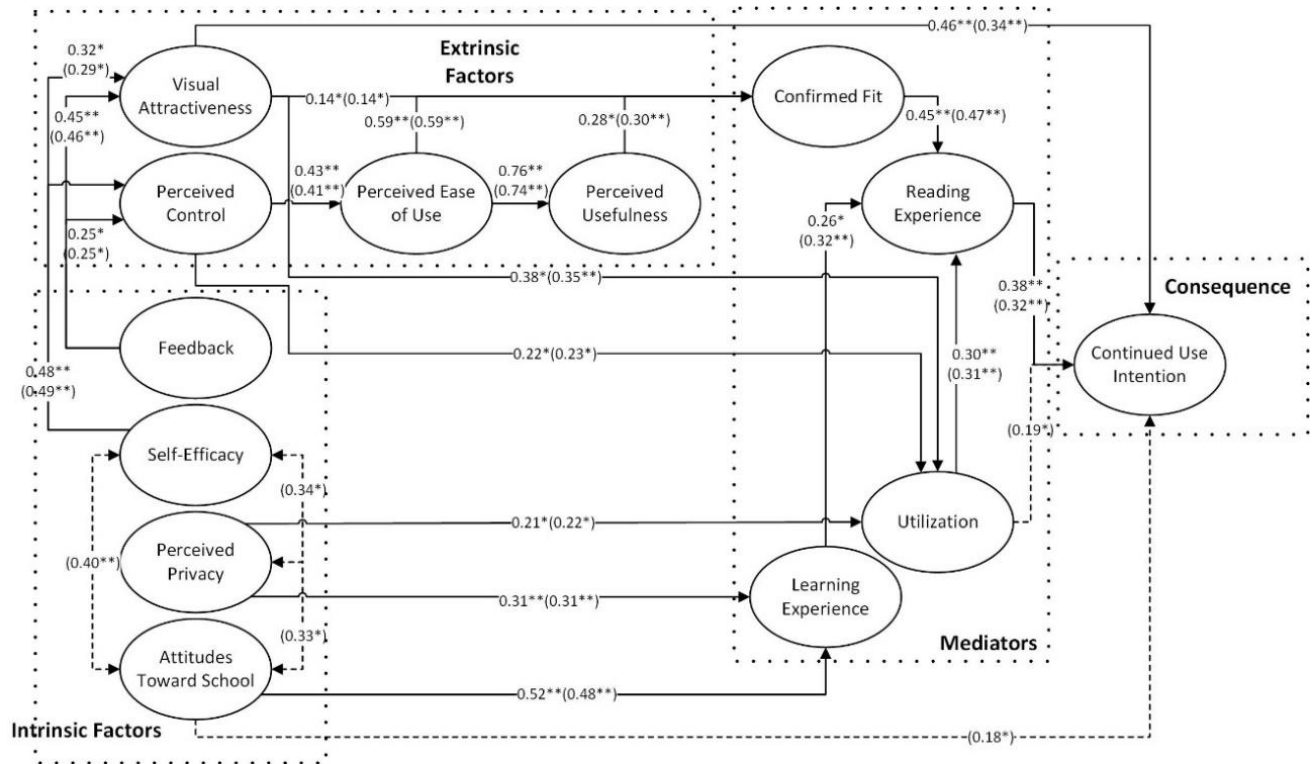


Fig. 4.5 The quantified motivation model showing the grouping and sequencing of factors

PLS-SEM path coefficients shown out of the brackets and CB-SEM shown in the brackets; *significant at 0.05 level; **significant at 0.001 level; dashed paths only existing in CB-SEM result model

Prior research which linked user motivations to behavioural intentions has either relied on general technology perceptions (e.g., [188]) or socio-psychological perceptions (e.g., [189]) as motivators behind the behaviour, but the modelling of motivational factors reflecting extrinsic motivation, intrinsic motivation, and potentially important system-specific and user-specific features were rarely taken into account [65]. In contrast, the present study has progressed insights into the motivations of users with dyslexia behind the engagement in e-learning systems by proposing a motivation model combining extrinsic motivation, intrinsic motivation and user/system-specific features. The present study suggests that continued use intention for an e-learning system is determined by a combination of extrinsic and intrinsic motivation, which function directly or indirectly through user/system-specific factors (i.e., mediators), confirming that both types of motivation exert a joint effect on users' intention of continued usage.

At the extrinsic level, Visual Attractiveness, Perceived Control, Perceived Ease of Use, and Perceived Usefulness are found as important extrinsic motives driving users' continued intention to use an e-learning system, either directly or indirectly through the mediators. The cognitive-affective framework indicates that environmental factors can cause both cognitive and affective reactions, resulting in behaviour, which has successfully been applied in a large quantity of online consumption settings (e.g., [190]; [65]). This might explain why the studied factors of the e-learning system environment pertaining to extrinsic-level factors influence continued use intention not only through utilization (mainly cognition-based) but also through reading experience and confirmed fit (mostly affect-based); Confirmed Fit combining a user's confirmation of expectation and perceived system-user fit involves both cognitive and affective aspects, corroborating with the cognitive-affective framework. Visual Attractiveness is found to be the most important among the extrinsic factors in terms of the total effect on Continued Use intention, and it has a direct effect on Continued Use Intention.

At the intrinsic level, Self-efficacy, Feedback, Perceived Privacy and Attitudes Toward School are found as important intrinsic motives driving users' continued intention to use an e-learning system, mainly indirectly through the mediators. From CB-SEM, Attitudes Toward School is found to have a direct effect on users' continued use intention, while it is not corroborated by PLS-SEM, where it is found to function through full mediation of Learning Experience and Reading Experience. Feedback is found to be the most crucial factor in terms of its total effect, meaning the importance of positive and informative feedback that users receive in time during a learning process. Similar with the extrinsic level, the intrinsic-level factors drive continued use intention through the mediators, i.e., Learning Experience and Reading Experience (mainly affect-based) and Utilization (mainly cognition affected), indicating that e-learning systems are expected to have both hedonic and utilitarian benefits. The effects of some intrinsic factors (i.e., Self-efficacy and Feedback) on continued use intention are also found to be mediated by extrinsic-level factors (i.e., Perceived Control and Visual Attractiveness).

4.4.3 Mediators

The present study indicates that Confirmed Fit, Learning Experience, Reading Experience and Utilization are the important mediators of the intrinsic/extrinsic motivation-

consequence relationship. This has gone beyond the findings of prior research. For example, Zhao et al. [191] have revealed in their study that users' subjective factor about perceived quality of system acts as a mediator between users' concern and acceptance of the system, but it was not illustrated what factors are included in the quality of the system. The mediators identified in the present study combine the aspects of both users and e-learning systems, reflecting both system-specific features (i.e., Confirmed Fit, Utilization) and user-specific experience (i.e., Learning Experience, Reading Experience). This also corresponds with the cognitive-affective framework mentioned before.

Prior research about information system that has considered the impact of user experience and system functions on user motivation for continued usage has yielded equivocal findings (e.g., [63]; [191]; [192]). Although reading experience clearly has the potential to impact students' motivation to engage in e-learning systems, especially for dyslexic users, a paucity of work has examined its influence. The present study emphasises the importance of Reading Experience (and Utilization from CB-SEM) which directly drives the motivational consequence, while Confirmed Fit and Learning Experience (and Utilization from PLS-SEM), mediating the effect of extrinsic and intrinsic factors, respectively, work indirectly on Continued Use Intention through Reading Experience.

In the present study, it was found that the extrinsic factor, Visual Attractiveness also directly impacts the motivational consequence, and it is found to be the most predictive of users' Continued Use Intention, whose total effect is stronger than that of Reading Experience, Utilization, Confirmed Fit and Learning Experience. Attitudes Toward School also emerged as a predictor of the consequence from CB-SEM analysis, the strength of the path was, however, relatively weak. Dyslexic students' learning motivation is likely to be intrinsically compromised as they tend to have lower academic self-worth and more coping issues, potentially leading to learned helplessness. A positive attitude toward school is the necessary rather than the sufficient condition of continued use intention for e-learning systems. This is backed by the PLS-SEM analysis, where the effect of Attitudes Toward School is found to be fully mediated by Learning Experience and Reading Experience.

From a modelling perspective, the motivation model provides a more comprehensive view for explaining or predicting continued use intention of dyslexic students for e-

learning systems. The parsimony of prior research of users' IT acceptance has brought about large amounts of debate on the determinants of users' intention of continual usage (see [68]; [193]; [194]). To provide greater insights to this end, a mixture of extrinsic/intrinsic motivations and system/user characteristics has been modelled that work as underlying mechanisms behind the motivation to engage in e-learning systems. The connections identified between two types of motivation, as well as their common subsequent dependent variables about system/user characteristics, support the advocacy made by Malhotra et al. [195] that we ought to look beyond the distinct taxonomy of extrinsic and intrinsic motivation and treat system usage as a consequence of both intertwined motivations and primary system beliefs. This is especially relevant to e-learning system usage, for which the categorising line between intrinsic and extrinsic motivation may be vaguer, compared to systems with features of only one of utilitarian or hedonic purposes.

Two examples that support this claim were provided by Verhagen et al. [65] and Standage et al. [156] who included both extrinsic and intrinsic motivations into their models to explain the motivation to engage in multipurpose information systems and physical education, respectively. Though their models did not directly point out the interconnections of these motivations, and thus seemed to regard them as a dichotomy, they did find that both motivations and their antecedents were correlated. As the combination of extrinsic motivation, such as obtaining good scores or compliments, and intrinsic motivation, such as acquiring knowledge, is essential to explain e-learning system usage, again the novel perspective which identifies the interrelationships and indivisibility of both motivations can enrich the explanations and understandings behind e-learning system usage.

4.4.4 Limitations

It is worth noting that the sample is self-selected from the student members of Dyslexia Norway, inevitably leading to self-selection bias. Though the student members of Dyslexia Norway are also from different schools with different backgrounds, future work is expected to involve more diversity of individuals and school levels. Hierarchical linear modelling techniques allowing the hierarchical and concurrent investigation of individual,

group, and cross-level effects within a hierarchical structure will be most applicable in such examinations [156], [196].

Furthermore, according to Standage et al. [156], perceptions of contextual cues, also called motivational climate (i.e. mastery climate and performance climate), has an effect on cognition, behaviour, and affective responses of physical education students pertaining to achievements [197], [198], [199]. The present study is in the context of “mastery climate” without interpersonal competition. Though it would have been useful to conduct comparable study to investigate the role of contextual cues, the sample size and sample structure did not allow such tests.

Another potential limitation of this study is that the e-learning systems investigated and described in Section 4.2 are all web-based e-learning tools. While the functions of the systems examined are comparable to those of other e-learning tools, it is suggested researchers re-examine and cross-validate the research findings with varying data sets collected in several e-learning systems with contrasting features. Additionally, the intrinsic factors, Attitudes Toward School, Perceived Privacy and Self-efficacy are correlated with each other significantly and reflected in the structural model from CB-SEM analysis, whereas PLS-SEM does not support incorporation of correlations between factors into the structural model [183].

4.5 Conclusion

An in-depth, comprehensive understanding of motivation to learn is unquestionably crucial in the context of e-learning systems for students with dyslexia. In this chapter, following the conceptual motivation modelling, a multi-item questionnaire has been designed and an online questionnaire study has been conducted to further specify the model with parameters specifying the quantified relationships between motivational factors and quantified influence of the factors on the motivational consequence, through the use of SEM techniques including both CB-SEM and PLS-SEM to consolidate the findings. Specifically, research findings have suggested that:

A) overall the impact of learner’s intrinsic motivation and extrinsic motivation on continued use intention for e-learning systems is mediated by their learning and reading experience, confirmation of the system-user fit and utilization of system functions;

B) in the e-learning context, the extrinsic factors and intrinsic ones are not clearly cut, and the factors function in an intertwined manner: the impact of some intrinsic factors on the motivational consequence is mediated by extrinsic factors: both technology self-efficacy and feedback output to users have an influence on the visual attractiveness of e-learning systems and users' perceived control.

This chapter results in a quantified motivation model, providing great insights into how educators and e-learning system designers should prioritise motivational factors to struggle against the decrease in motivation and engagement of students with dyslexia. However, research gap remains in terms of measuring the motivational factors in the model in real time during a user's learning process in an e-learning system to provide the user with personalised learning environment according to the level of the factors detected, as practically it is unfeasible to measure motivational states in a self-report manner while users are learning, and frequently asking users to input self-report data is very intrusive and disruptive to their learning and thus involves more bias. The next chapter will introduce the sensor-based approach to motivation computation and describe an experiment with participants with dyslexia. The experiment is designed to capture dynamic sensor data during their interaction process with an e-learning environment to train classification models to allow the motivational factors to be computed in real time.

Chapter 5 Real-time Sensor-based Motivation Computation

5.1 Introduction

Automatic recognition of learners' motivational states is necessary for personalised services and interventions to be provided dynamically in e-learning environments. Traditional approaches to motivation computation often rely on learners' explicit self-reported data, which is outweighed by implicit sensor data. Motivation computation based on sensor data allows learners' states to be assessed in real time without interruption to the learning process. The increasing availability of sensing instrumentation offers the potential to capture data which serve as diagnostic input for monitoring learners' states. Among various kinds of sensing technology such as health monitoring devices (e.g., blood pressure monitors) and dense sensor networks (e.g., motion, video, pressure sensors), electroencephalography (EEG) and eye tracking sensors have been employed to obtain useful indications for learners' states such as attention and emotion (e.g. [92]; [200]), but those two sensors have never been combined for the purpose of assessing learners' motivational states though both brain activities and eye movements have been found indicative of human's behaviour and mind.

In Chapter 3 and 4, the motivation model has been developed using both qualitative and quantitative approaches, and the quantitative mapping has been specified between the factors in the model. That allows the motivational consequence, contextualised as continued use intention in e-learning environment, to be predicted based on learners' self-reported data on the motivational factors. In this chapter, an eye tracker and an EEG sensor are combined for computing the motivational factors involved in the model that represent different dimensions of motivation. Specifically, this chapter addresses the following question:

Can dynamic eye gaze and EEG data be used together to develop a classification model that distinguishes the low level from the high level of each motivational dimension?

By answering this question, the possibility of the real-time assessment of learners' motivational states will be explored. A novel approach is introduced for computing the motivational factors based on sensor data that combines eye-tracking data and EEG data. An empirical experiment is then conducted to validate the approach with students having

learning difficulties including dyslexia. The two sensors are employed simultaneously in the experiment to record physiological and behavioural data from learners while they are interacting with an e-learning system. A classification model is developed using logistic regression algorithm for predicting the level of each motivational factor based on the sensor data.

The remaining part of this chapter is organised as follows: the proposed approach combining EEG and eye-tracking data to motivation computation is described in Section 5.2, and then the experiment methodology is described in Section 5.3, followed by the sensor feature analysis and results presented and discussed in Section 5.4. Furthermore, different approaches to motivation computation, namely the self-reported approach using the quantified motivation model described in Chapter 4 and the sensor-based approach using the classification model described in this chapter, are discussed in Section 5.5, and finally the chapter is concluded in Section 5.6.

5.2 A Novel Approach to Motivation Computation

In pursuance of the goal, i.e., assessing learners' motivational states while they are interacting with e-learning systems, an approach is proposed that combines eye tracking and EEG to compute the motivational factors. The motivational factors included in the motivation model have been described in Chapter 3 and 4. Starting from there, this chapter will demonstrate the role played by sensor data in assessing the levels of learners' motivational states. The assessment includes different dimensions of motivation, represented by the factors in the motivation model. The high-level structure of the motivation model that integrates the sensor data to compute the motivational factors is presented below in Fig. 5.1 to provide a holistic picture of the approach.

As stated before, while users are interacting with e-learning systems, data captured by sensors about their behaviour or physiological responses can indicate their mental states. Therefore, in contrast to the traditional approach that measures motivational factors based on self-reported data, the proposed approach combines an eye tracker and an EEG device to capture sensor data and uses logistic regression as the classification mechanism, i.e., the computation method, for the purpose of assessing the motivational states in real time. This will enable corresponding real-time personalisation to be provided based on the

motivational states. “Real-time” indicates sufficiently rapid measurement or responses, but the answer to how rapid it should be can vary much in different problem domains. For example, self-driving cars require milliseconds as the time unit of real-time computing, whereas receiving a message of delivery notification within 10 minutes of the arrival time of the delivery is satisfactory. In the present context, computing learners’ motivation during their learning process in real time aims at automating personalised services, i.e., motivational strategies, to maintain or enhance their motivation. Seconds or minutes as the time unit will satisfy the needs of motivation computation. Therefore, the experiment in this chapter uses a time slot of 10 seconds as well as the length of a short lesson (5-10 minutes) to extract features from sensor data. Different time slots are also worth experimenting, but too frequent measurement of motivational states and corresponding system responses should be avoided, as this will generate interruption experienced by learners during the learning process.

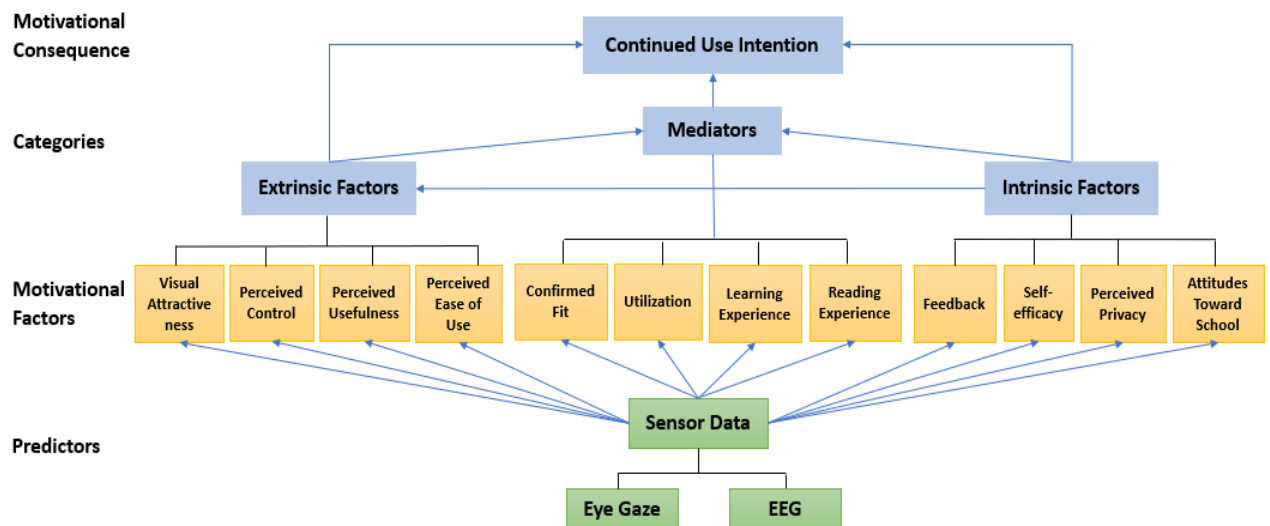


Fig. 5.1 The high-level structure of motivation model with incorporation of sensor data

The approach hypothesises that the brain activity and eye gaze captured from eye trackers and EEG sensors over time or between users in e-learning systems correspond to predictive variables of the users’ motivational states. By proposing this novel approach, this chapter intends to characterise the high level and low level of the motivational factors with features obtained from the two kinds of sensor data and explore the possibility of assessing the motivational states based on the sensor data.

5.3 Experiment Methodology

To validate the proposed hypothesis and research question, an experiment was conducted to develop classification models to predict the level of each motivational factor based on sensor data. It collects self-reported motivation three times during each participant's learning process in an e-learning environment, while monitoring and recording both EEG data and eye gaze data. This experiment has got the ethical approval in the Faculty of Computing, Engineering and Media at De Montfort University.

The participants, materials and system setup for the experiment are firstly introduced in this section, following which the experiment procedure is described. The process and results of data analysis are presented in Section 5.4, including feature extraction and selection, as well as the classification models for computation of the motivational factors and their prediction results.

5.3.1 Participants and Learning Materials

Twenty-five participants (16 females and 9 males) were recruited for the experiment. All of them are from Leicestershire, most of which are university students with one from a middle school; the mean age of them is 25.5 (SD=8.4). Thirteen of them have been diagnosed as dyslexic, and the others have self-reported learning difficulties without formal diagnosis.

The learning materials consist of three lessons with each taking about 5-10 minutes to complete. Each lesson contains both text and picture as well as quizzes at the end. Lessons have been designed which taught transferable skills about learning and reading such as reading strategies and time management skills to avoid procrastination. All participants did not learn about the same knowledge before the experiment. Teaching knowledge about transferable skills is to minimise the effect of difficulty levels of the learning materials compared to the like of scientific lessons.

5.3.2 System Setup

The Open Gaze And Mouse Analyzer (OGAMA) 5.0, an open source software [201], was used for eye-tracking data recording and analysis (see Fig. 5.2(a) for an example

screenshot of the OGAMA learning environment). The three learning lessons were adapted to the OGAMA environment. Tobii X120 tracker with a sampling rate of 60 Hz was employed to collect eye movements. The eye tracker is a standalone device that did not restrain participants from head movements.

A wearable EEG headset, provided by Emotiv Inc. called Emotiv EPOC+ with the bandwidth of 0.16-43Hz, was employed to collect brainwave data. The EEG device has fourteen electrodes with metal contacts and felt sensors which need saline solution for adequate contact quality. The electrodes are in line with the international 10–20 system, with placements of the electrodes (i.e., AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) shown in Fig. 5.4(a), where the corresponding brain regions are also annotated [202]. It is wireless, mobile and able to transmit data via Bluetooth, thus with little discomfort compared to traditional EEG with wires and gel solution. Meanwhile, EmotivPro 1.8, also provided by Emotiv Inc. was used in conjunction with Emotiv EPOC+ to observe and record the EEG data [203]. The headset was configured at 128 Hz as the EEG sample rate. The software also enables observation of a real-time Fast Fourier Transform (FFT) plot of raw data and recording of the power in each of the five frequency bands, i.e. theta (θ : 4 – 8 Hz), alpha (α : 8 – 12 Hz), low beta (low β : 12 – 16 Hz), high beta (high β : 16 – 25 Hz) and gamma (γ : 25 – 45 Hz) (see Fig. 5.3 for an example screenshot of a raw EEG interface). The experiment setup is displayed in Fig. 5.4(b).

In addition to sensor data from the eye tracker and EEG headset, collecting self-reported data about the motivational factors is necessary in order to develop classification models to predict the levels of motivational factors based on the sensor data. Each participant was asked to fill in a simplified multi-item motivation questionnaire after each lesson (see Fig. 5.2(b) for a screenshot). The questionnaire constructed based on the conceptual motivation model has been described in Chapter 4. The original questionnaire consists of 61 statements in total with about 3 to 5 statements for each motivational factor, while the simplified version has totally 33 statements. The questionnaire was simplified in order to reduce the time learners spent on the questionnaire between the lessons and thus the effect of interruption during their learning process.

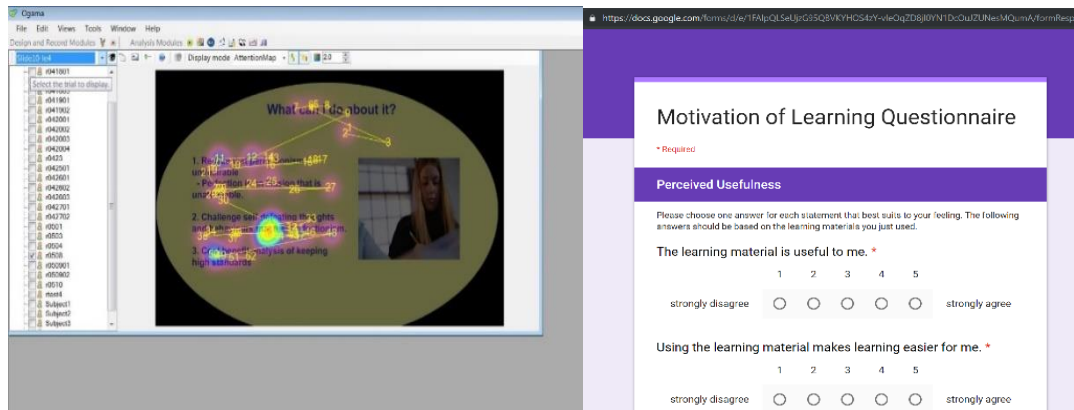


Fig. 5.2 On the left (a): the screenshot of an e-learning interface with the attention map in OGAMA; on the right (b): the multi-item motivation questionnaire in Google Form

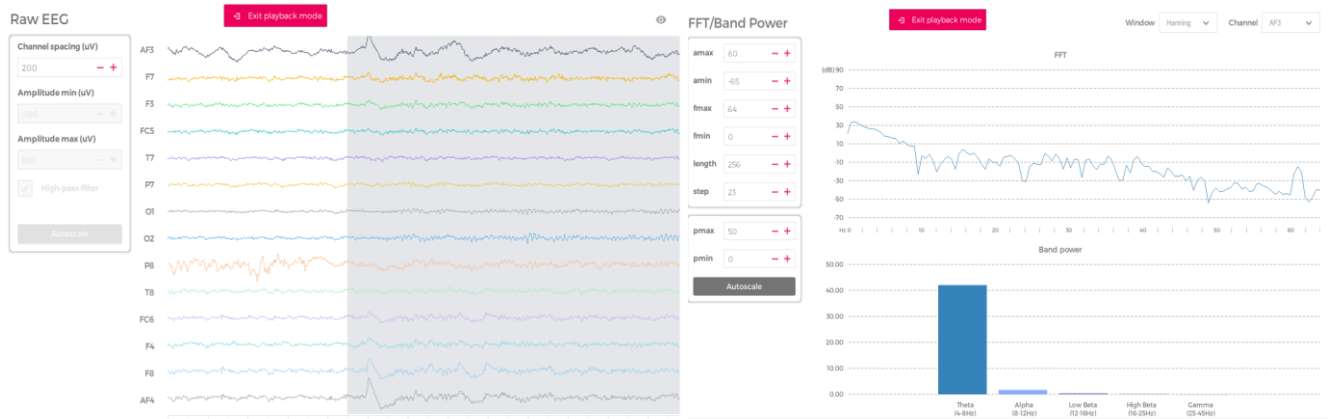


Fig. 5.3 The raw EEG interface in EmotivPro

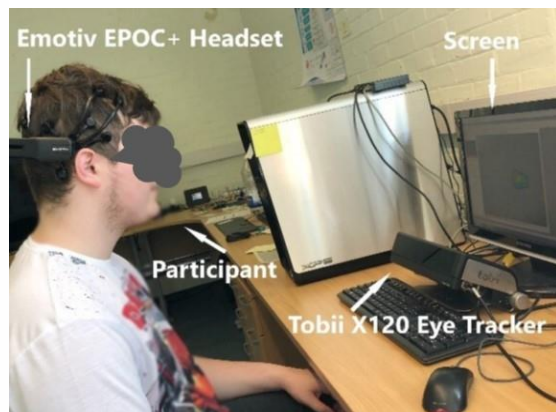
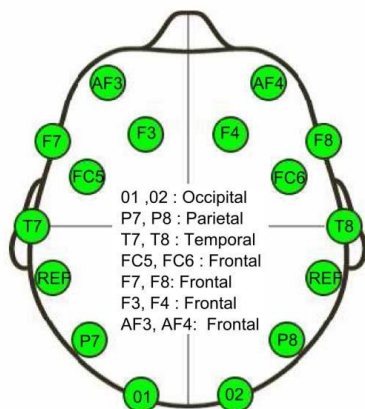


Fig. 5.4 On the left (a): the international 10-20 system with electrode positions corresponding to brain lobes [202]; on the right (b): the experiment setup

5.3.3 Procedure

The experiment was conducted individually for each participant. Before the experiment, the participants were provided with an information sheet and a consent form to be signed, which clearly explained the study objectives, data collection process and privacy protection, the rights of participants, etc. After the experiment, a voucher worth 10 British pounds from Amazon/Tesco/John Lewis was given to each participant as compensation.

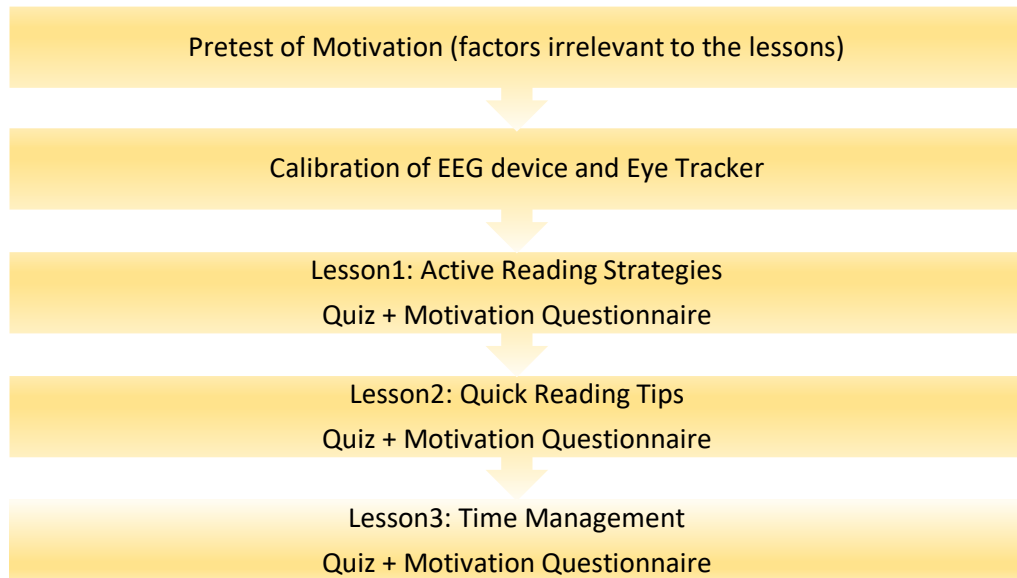


Fig. 5.5 The flow diagram of the experiment procedure

The experiment procedure is summarised in a flow diagram in Fig. 5.5. At the beginning of the experiment, participants were asked to complete a short questionnaire pertaining to intrinsic motivation including attitudes toward school and self-efficacy. The two intrinsic motivational factors were measured in the pretest instead of during the learning process, because they are both kept at a relatively stable level, formed by learners' long-term learning and life experience, not likely to change due to different circumstances in a short time period. After that, the eye tracker and EEG headset were calibrated, and then each participant was asked to complete three learning tasks (i.e., lessons) with a quiz and the motivation questionnaire after each lesson.

5.4 EEG and Eye Tracking Feature Analysis and Experiment Results

5.4.1 Data Pre-processing

The data was collected from the participants including a total of seventy-five trials from the experiment. It contains self-reported data on the simplified motivation questionnaire, basic demographic data such as gender and age, learners' task performance data including time spent on a lesson and quiz scores, and sensor data including EEG and eye gaze. Questionnaire data was exported from Google Form, while eye gaze data and EEG data were exported from OGAMA and EmotivPro, respectively, and then computed to extract features.

After removing the outliers of EEG data and eye-tracking data according to the descriptive statistics, the features were extracted from the sensor data, detailed in the next section. After extracting all the features, in order to examine whether the simplified motivation questionnaire is reliable for measuring each motivational factor or not, a Cronbach's Alpha was employed on the questionnaire data. The Cronbach's Alpha for Continued Use Intention, Perceived Usefulness, Perceived Ease of Use, Confirmed Fit, Feedback, Visual Attractiveness, Learning Experience, and Reading Experience was 0.91, 0.78, 0.81, 0.91, 0.70, 0.70, 0.76, and 0.77, respectively. However, Perceived Control, Utilization and Perceived Privacy have been removed, as the reliability of the corresponding statements did not pass the threshold. The short questionnaire used to measure intrinsic motivation at the beginning of the experiment was also examined with Cronbach's Alpha, and the reliability of Self-efficacy and Attitudes Toward School was 0.74 and 0.60, respectively. The results showed that the simplified motivation questionnaire used in the present study was overall reliable, with the removal of three factors.

5.4.2 Feature Extraction

The following features were extracted. The EEG features were 5 power bands * (1 mean+2 extreme value+4 brain lobe mean+2 hemisphere asymmetry). In detail, they are categorised into four:

A) The mean power (dB) of theta, alpha, low beta, high beta and gamma bands among all the channels;

B) The extreme values (both maximum and minimum) of each of the five bands;

C) The mean power of each of the five bands for each of the four regions, i.e., occipital, parietal, frontal and temporal lobe;

D) The hemisphere asymmetry of each of the five bands, including both the intra-hemispheric power asymmetry and inter-hemispheric power asymmetry. According to the “neurometrics” formulas from John et al. [204] and Prichep and John [205], inter-hemispheric power asymmetry for each band is computed with the formula $[(R-L)/(R+L)]$, where R and L refers to the right hemisphere and left one, respectively, and the intra-hemispheric asymmetry is computed with the formula $[(A-P)/(A+P)]$, where A and P refers to the anterior (i.e., frontal) region and posterior (i.e., back) one, respectively.

Amongst the eye gaze features extracted, 9 of them from fixation domain, 3 of them from saccade domain and 5 others are all specified below. Some gaze features were extracted from data collected for specific areas of screens called Areas of Interest (AOIs). That allows the screen areas related to learning contents to be separated from the blank areas. Z score standardisation was performed for pupil diameter, and the unit of all the time measures is unified as seconds, and all length measures are computed as pixels. Specifically, they are categorised into three:

E) 9 features from fixation domain: fixation number in AOI, fixation duration in AOI, fixation number in all screen areas (during a lesson overall and last 10 seconds of the lesson), fixation connection length, fixation spatial density, path velocity, regressions (i.e., regressive eye movements, during a lesson overall and last 10 seconds of the lesson);

F) 3 features from saccade domain: average saccade velocity, saccade duration, average saccade length;

G) 5 others: fixation saccade ratio, pupil diameter (mean and maximum), samples out of monitor, data loss (due to blinks and out of monitor).

In addition, time duration and quiz score of a lesson for each participant was recorded as two features. Then the feature selection is based on: 1) statistical analysis on sensor data and motivational factors; 2) the relationships between factors in the motivation

model, and the detailed process and results. The details of feature selection for generating classification models will be explained in Section 5.4.4.

5.4.3 Individual Differences

Before exploring the sensor-based approach to predicting the levels of the motivational factors, the differences between different individual participants are firstly examined. In other words, the aim of the following analysis is to figure out if different groups of participants have significant differences in the eye gaze and EEG features, learning performance and self-report motivation.

The participants are differentiated by the diagnosis status of dyslexia and the levels of intrinsic motivation. In the pretest, data are collected about some characteristics of participants, including the information about whether they have been formally diagnosed as dyslexic, two intrinsic motivational factors (Attitudes Toward School and Self-efficacy) measured by the 5-point Likert scale from the motivation questionnaire. Participants are divided into two groups; specifically, according to the diagnosis situation, they are divided into “diagnosed” group and “undiagnosed” group; according to the mean scores of the two intrinsic motivational factors, they are divided into “above” group and “below” group for each factor.

Dyslexia Diagnosis

According to the independent-samples Mann-Whitney test, amongst all the participants with self-reported learning difficulties, it is found that whether they were formally diagnosed as dyslexic or not does not have a significant effect on their self-reported motivation, including the studied motivational factors and task performance.

However, significant different results are found from eye tracking and EEG, detailed in Table 5.1. Diagnosed participants have smaller values of both pupil diameter and fixation duration in AOI, indicating that they may have less cognitive effort and have been less engaged in the learning process. Diagnosed participants also have smaller values of alpha, beta and gamma band power, indicating that they may have less engagement in the focused mental activities in the learning process. The difference of beta band hemisphere asymmetry has also been found from the experiment, and it is worth further investigation on the specific exhibition on the brain asymmetry. Diagnosed participants

have the positive value of inter-hemisphere asymmetry indicating greater right than left hemisphere power, and the bigger value of intro-hemisphere asymmetry that may indicate more emotional activities in diagnosed participants according to [115].

Table 5.1 The significant differences between diagnosed participants and the undiagnosed according to Mann-Whitney Test

	Category	Variable/Feature	P value
Lesson 1	EyeTracking	PupilDiameter-average	0.029
	EEG	Alpha-mean	0.016
		LowBeta-mean	0.016
		HighBeta-mean	0.019
		Gamma-mean	0.023
		Alpha-occipital	0.027
		LowBeta-occipital	0.027
		HighBeta-occipital	0.032
		Gamma-occipital	0.013
		Alpha-parietal	0.027
		LowBeta-temporal	0.023
		HighBeta-InterAsymmetry	0.007
Lesson 2	EyeTracking	FixationDuration-AOI	0.046
	EEG	Alpha-occipital	0.037
		Gamma-occipital	0.023
		Alpha-parietal	0.037
		Gamma-parietal	0.032
		LowBeta-IntroAsymmetry	0.019
Lesson 3	EEG	LowBeta-InterAsymmetry	0.044
		PupilDiameter-average	0.020
	EEG	Alpha-parietal	0.044

Attitudes Toward School

No significant difference of the task performance and self-reported motivation is found including all the studied motivational factors between the two groups of participants, divided over the scores of Attitudes Toward School.

Table 5.2 The significant differences between two groups of participants for Attitudes Toward School according to Mann-Whitney Test

	Category	Variable/Feature	P value
Lesson 1	EEG	Theta-mean	0.016
		Theta-occipital	0.039
		Theta-parietal	0.009
		Theta-temporal	0.019
Lesson 3	EyeTracking	FixationNumber-overall	0.028
		FixationConnectionLength-overall	0.017
	EEG	Alpha-InterAsymmetry	0.005

However, significant differences between the two groups of participants are found from EEG and eye tracking, detailed in Table 5.2. In addition, results for fixation in text area ($p=0.053$) and fixation number in text area/number of words ratio ($p=0.053$) for Lesson 3 also reach the significance thresholds.

Participants with higher scores of Attitudes Toward School, i.e., those in the “above” group, have smaller values of fixation number and fixation connection length as well as fixation number in text area and the ratio of fixation number in text area/number of words, suggesting that they have more focused attention and more efficient learning. Participants with different attitudes toward school showed differences in the EEG data with inconsistent results between lessons, suggesting further investigation on the brain mechanisms using either larger samples or advanced equipment like functional magnetic resonance imaging (fMRI).

Self-efficacy

There is no significant difference of task performance between the two groups. Significant effects are found on Perceived Ease of Use and Perceived Usefulness as well as features

from eye tracking and EEG, detailed in Table 5.3.

Participants with a higher score of Self-efficacy, i.e., the “above” group, perceive the e-learning system to be more useful and easier to use and also have less samples of eye gaze data out of monitor, and also they have less eye blinks. That indicates that they may have a higher workload than those with a lower level of Self-efficacy. The “above” group also have bigger value of gamma band power in frontal brain region and lower value of theta intro-hemisphere asymmetry, which may indicate more involvement in working memory tasks and less emotional activities, compared with the “below” group [115].

Despite the current shortage of the relevant research and explanation on the differences of the different eye gaze and EEG features, the findings above have excitingly indicated that different individuals with different levels of intrinsic motivation have significant differences in the sensor data, and thus the sensor data including eye gaze and EEG has the potential to predict individuals’ different levels of motivation.

Table 5.3 The significant differences between two groups of participants for Self-efficacy according to Mann-Whitney Test

	Category	Variable/Feature	P value
Lesson 1	EyeTracking	SamplesOutOfMonitor	0.035
	EEG	Gamma-frontal	0.028
		Theta-IntroAsymmetry	0.033
Lesson 2	MotivationalFactors	Perceived Ease of Use	0.023
		Perceived Usefulness	0.043
	EEG	HighBeta-frontal	0.039
		Gamma-frontal	0.013
		Theta-IntroAsymmetry	0.005
Lesson 3	MotivationalFactors	Perceived Ease of Use	0.049
	EEG	HighBeta-frontal	0.013
		Gamma-frontal	0.004

5.4.4 Feature Selection

From the extracted features listed in Section 5.4.2, it is essential to select the most relevant

features to be used as inputs of the classification model to improve the prediction success and reduce the computing complexity. Firstly, statistical analysis was conducted to generate salient EEG features in a data-driven manner from Spearman correlation test and ANOVA test (alternatively Kruskal Wallis Test for variables with a non-normal data distribution). The features with a statistically significant correlation with the motivational factors are listed in Table 5.4, and the features with a significant difference between the high level and the low level of each motivational factor are reported in Table 5.5.

Table 5.4 The significant EEG and eye tracking features ($p < 0.05$) according to Spearman Correlation Test

Motivational Factors	Significant Features	Category
Perceived Ease of Use	LessonDuration	OtherBehaviour
	Gamma-mean; HighBeta-occipital; Gamma-occipital; HighBeta-temporal; Gamma-temporal; HighBeta-frontal	EEG
	FixationNumber-overall; FixationSpatialDensity-overall; Regressions-overall	EyeTracking
Reading Experience	LessonDuration; QuizPerformance	OtherBehaviour
	Theta-max	EEG
	FixationConnectionLength-overall; FixationSpatialDensity-overall; FixationNumber-overall; Regressions-overall	EyeTracking

Table 5.4 and Table 5.5 take the examples of Perceived Ease of Use and Reading Experience, and the full lists corresponding to Table 5.4 and Table 5.5 are shown in Appendix 4 and Appendix 5, respectively. The significant features involve all feature types from the EEG, eye gaze and learners' task performance, indicating the potential effectiveness of the extracted features at inferring the levels of the motivational factors.

Table 5.5 The significant EEG and eye tracking features ($p < 0.05$) according to one-way ANOVA or Kruskal Wallis Test

Motivational Factors	Test	Significant Features	Category
Perceived Ease of Use	One-way ANOVA	FixationNumber-overall	EyeTracking
	Kruskal-Wallis Test	LessonDuration	OtherBehaviour
		Gamma-mean; HighBeta-mean, Gamma-occipital, HighBeta-occipital, Gamma-temporal, HighBeta-temporal, Gamma-parietal, HighBeta-frontal, Alpha-IntroAsymmetry	EEG
		FixationSpatialDensity-overall	EyeTracking
Reading Experience	Kruskal-Wallis Test	LessonDuration, QuizPerformance	OtherBehaviour
		Theta-max, Alpha-max, HighBeta-min	EEG
		AverageSaccadeLength-10s, FixationSpatialDensity-overall	EyeTracking

Secondly, a knowledge-drive approach to feature selection was then employed to avoid omission of the features that can potentially enhance the classification accuracies. In detail, according to the quantified relationships between the factors in the motivation model from SEM analysis described in the Chapter 4, the significant features identified from the statistical analysis for a motivational factor will also be adopted for its direct dependent factors. For example, Attitudes Toward School (Factor A) is the direct independent factor of Learning Experience (Factor B), so the features selected for Factor A from the statistical analysis will also be selected as inputs for inferring the level of Factor B. In addition, the significance level, i.e., p value, of the effect of Factor A on Factor B is required to be less than 0.001 to be selected to reduce the possibility of redundancy; in the case that p value is between 0.001 and 0.05, only the features of Factor A that were selected by the statistical analysis with the significance level of less than 0.001 are adopted for classification of Factor B. The details of the selection results are reported in Table 5.6.

Table 5.6 The features from direct independent factors

Dependent Factors	Independent Factors with Direct Effects
Perceived Usefulness	Perceived Ease of Use
Confirmed Fit	Visual Attractiveness*, Perceived Usefulness, Perceived Ease of Use
Learning Experience	Attitudes Toward School
Reading Experience	Confirmed Fit, Learning Experience
Visual Attractiveness	Feedback, Self-efficacy*
Perceived Ease of Use	Self-efficacy
Continued Use Intention	Attitudes Toward School*, Reading Experience, Visual Attractiveness

** $0.001 < p < 0.05$ for the causal relations between two motivational factors, where only features selected from the statistical tests with $p < 0.001$ are adopted. All the other factors in the right column have direct causal effects on the corresponding factors in the left with p value of less than 0.001.*

5.4.5 Prediction Results of Classification Models

This section presents the process of generating a classification model using logistic regression for each motivational factor to infer the high/low level based on the sensor data.

From the statistical analysis and the knowledge-driven feature selection process just described, a set of eye gaze and EEG features was selected for the classification of the level of each motivational factor. Afterwards, logistic regression is used as the classification mechanism to generate models for the high/low level classification of each motivational factor based on the features selected from EEG, eye gaze and other learning performance data.

Logistic regression performs the classification by computing a probability of a motivational factor M_1 being at high level $P \in [0, 1]$, using:

$$P(M_1) = \frac{1}{1+e^{-z}} \text{ , where } z = \sum_{i=0}^n \beta_i X_i \text{ , and } X_0 = 1 \quad (1)$$

where coefficients β_i measures the effect of a predictor X_i being significant on the probability of high level of the motivational factor. Thus, for positive β_i the greater the value of predictor X_i , the greater the increase in the probability of motivational factor being high level and vice versa. β_0 is the constant which is the log of the odds when all

X_i equal 0. Then π is deduced from P via a threshold $\gamma \in [0, 1]$ for the assumed uncertainty of the solution:

$$\pi(M_1) = \begin{cases} 1, & P(M_1) > \gamma \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where π refers to the level of a motivational factor, and $\pi(M_1)$ being 1 or 0 represents that M_1 is classified into the high or low level, respectively. Firstly, only eye gaze features are used to perform the classification, published in a paper [206], where Enter method is used for variable selection in SPSS. Enter method means all the explanatory variables, i.e., the features, were entered into the logistic regression model in a single step. The results of classification based on only eye gaze data shown in Table 5.7 have achieved good classification accuracies for most of the motivational factors, but there exists a number of non-significant features for each motivational factor in the model when using Enter method to include all the extracted features, and also the prediction power of the classification models of Self-efficacy and Continued Use Intention are not significant or close to threshold.

Table 5.7 Model coefficients and accuracy based on gaze features

Motivational Factors	Chi-Square	df	Sig.	Nagelkerke R Square	Model Accuracy
Perceived Usefulness	34.513	15	0.003**	0.506	78.7%
Perceived Ease of Use	28.547	15	0.018*	0.423	77.3%
Visual Attractiveness	31.817	15	0.007**	0.466	81.3%
Feedback	30.526	15	0.010*	0.454	78.7%
Self-efficacy	17.999	15	0.263	0.293	69.3%
Attitudes Toward School	39.578	15	0.001**	0.549	78.7%
Confirmed Fit	37.092	15	0.001**	0.524	81.3%
Learning Experience	49.946	15	0.000**	0.648	81.3%
Reading Experience	37.580	15	0.001**	0.526	78.7%
Continued Use Intention	25.316	15	0.046*	0.386	72.0%

* $p < 0.05$, ** $p < 0.01$

Introducing other data source especially EEG data to the models is expected to improve the model quality. Secondly, the integrated set of EEG and eye gaze features selected was then applied to generate classification models for each motivational factor.

By default, the 0.5 cut-off point was set as the decision threshold to infer the level (i.e., π in (2)). To maximise the classification accuracy for each motivational factor, a Receiver Operating Characteristic (ROC) curve was employed to identify an optimal cut-off point. ROC curve consists of “Sensitivity” as Y-axis and “1-Specificity” as X-axis generated from all possible cut-off points, where sensitivity is the ratio of true positive predictions and specificity is the ratio of true negativity predictions. Therefore, the optimal cut-off point is the closest to the position (0, 1) in the ROC curve. Taking the motivational factor Visual Attractiveness as an example, the ROC curve is shown in Fig. 5.6, and part of the possible cut-off points with the corresponding X-axis and Y-axis values is displayed in Table 5.8.

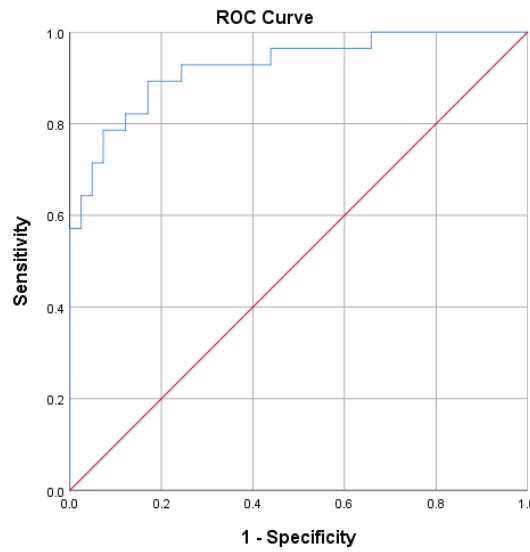


Fig. 5.6 ROC curve for Visual Attractiveness

Table 5.8 Part of coordinates of the ROC curve for Visual Attractiveness

Positive if Greater Than or Equal To*	Sensitivity	1 - Specificity
0.2879672	0.929	0.244
0.3160239	0.893	0.244
0.3340052	0.893	0.220
0.3408276	0.893	0.195
0.3475657	0.893	0.171
0.3573349	0.857	0.171
0.3669414	0.821	0.171
0.4225623	0.821	0.146
0.4800537	0.821	0.122
0.4915688	0.786	0.122

*Test Result Variable(s): Predicted probability. *All the other cut-off values are the averages of two consecutive ordered observed test values.*

Combined with the Fig. 5.6 and Table 5.8, the cut-off point, 0.348, with the position (0.89, 0.17) in ROC curve in Fig. 5.6 is adopted as the optimal decision threshold to perform classification of Visual Attractiveness. Similarly, the decision thresholds for all the motivational factors have been identified. In order to improve the model quality and remove the EEG and eye gaze features that contribute little to the classification of the motivational factors, the Backward stepwise method was then adopted instead of Enter method, which removes the explanatory variables from the model that initially contains all the explanatory variables stepwise to make the model least prone to error according to the statistic of likelihood ratio (LR). The coefficients of the classification model are reported in Table 5.9, showing that adding the EEG and eye gaze features has significantly improved the classification ability to differentiate the high level from low level for all the motivational factors.

Table 5.9 Omnibus tests of model coefficients using logistic regression

Motivational Factors	Chi-square	df	Sig.	Nagelkerke's R Square
Perceived Usefulness	18.072	4	0.001	0.314
Confirmed Fit	21.521	4	0.000	0.359
Feedback	35.448	6	0.000	0.550
Attitudes Toward School	27.170	4	0.000	0.441
Learning Experience	34.087	4	0.000	0.520
Reading Experience	45.880	9	0.000	0.648
Continued Use Intention	28.242	5	0.000	0.452
Visual Attractiveness	45.386	9	0.000	0.651
Perceived Ease of Use	17.872	3	0.000	0.305
Self-efficacy	58.529	5	0.000	0.775

The prediction results of the classification models generated from both the default value and the optimal value of decision threshold for each motivational factor are displayed in Table 5.10, along with the significant features for the classification. Nagelkerke's R square from 30.5% to 77.5% suggests a moderately high relationship between predictors and the corresponding motivational factor. The accuracy of between 68.1% and 92.8% for the motivational factors with the optimal cut-off values suggests good prediction power of the models.

For Perceived Ease of Use, the Nagelkerke's R square, the prediction accuracy value and the degree of freedom are the smallest, which may indicate that more predictors from other sources of data will help improve the prediction power, such as mouse movements data to reflect the ease of use of a system. Following Perceived Ease of Use, the relatively low prediction ability appears for the classification models of Perceived Usefulness and Confirmed Fit. In addition to involving more data sources as predictors, increasing the variability of the learning materials and presentation styles may be helpful to improve models for the two factors, because it will lead to the ceiling effect when all participants perceive the e-learning environment and materials as useful and suitable for their learning, as indicated in the optimal decision thresholds higher than 0.5 for both factors. For all the rest motivational factors studied, the Nagelkerke's R square values are between 44.1%

and 77.5%, and classification accuracies are between 76.8% and 92.8%, suggesting very good model quality.

Table 5.10 Classification accuracies for the motivational factors with cut-off points and significant features

Motivational Factors	Cut-off points	Classification Accuracy (%)	Significant Features (with significance level of 0.05)
Perceived Usefulness	0.5	72.5	QuizPerformance; Gamma-occipital; HighBeta-temporal; HighBeta-IntroAsymmetry
	0.600	76.8	
Confirmed Fit	0.5	68.1	FixationNumber-overall; Gamma-mean; Gamma-occipital
	0.640	73.9	
Feedback	0.5	72.5	Gamma-max; Gamma-temporal
	0.371	79.7	
Attitudes Toward School	0.5	76.8	FixationNumber-overall; Alpha-InterAsymmetry
	0.496	76.8	
Learning Experience	0.5	81.2	PupilDiameter-average; FixationSpatialDensity; HighBeta-frontal; Gamma-occipital
	0.530	81.2	
Reading Experience	0.5	88.4	LessonDuration; QuizPerformance; PupilDiameter-max; SaccadeLength-average; HighBeta-max; HighBeta-min; HighBeta-occipital
	0.536	88.4	
Continued Use Intention	0.5	75.4	FixationNumber-10s; Theta-mean; Alpha-min; Alpha-max; HighBeta-frontal
	0.438	82.6	
Visual Attractiveness	0.5	84.1	FixationSaccadeRatio; FixationNumber-overall; Theta-max; HighBeta-frontal; HighBeta-temporal; Gamma-temporal; LowBeta-occipital
	0.348	85.5	
Perceived Ease of Use	0.5	62.3	FixationSpatialDensity; Gamma-temporal; Alpha-IntroAsymmetry
	0.416	68.1	
Self-efficacy	0.5	92.8	Gamma-frontal; Gamma-occipital; Alpha-frontal; HighBeta-frontal
	0.481	92.8	

5.4.6 Discussion

Remarkable results have been achieved for the prediction success of the classification models for the motivational factors based on the integrated EEG and eye gaze features. The details of the classification tables for the motivational factors are presented in Appendix 6. Compared with the classification models based on only eye gaze features, using the integrated set of both EEG and eye gaze features has generated better results in terms of the model quality and classification accuracy. Particularly in contrast to using only eye gaze features as predictors for predicting levels of Self-efficacy and Continued Use Intention with unsatisfying model significance [206], using both EEG and eye gaze features has significantly improved the model significance and classification accuracy for the two motivational factors.

Among all the factors studied, the classification accuracies for Self-efficacy, Reading Experience and Visual Attractiveness are the highest (over 85%), and as shown in the tables, generally more significant predictors result in better prediction ability and vice versa. In addition, what is worth noting is that the classification models of Feedback and Self-efficacy have achieved high classification accuracies, but both have a small number of significant predictors that are all EEG features. That suggests the crucial role that EEG data plays in predicting the levels of the two motivational factors.

Another remarkable result has been obtained on the statistical differentiation of the features extracted from sensor data between the high and low level of each motivational factor. Specifically, both the maximal gamma band power among all the electrodes and the mean gamma band power in the temporal brain region have significant differences between the two levels of the factor Feedback. The feedback was designed after each quiz in the e-learning environment, consisting of both emoticon and text with relevant information and positive encouragement. The reason of the difference may be that gamma band is related to learning, memory and information processing, and the temporal brain region is responsible of sensory processing about visual memories, language comprehension and emotion association, which are all related to the brain activities involved by feedback during the learning process. Brainwaves from frontal brain regions have been found to have significant contributions to the classification model of Self-efficacy, and this may be explained by the rich dopamine-sensitive neurons in the frontal brain region related to reward, planning, motivation and short-term memory [207].

For all the motivational factors studied, it can be found that no EEG features from parietal brain region have significant contribution to the classification. The reason may be that the learning materials used in the experiment only include the visual information of text and images, while the parietal brain lobe is mainly responsible of integration of sensory information from different modalities, including spatial sense and navigation [208]. Therefore, it can be also expected to achieve higher prediction ability with EEG data from parietal region, when learning materials that involves multiple modalities are used.

Furthermore, the EEG features from gamma and high beta bands have been found to have significant contribution to the classification models for most of the motivational factors. Eye gaze features including fixation and saccade domain have also performed well in the classification task. Amongst the eye gaze features, fixation number and pupil diameter have been found to have significant prediction power in the classification task for most of the motivational factors.

Prior research suggested that pupil diameter was useful to indicate emotional arousal [209] as well as mental effort of viewers when they were doing tasks requiring cognitive effort [116], [117], and fixation number was a useful indicator of mental processes such as task efficiency (e.g., [210]) and interest (e.g., [211]). That explains why using gaze data solely to train the classification models has achieved good results in the present study [206]. Incorporation of EEG features has improved the prediction results, and it is also worth noting that amongst all the motivational factors studied, all the features that have significant prediction power involve EEG features, which corroborates the approach proposed in the present study that has combined the EEG features with eye gaze features for motivation computation.

5.5 Different Approaches to Predicting Motivational Consequence

5.5.1 Towards an Integrated Motivation Model

So far, the motivation model has been described in previous chapters including the motivational factors, the motivational consequence and their quantified interrelationships, and this Chapter has also described the sensor-based approach to computing the

motivational factors by classifying their levels using logistic regression models. The motivation model and the sensor-based classification model correspond to the two approaches to predicting the motivational consequence. In many circumstances, it is useful to predict users' continued intention to use an e-learning system. Specifically, the motivational consequence can be predicted using self-reported data on the factors in the quantified motivation model described in Chapter 4, and it can also be predicted using the classification model generated for Continued Use Intention based on sensor data captured during the learning process.

Systematically looking at the two different approaches, the classification model for predicting the level of each motivational factor can be integrated into the motivation model. The integrated model is shown in Fig. 5.7. Each motivational factor is computed based on the real-time data collected during user's interaction with e-learning systems, and the levels of the motivational factors predicted from the computation can be further used to predict the motivational consequence.

For each motivational factor, there is a specific set of predictors which are the features extracted from real-time data including gaze and EEG data. Therefore, the circle of "real-time data" in Fig. 5.7 does not represent one single predictor. The predictors of different motivational factors have been described before in this chapter, and they will not be listed here again for each motivational factor, while one example for the factor Attitudes Toward School, is shown in Fig. 5.8.

As stated, logistic regression performs the classification by computing a probability, P , of a motivational factor, M_i , being at high level $P \in [0, 1]$, using the formula shown in (1). Therefore, in the integrated motivation model in Fig. 5.7, it uses logistic regression to compute P for the motivational factors based on real-time data, and the results are then used further to compute P for the motivational consequence. Therefore, the output data for the consequence will also be continuous representing its probability being high level, and then it can be classified into categories with a decision threshold, and the number of the categories depends on whether binary or multinomial logistic regression is applied.

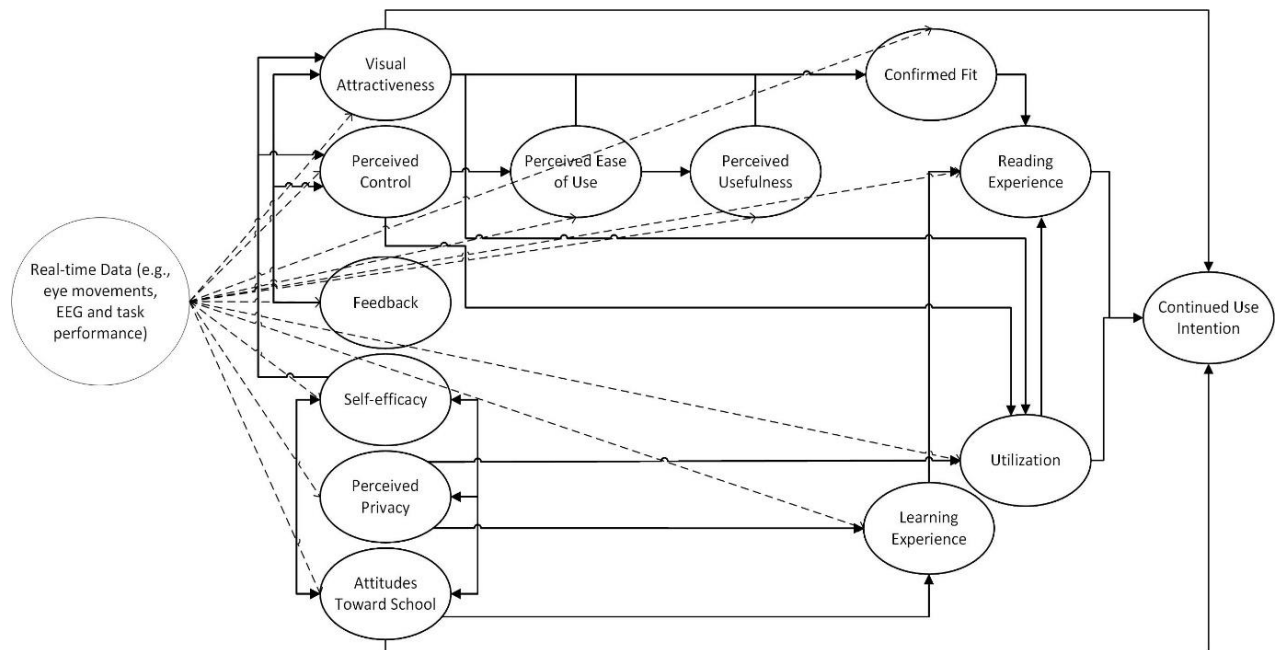


Fig. 5.7 Specification of an integrated motivation model for people with dyslexia in e-learning environment

Dashed lines represent logistic regression analysis and solid lines represent linear regression analysis.

The parameter estimates between all predictors of Continued Use Intention should be re-estimated in the integrated model after including the logistic regression models, this can be done using advanced SEM programming that allows logistic regression to be included with linear regressions; however, as explained before in this chapter, Perceived Control, Utilization and Perceived Privacy have been excluded from the logistic regression analysis due to the insufficient reliability of the corresponding items measuring them in the simplified questionnaire used in the experiment. That does not allow for conducting the integrated analysis to conclude the exact factor loading; also importantly, it's better to conduct an experiment that uses the same sample to obtain the data for all the variables, unlike the present project containing different pieces of studies that involves different samples. Therefore, the effects of variables (i.e., parameter estimates) are not displayed in Fig. 5.7.

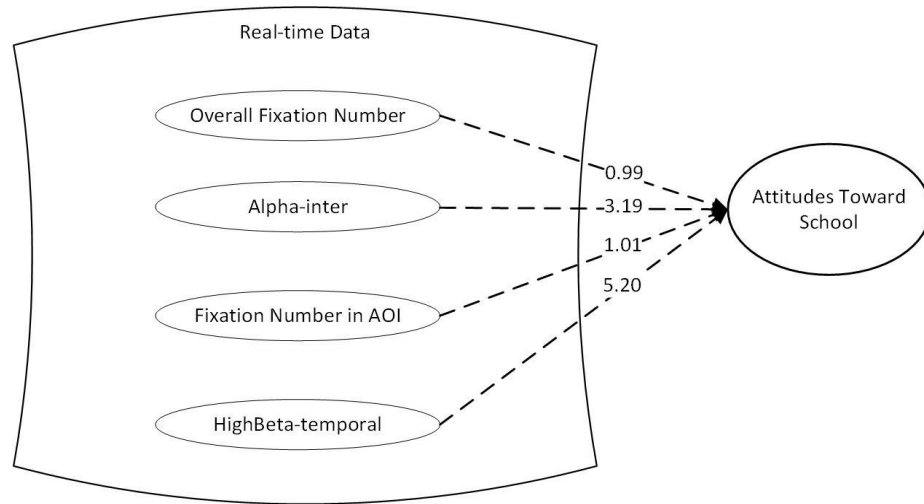


Fig. 5.8 The logistic regression model predictors for Attitudes Toward School as an example for those shown in Fig. 5.7

The parameter coefficients shown with the dash lines are the odds ratios.

In the motivation model from the SEM analysis described in Chapter 4, the effect of a predictor (i.e., independent variable) is shown as beta coefficient along with the arrow linking the independent variable to the dependent one. Likewise, when including classification models using logistic regression, the effect of a specific predictor should also be represented. In logistic regression, the odds ratio is a summary score representing the effect of a predictor, on the likelihood that one outcome will occur. Odds ratio for the total effect of a predictor can be estimated by exponentiation of the regression parameters [212]. In Fig. 5.8, the odds ratio of each predictor of Attitudes Toward School is shown with the arrow of their relationship. Likewise, the other logistic regression models for the other motivational factors can be integrated into the motivation model to obtain the integrated model shown in Fig. 5.7.

5.5.2 Comparing the Different Approaches

As stated before, on the one hand, using the sensor-based approach described in this chapter, a classification model using logistic regression is generated to predict the level of motivational consequence, based on the real-time sensor data collected in the experiment. Therefore, the EEG and gaze features can be used to predict on the motivational consequence directly. The classification model is shown in Fig. 5.9. Using

the motivation model with the quantitative mappings obtained from CB-SEM and PLS-SEM approaches, described in Chapter 4, on the other hand, self-reported data on the motivational factors can be used to predict the motivational consequence. Therefore, between the logistic regression model that uses real-time data to predict the consequence directly and the quantified motivation model that uses self-reported data on motivational factors to predict the consequence, is there a way of comparing the different approaches to conclude the preferable one?

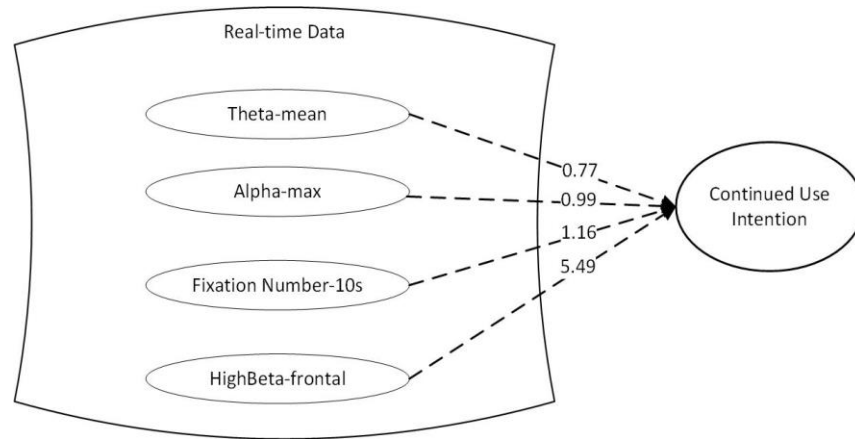


Fig. 5.9 Logistic regression model for predicting Continued Use Intention based on real-time sensor data

Parameter estimates are odds ratios.

To answer this question, we need to seek possible criteria for model selection. The most common index is R^2 which represents the explained variance of the dependent variable, but it is not a good choice because it is biased by the sample size and number of covariates. In fact, none of the “traditional” model fit indicators such as comparative fit index or the root mean square error of approximation are applicable for this purpose.

The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) can be used to test competing models against each other, which depend on the number of parameters in the model and the likelihood function of the model [213]. It is recommended by prior researcher to prefer the model with the smallest AIC and BIC, which means the model is closer to the truth or more likely to be the true model [214]. AIC and BIC values are calculated using:

$$AIC = -2*\ln(\text{likelihood}) + 2*n \quad (3)$$

$$BIC = -2*\ln(\text{likelihood}) + \ln(N)*n \quad (4)$$

where n is number of predictors in the model and N is the number of observations. Clearly, AIC does not depend on sample size directly. Generally, AIC presents the danger that it might overfit, whereas BIC presents the danger that it might underfit, simply in virtue of how they penalize free parameters ($2*n$ in AIC; $\ln(N)*n$ in BIC).

Table 5.11 AIC and BIC for the three models resulting from different approaches for predicting the motivational consequence

Information Criteria	Logistic Regression	CB-SEM	PLS-SEM
AIC	73.65	147.52	25.59
BIC	82.91	239.18	55.32

It can be found from Table 5.11 that the PLS-SEM approach has obtained the motivation model that is the most likely to be the true one for predicting Continued Use Intention, based on the self-reported questionnaire data measuring the motivational factors in the model, followed by the classification model from logistic regression to predicting Continued Use Intention based on both eye gaze data and EEG data. The least preferable model among the three, according AIC and BIC, is obtained from CB-SEM analysis using the same sample as PLS-SEM analysis. This is probably because that the sample size and data failed to meet the assumption of CB-SEM, and the sample used for SEM and that used for logistic regression are different. Therefore, the comparison here cannot lead to the conclusion about whether the quantified motivation model based on self-reported motivational factors or classification model based on eye gaze and EEG data is better for predicting the motivational consequence.

More importantly, the different approaches, namely the knowledge-driven motivation model with quantified parameters obtained from CB-SEM or PLS-SEM analysis, and the data-driven classification model for motivation computation, are more complementary than competitive. Neither of the approaches is created to mimic another but to complement the drawbacks of other methods. Specifically, in addition to the different data assumption, the most important criteria to choose between CB-SEM and PLS-SEM

is the purpose of the research. As recommended by Hair et al. [215], PLS-SEM should be selected when the goal is to predict a key factor or identify key predictors, while CB-SEM is preferred for theory testing and confirmation. Despite the limited theory interpretability, the logistic regression algorithm is used for classifying the levels of the motivational factors into different levels, because it allows: 1) using real-time sensor data to predict learners' motivational states; 2) personalising the e-learning environments in real time based on the predicted level of the motivational factors in future. In the present research project, these purposes are all involved and not clearly cut, so all the aforementioned approaches are adopted to provide a comprehensive view from different perspectives for motivation modelling and computation.

5.6 Conclusion

This chapter has proposed a sensor-based approach to motivation computation that combines EEG and eye gaze data to assess the levels of the motivational factors. To collect necessary data to validate the approach, an experiment has been conducted with students with learning difficulties including dyslexia using three lessons in an e-learning environment, and the sensor data were captured from the participants while they were learning. In summary, the types of features extracted from EEG and eye-tracking data are described, and the feature selection process is explained in detail. Using both statistical analysis and the interrelationships of the factors in the quantified motivation model, the EEG and eye gaze features were selected with most relevance to the differentiation of high level from low level of each motivational factor. The selected features were then used as inputs of the logistic regression algorithm to generate classification models for predicting the level of the motivational factors, and the optimal decision threshold was identified via ROC curve for each motivational factor to obtain the highest classification accuracy. At the end of this chapter, the different approaches to predicting the motivational consequence, based on sensor data using the classification model or self-reported data using the motivation model, are discussed and compared, which provides a systematic, holistic view of the pros and cons of different approaches.

The experiment results have indicated that different dyslexic individuals with different levels of intrinsic motivation have statistically different eye movements and brain activities. The prediction results of classification models have shown that using the

integrated set of EEG features pertaining to frequency band power, brain regions and hemisphere asymmetry and eye gaze features from fixation, saccade and other domains (especially pupil diameter) has achieved classification models with satisfactory prediction accuracies for all the motivational factors studied. The experiment has also revealed that all the feature types extracted from EEG and eye-tracking data are involved in the features contributing significantly to the classification task. The empirical results have validated the proposed sensor-based approach to motivation computation combining EEG and eye tracking. This allows the motivational states including multiple dimensions to be assessed in real time, and thus enables dynamic provision of personalised strategies during learners' integration process with an e-learning system to address individual motivational needs.

In Chapter 6, following the ontological motivation model described in Section 3.4, ontology is also exploited to manage the complex sensor features for motivation assessment in a structured way. Based on the motivation model described in previous chapters and the classification mechanism using logistic regression described in this chapter, a systematic architecture of sensor-based motivation assessment is provided in Chapter 6, which includes ontological models representing EEG and eye tracking information and motivational factors, quantitative feature analysis, and the classification mechanism inferring levels of the motivational factors. The motivation-based personalisation is then described in detail using motivational strategies and rule-based reasoning mechanism.

Chapter 6 Motivation-based Personalised Learning

6.1 Introduction

With the emergence of pervasive computing, growing attention has been paid to facilitate the context-aware technologies that enable service personalisation to reflect a users' changing situation or behaviour. Learners' motivational needs including multiple dimensions represented by the factors in the motivation model have been described before. Instead of a one-size-fits-all solution, effective personalisation in e-learning environments needs to address learners' motivational needs to keep learners motivated to achieve learning goals. In previous chapters, motivation has been modelled using a hybrid approach and the computation method has been described to assess learners' motivational states in real time, but e-learning systems still cannot provide solutions to different motivational needs without personalisation techniques. There is still a distinct lack of research investigating or explaining how e-learning systems should respond to learners' motivational states.

In e-learning environments, embodied pedagogic agent is usually employed to provide support for learners to maintain their interest or re-engage them in the active learning process while playing the role of companion or instructor. Woolf et al. [216] have found that pedagogic agents providing affective feedback in an intelligent tutoring system can improve the affective outcomes of students with learning disabilities such as reduced frustration and anxiety. The support output by a pedagogic agent is ideally in a non-authoritative style to avoid coercion but maximise learners' intrinsic motivation to continue learning, as intrinsic motivation has been found more effective at directing human behaviour in long term [217]. So far, the use of pedagogic agents has attempted to address both cognitive and affective aspects of learning, but more research has been focused on cognitive aspects rather than affective aspects of learning [216], [218]. While some effort has been made to create affective agents [219] that provide feedback such as smiley faces and guidance, personalised feedback provided by pedagogical agents based on user modelling is still limited, let alone personalised response targeting at learners' motivational needs.

This chapter proposes a semantic rule-based approach for supporting motivation-based personalised learning based on learners' motivation in e-learning systems. Rule-based personalisation outweighs the use of other techniques in this domain, such as collaborative filtering, as it deals with data scarcity issues well without relying on previous users' information, and the uniformity allows all knowledge in a system to be expressed in the same format [96]. Additionally, presenting personalised services explicitly in the form of rules improves the manageability of e-learning systems, as designers and developers can easily inspect, modify and expand the rules without influencing the low-level software engine implementation.

Motivation-based personalised learning aims at providing learners with motivational strategies corresponding to the motivation model to address their motivational needs, during the learning process in e-learning systems. Ontologies enables representing the knowledge domain; semantic rules provide explicit definition of personalised motivational strategies in the system to facilitate the reusability and modifiability of the personalisation rules. Ontologies and rules interoperate semantically and inferentially to enable the reasoning in order to dynamically derive personalised strategies.

The starting point in this chapter is a sensor-based motivation assessment system architecture. Specifically, computational representation of the sensor features and motivational factors using ontology, quantitative data analysis for feature selection, and the classification mechanism for assessing motivational states are structured in a holistic picture and described in Section 6.2. Following that, personalisation of motivational strategies is explained in Section 6.3, including personalised motivational strategies corresponding to the factors in the motivation model, evaluation of the motivational strategies based on real-time sensor monitoring, and the reasoning mechanism using semantic rules. Finally, the conclusion is drawn in Section 6.4.

6.2 Sensor-based Motivation Assessment Using Ontology and Classification Mechanism

6.2.1 The Sensor-based Motivation Assessment System Architecture

This section introduces a sensor-based motivation assessment system architecture to enable motivation-based personalisation. The architecture puts emphasis on the use of ontology representing EEG and eye gaze features for motivation assessment and learners' motivational states including the different dimensions in the motivation model to be assessed.

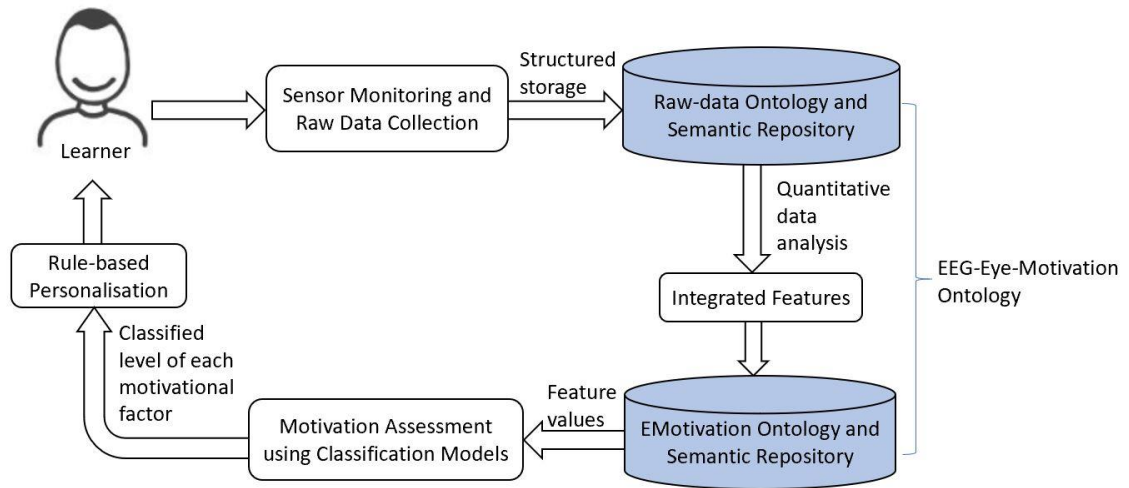


Fig. 6.1 The architecture of the sensor-based motivation assessment system for motivation-based personalised learning

In the present research context, the aim of motivation-based personalised learning is to help dyslexic learners keep motivated by enabling their motivational needs to be detected in real time and thus personalised support to be output by the e-learning environment. Fig. 6.1 presents the architecture of the sensor-based motivation assessment system for motivation-based personalisation. It works as follows:

A) Raw data are collected from both learners and sensors including an eye tracker and an EEG device during the learning process within an e-learning environment, and then saved in documents which are readable by humans rather than machines. Therefore, the raw data including sensor data from EEG and eye tracking and self-reported data from learners are mapped to the Raw-data Ontology with file parsing to allow the raw data to be organised in a machine-readable manner. The Raw-data Ontology is used to create semantic data using generic ontology editing tools such as the Protégé OWL Plugin and

then archived in a semantic repository. The semantic repository consists of Resource Description Framework (RDF) triples and is built on top of traditional database management systems by adding a semantic processing layer for semantic manipulation.

B) A variety of features are extracted from the raw data and employed for motivation assessment. EEG and eye gaze features are extracted and represented in the extended EMotivation ontology, where both the feature type and the data source are described, for example, the electrode from which an EEG feature is extracted and the screen area for which an eye gaze feature is calculated. Same as the Raw-data Ontology, the EMotivation ontology is then used to create semantic data archived in a semantic repository.

C) The ontological knowledge representation model in the architecture is termed EEG-Eye-Motivation Ontology, consisting of the Raw-data Ontology and EMotivation ontology. Using the information from the EEG-Eye-Motivation Ontology, based on a series of quantitative data analyses for feature selection and the classification mechanism using logistic regression models described in Chapter 5, the relevant features are employed to infer the high or low level of each motivational factor.

Finally, the results of the motivation assessment can be used further for providing personalised services in the e-learning environment to support learners' motivational needs. The personalised services contain various motivational strategies, and Semantic Rule Web Language (SWRL) is used for semantic rule-based reasoning to achieve personalisation based on the ontological representation and classification mechanism for motivation assessment, which is explained in detail in Section 6.3.

Though the system architecture is proposed based on the present context of motivation-based personalisation, the rationale and principle can be applied to any other e-learning context for a wider group of users and based on a more generic learner model. As the details about quantitative data analysis for feature extraction and selection, and classification mechanism to assess motivational states have been described in Chapter 5, the following two sections will explain the motivation assessment system architecture further and focus on the use of ontology for representing relevant knowledge for sensor-based motivation assessment.

6.2.2 Information Mapping and Raw-data Ontology

The ontological modelling in the architecture extends that described in Chapter 3 by involving the use of ontology to represent the structure of raw sensor data, the relevant features extracted from the sensor data to assess learners' motivational states, in addition to the motivational factors in the motivation model representing different dimensions of motivational needs.

The first step of the analyses for sensor-based motivation assessment is to store the EEG and eye-tracking data in a structured way that makes it readable by a computer. In the proposed architecture, the mapping process enables structural storage of the raw data. It consists of the approaches to document content identification (e.g., the identification of EEG power-band data, eye-tracking fixation data, etc.), as well as query and information description. SPARQL query language is adopted to map the raw data from the original files to the Raw-data Ontology, including the identification of the Instance locations in the ontology to enable information entry and description of the Instance with Properties.

The approaches are detailed in Fig. 6.2, where the Classes in the Raw-data Ontology have no Instances yet. After querying and searching are used to match keywords and enable Instances to be specified for the corresponding Classes, EEG and eye-tracking data and other relevant raw data obtained during a user's interaction process with an e-learning system are represented in the ontology, with Instances, Attributes and the relationships between Instances (Fig. 6.3). In this way, the raw data is stored in a structured way, and the EEG and eye-tracking data can be then analysed quantitatively to extract features.

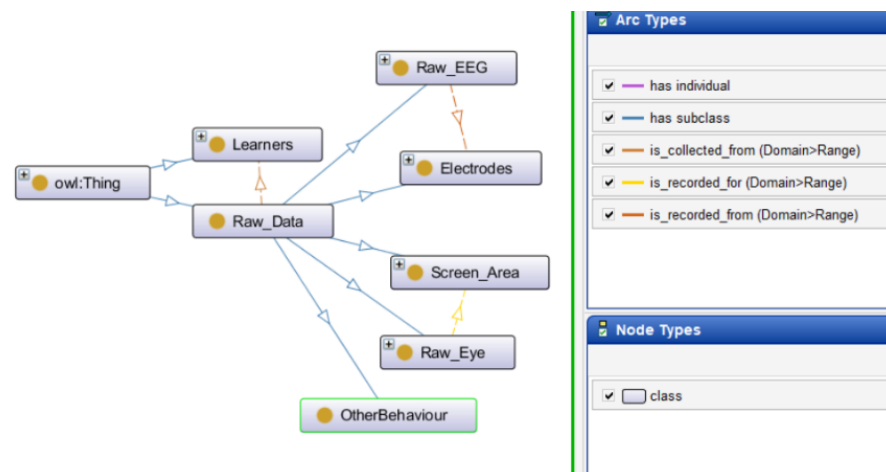


Fig. 6.2 “Raw-data Ontology” without any data

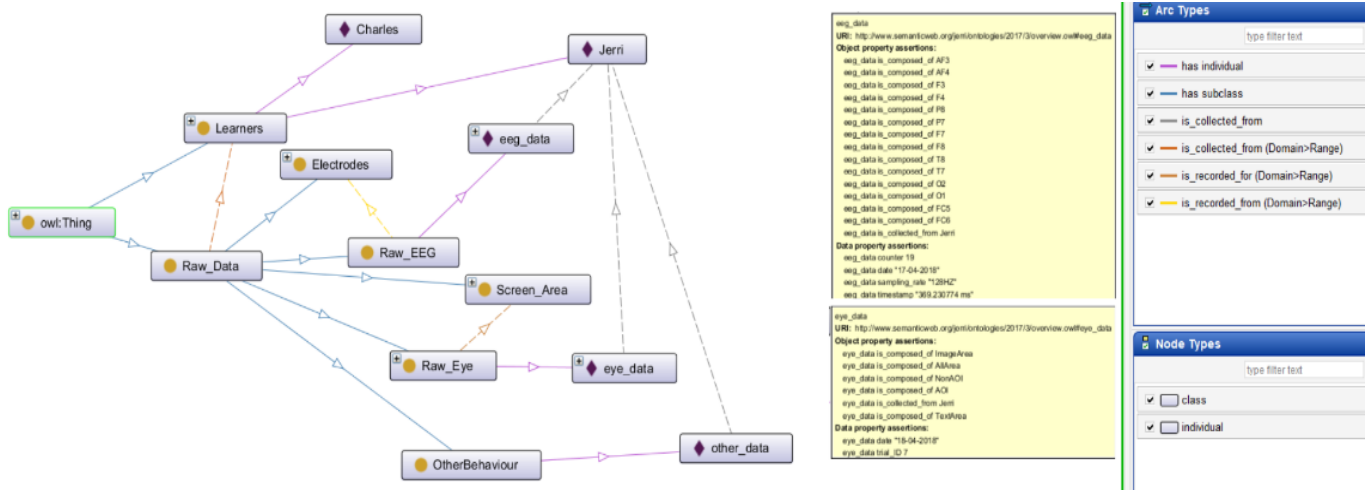


Fig. 6.3 “Raw-data Ontology” with EEG and eye-tracking data

6.2.3 EEG-Eye-Motivation Ontology and Motivation Assessment

The EEG and eye gaze features can be extracted from the raw data as inputs of the classification models to assess motivational states, as described in Chapter 5. Some self-reported data may also be collected from learners and it is in form of either Likert-style ratings or straightforward request and thus processed separately from EEG and eye gaze features to obtain the input for rule-based personalisation. Once the EEG and gaze features have been extracted, they will be stored in the extended EMotivation ontology.

To improve the capability of knowledge representation and information management about learners from an experiment, the EEG-Eye-Motivation Ontology structures the information about EEG and eye gaze features in addition to motivational factors, as displayed in Fig. 6.4. The structure consists of four layers. The domain layer is the name of ontology-based modelling, i.e., Motivation Assessment Based on EEG and Eye Tracking. The category layer defines four categories named EEG, Eye, Other Behaviour and Motivation representing the main aspects involved in the architecture for sensor-based motivation assessment. At a lower level, concepts about EEG and eye gaze features such as PowerBand_Mean and Fixation are defined in the class layer with a Class name and a set of Attributes. For example, Attributes can be defined for Fixation class representing the screen area the eye gaze feature is calculated on and the values of the feature vector calculated. Finally, each Class has the corresponding Instance in the

instance layer to store both the EEG and eye gaze features in a machine-readable format that are required to perform motivation assessment in the next step.

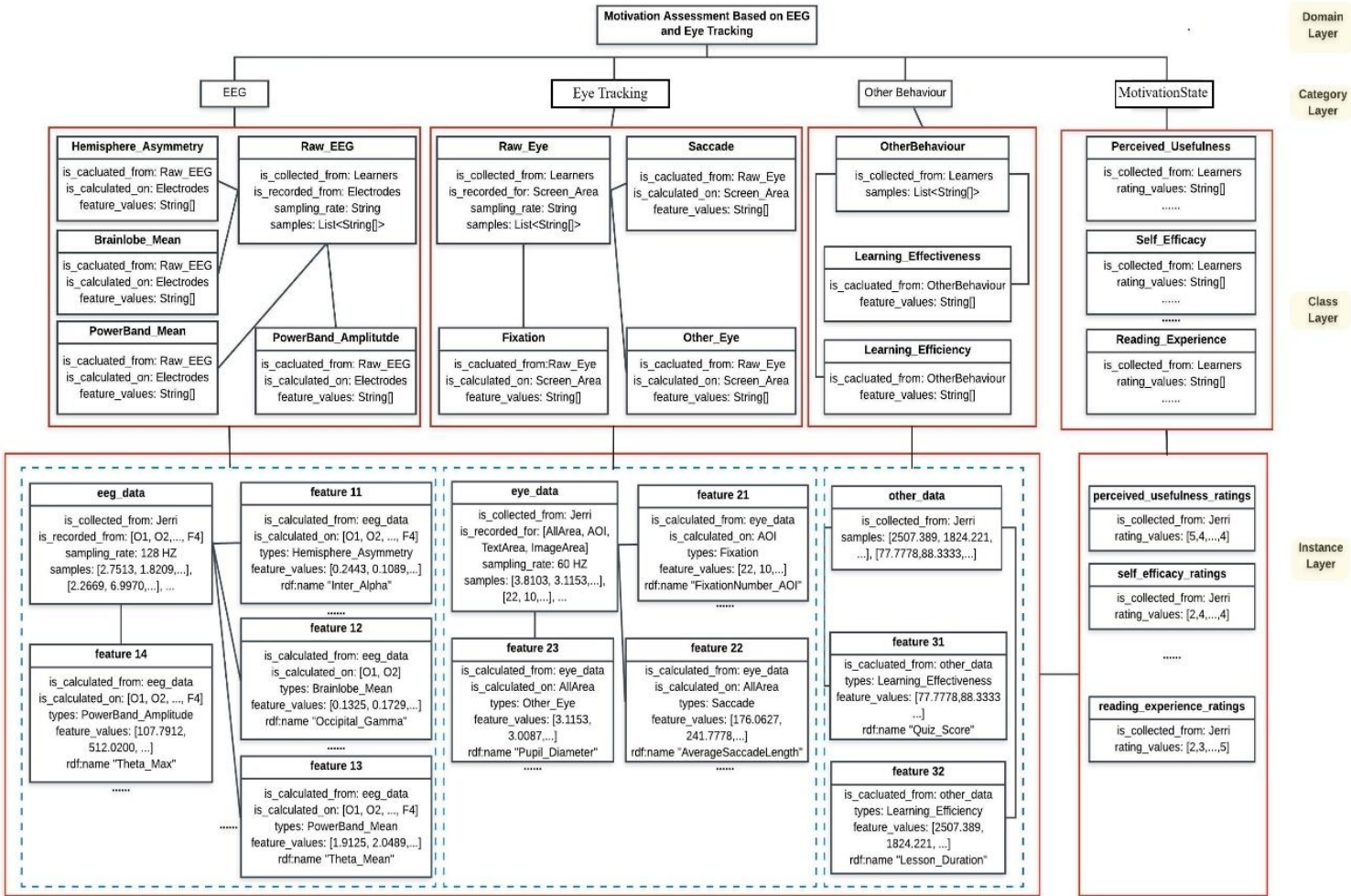


Fig. 6.4 The structure of the "EEG-Eye-Motivation Ontology"

The relationships in the EEG-Eye-Motivation Ontology include: the relations between two Classes or between two Instances, and those between a Class and the corresponding Instances. For example, the Instance feature 11 (from the extended EMotivation ontology) stores feature values extracted from the raw data on channel F7 (from the Raw-data Ontology). The Instance feature 11 has the Attribute set `is_calculated_on`, `types`, `feature_values` whose values equal to $\{F7, \text{PowerBand_Mean}, [-12.8180, -53.8990, \dots, -278.9780]\}$. In other words, feature 11 is calculated on the electrode F7; the feature is

an Instance of the Class `PowerBand_Mean`. The values of the feature vector equal to $[-12.8180, -53.8990, \dots, -278.9780]$.

After the features are extracted and stored in the EEG-Eye-Motivation Ontology, the features are then selected as inputs of the classification models to assess motivational states. The features selection process and the selected features for assessing the levels of different factors in the motivation model have been described in Chapter 5. The classification models generated using logistic regression algorithm to infer the level of each motivational factor have also been described in that chapter. The level of each motivational factor from the motivation assessment will be then used to provide personalised motivational strategies to address the specific motivational need. The strategies and reasoning mechanism will be illustrated in the next section.

6.3 Motivation-based Personalisation through Motivational Strategies

6.3.1 Motivation Strategies Corresponding to the Motivation Model

Motivational strategies in e-learning systems are indispensable to maintaining or enhancing dyslexic learners' motivation to keep learning in e-learning systems, given the difficulties such as reading and writing they encountered frequently and the subsequent sense of frustration and willingness to quit during the learning process. Based on the motivational factors in the motivation model and the classification models to compute the motivational factors, this section introduces the motivation-based personalisation through the use of motivational strategies that correspond to the motivational factors to address the learners' corresponding motivational needs.

Due to the multi-facet nature of motivation, both cognitive support and affective support are examined to be used for motivation-based personalisation. The conceptual motivation model has addressed different dimensions of motivation and will be used as the foundation and guidance to design the personalised motivational strategies. Accordingly, the motivational needs implied by each motivational factor should be addressed with corresponding motivational strategies [220]. Fig. 6.5 displays the high-level structure of motivational strategies addressing each factor in the motivation model.

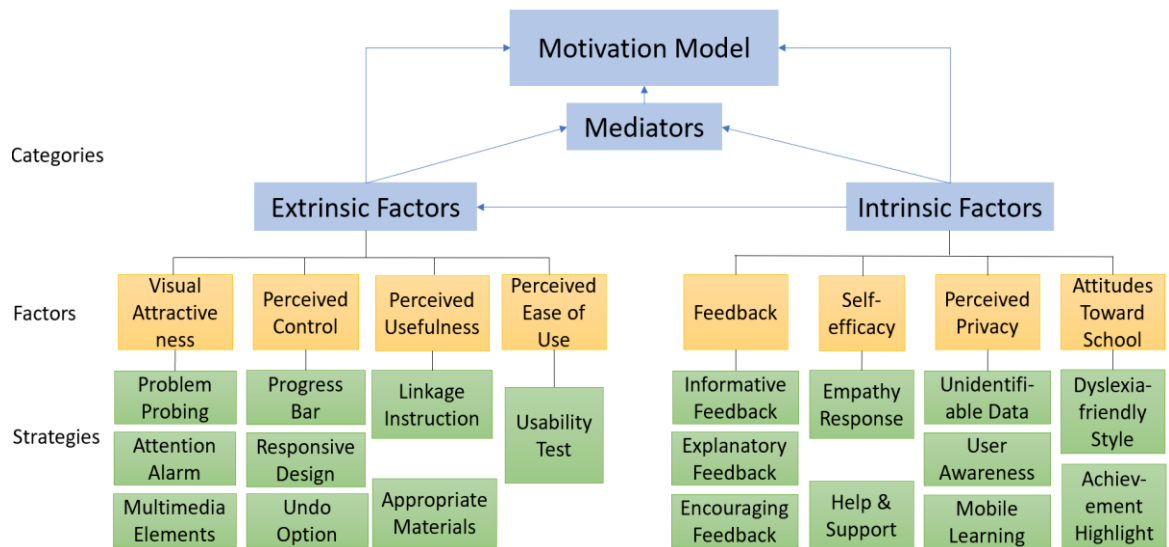


Fig. 6.5 Example motivational strategies corresponding to the factors in the motivation model

For all dependent variables including mediators, the strategies applied to their independent factors are also applicable to themselves.

Any part of design of an e-learning system that facilitates users' motivation to learn should be regarded as motivational strategies, otherwise it is no more than an element of the system. A motivational strategy can be a pre-designed part of the e-learning system or its interface, or it can be messages to be output by the system when triggered with the satisfaction of certain conditions. Specifically, Fig. 6.5 has displayed some typical motivational strategies as guidance for system design to address learners' motivational needs based on the motivation model. Corresponding to each factor from intrinsic or extrinsic motivation in the model, one or more personalised motivational strategies including the design instructions are put forward to tackle the motivational issues implied by the factor. The strategies can be used as a guidance and instruction both at the start of design process and during the design process for e-learning systems to support motivation-based personalisation, for example, to provide a user with tailored support when there is a motivational need identified from the motivation assessment during the learning process.

Visual Attractiveness

As the strongest predictor of continued use intention compared to the other extrinsic factors according to the quantified motivation model, visual attractiveness indicates that an e-learning environment should be visually attractive to learners to maintain their motivation to learn. In particular, for learners with dyslexia, visual attractiveness is more important to attract their attention and make them stay in the e-learning system when difficulties are encountered in their learning process.

Relevant support to this factor includes problem probing, multimedia elements and attention alarm. Like the approach used by teachers in classroom learning environments, probing a problem in an e-learning environment, which is usually related to the learning materials and the real world, can trigger learners' interest and curiosity to learn the knowledge. Learners can also benefit from multimedia elements for presentations of course elements, especially for those with dyslexia. For example, incorporating the appropriate animation and auditory materials instead of monotonous text presentation style will help improve the visual attractiveness of the system. Attention alarm can be applied to a e-learning system along with a progress reminder that reminds learners of their progress made, and it can also be combined with a rewarding scheme that re-engages learners by reminding them of the potential rewards and the closest milestone ahead as well as the potential loss of rewards in case of quit.

Perceived Control

As the extrinsic factor emerging from the empirical study with dyslexic students, perceived control in e-learning environments refers to sense of autonomy to freely act or control the progress in the learning process. Relevant support to this factor includes progress bar, responsive design and undo option. Progress bar is in nature a continuous positive reinforcement for learners. It shows the progress of learning that proceeds as a learner moves forward in the learning process. Progress bar can drive learners toward the completion of learning tasks by exposing them to the progress made continuously. Responsive design refers to the design of e-learning systems that can respond to the size and orientation of a screen, thus minimise learners' effort to adjust their ways of reading and learning to the layout in different screens. Undo option available in an e-learning system allows learners to cancel, redo, or repeat an action due to either accident or regret;

also, the design of the responses to any action taken by a learner should make clear sense to avoid users' confusion and ensure their perceived control during their interaction process with the system.

Perceived Usefulness

As one of the two factors emphasised by TAM, perceived usefulness is also an identified extrinsic factor in the present motivation model. In context of e-learning systems, learners are more likely to accept the system for learning when they perceive the system to be useful and effective at facilitating their learning. Relevant strategies to this factor include linkage instruction and appropriate materials. Linkage instruction helps link the current learning materials or goals to learners' own interest or experience to make them feel the relevance of the course to their needs. Appropriate materials refer to the learning materials used in the system as well as the presentation styles of the materials that need to be appropriate to fit specific learners' learning needs and preference. For example, the materials should be pre-evaluated to ensure the appropriateness in terms of both the presentation style and the difficulty level of the knowledge.

Perceived Ease of Use

As the other factor emphasised by TAM in addition to perceived usefulness, perceived ease of use indicates that an e-learning system should be designed in such a way that learners only need to take effort to learn the knowledge in the course without struggling for getting familiar with the system navigation or effort for learning how to use the system. To tackle the issues relevant to this factor, it is imperative to conduct usability tests and improve the system design iteratively to ensure that the system can function well with smooth navigation and clear layout.

6.3.1.2 Motivational Strategies Corresponding to the Intrinsic Factors

Feedback

Feedback provided by an e-learning system can not only benefit learners' intrinsic motivation by reinforcing their effort and providing the necessary information, but also positively influence perceived control and visual attractiveness, thus leading to better utilization and experience and eventually the continued use intention.

Relevant support to this factor consists of informative feedback, explanatory feedback, encouraging feedback or a combination of them. Informative feedback provides learners with the information about where they are, what they are doing, the consequence of their previous actions, such as informing a learner about the fact that the learner is in the last step toward a goal or whether the answer to a self-assessment quiz is correct. Explanatory feedback enables learners' deep thinking and reflections on the consequences of their actions by providing them with relevant explanations, such as revealing the relevant knowledge behind a quiz to facilitate their understandings about why their answers are correct or incorrect. Encouraging feedback refers to direct motivating feedback that encourages learners to excise more or move forward in the learning process. It can consist of text, voice or animation or a combination of them, usually used with a rewarding scheme from a virtual tutor, i.e., a pedagogic agent, embedded in the e-learning system.

Self-efficacy

Different from the general concept of confidence, self-efficacy refers to the internal belief of a learner that he or she can achieve a specific goal, i.e., completing the learning tasks using an e-learning system successfully in the present context. High level of self-efficacy is formed by the long-term positive cycle. In other words, achieving learning goals in an e-learning system improve learners' self-efficacy, which further improves their continued intention of learning in the system, leading to more achievements and improved self-efficacy in turn. Despite the difficulty of improving self-efficacy in a short time period, strategies should be designed and applied to e-learning systems to direct learners toward the completion of the learning task, because this will benefit self-efficacy as the experience of "completed" or "achieved" accumulates.

Relevant support to this factor includes providing learners with empathy response and necessary help and support. Empathy response refers to the empathy expressed by a pedagogic agent in response to learners' feelings during their interaction process with e-learning systems, such as showing a happy face when certain progress has been made. Learners with a low level of self-efficacy often need necessary help and support, this can be available in e-learning systems by providing them with personalised resources automatically or allow the remote connection to access a distant teacher's help.

Perceived Privacy

As the intrinsic factor emerging from the empirical study with dyslexic students, privacy issue is rarely mentioned in the design of e-learning systems. This can be explained easily as learners with dyslexia may care more for the privacy issues to avoid potential negative impact of failing to protect their personal information such as overwhelming peer pressure on their learning and confidence.

Relevant support to tackle privacy issue includes unidentifiable data, user awareness and mobile learning. Unidentifiable data means that the personal data collected by an e-learning system should not allow the learners to be identified in order to protect their privacy. User awareness refers to the good manner of the system design to keep users aware of the information about data usage including the purpose of the data collection, the way the data will be used and the people having the right to access the data. Mobile learning, also called m-learning, is a type of e-learning using portable electronic devices such as tablets or smartphones with a smaller screen and a mobile device, which will apparently improve users' perception of data safety by avoiding or minimising the possibility of data leakage from others' observation on the screen. There are also many other methods and techniques to support users' perceived privacy and trust for a system, such as authentication and encryption at the login stage.

Attitudes Toward School

As the only intrinsic factor that directly influences continued use intention for e-learning systems, attitudes toward school plays a key role in a user's attitudes toward an e-learning system, affecting the user's learning experience and the continued intention to use the system. Same as self-efficacy, attitudes toward school is formed by learners' long-term experience and hard to be altered in a short time period. In respect to learners with dyslexia, if they have a negative attitude toward school, it is probably attributed to their long-term negative learning experience such as the innate reading difficulties and the lack of motivational affirmation about their learning achievement.

Introducing gamification or using serious games may motivate learners by engaging them in a game-like experience and helping learners identify the interesting or challenging aspect of learning, but this has been found to have less effect on older adults [10], also hard to be generalised or applied to general e-learning environments which are much more commonly used. What is worth noting is that one of the most important principle of motivators in gaming environments is associated with various kinds of

positive reinforcement to highlight players' achievements in time. Motivational strategies in e-learning systems can use the same principle by providing affective support to highlight the achievements learners have made such as applying score or badges to the improvement of their confidence and intention to keep learning. Another relevant strategy is to apply dyslexia-friendly presentation style to the e-learning system to improve the attitudes toward learning by supporting the cognitive aspects of learning needs, such as using fonts specially designed for dyslexic viewers and text accompanied by supplementary icons to facilitate understanding.

6.3.1.3 Considering the Relationships between Motivational Factors

In addition to the strategies addressing each motivational factor straightforward, the relationships between factors in the motivation model should also be taken into account. For example, if we aim to address the issue relevant to perceived ease of use, it is undoubtedly that a usability test will help improve the design of the system and interfaces, which is time consuming and does not address the goal of providing “real-time” personalised support for users. It is worth noting that the word “perceived” refers to the subject feelings of a user in e-learning environments, which means it is not only related to the external situations about the system, but also the internal factors from the user's intrinsic motivation. That's also corroboratively supported by the relationships shown in the motivation model: a user's perceived ease of use is affected by perceived control, and perceived control can be influenced by feedback that the user received from the system and the user's self-efficacy.

Therefore, given the relationship between motivational factors, when a user is detected to have a low level of perceived ease of use, the system can then output feedback to the user to benefit his or her self-efficacy. This way of developing personalised strategies for the motivational factors also works for the mediators in the motivation model particularly, because the factors belonging to “mediators” function as the intermediary between the intrinsic or extrinsic motivation and the motivational consequence. To address the issues relevant to mediators, it is necessary to find their independent motivational factors, i.e., intrinsic or/and extrinsic motivation, and then to provide the corresponding strategies. For example, if we aim to support users pertaining to the factor, confirmed fit, the issues need to be tackled about perceived usefulness, perceived ease of use and visual attractiveness

that have influences on confirmed fit. Personalised strategies should be designed to address the corresponding motivational needs in this way that the relationships between motivational factors are considered. More importantly, providing personalised learning services and support in e-learning environments in multiple aspects of learners' needs as a whole will maximise the effectiveness of the e-learning system and learners' continued use intention, which will in turn improve learners' intrinsic motivation that can direct their learning behaviour more effectively in long term.

6.3.2 Sensor-based Evaluation of Motivational Strategies

While some effort has been made to evaluate relevant strategies in serious games, the lack of empirical investigation on the effect of the motivating strategies in e-learning environment is still outstanding, especially for students with dyslexia. In the empirical experiment described in Chapter 5, four typical motivational strategies have been applied to the three learning lessons in OGAMA, and the strategies can be linked to the motivational factors in the motivation model. The four strategies examined in the empirical study have been mentioned in Section 6.3.1, which are summarised below:

Introduction Page

Learners need to perceive the learning materials and the e-learning system to fit their learning needs and preferences in order to be motivated. Linking the learning materials to learners' interest, needs and goals in an introduction page is to improve their perception of user-system fit and to motivate their learning. This corresponds to Confirmed Fit in the motivation model. An introduction page is used at the beginning of each lesson to introduce what will be covered and what are the aims of the lesson to motivate learners by setting objectives for them in the specific learning course.

Problem Probing

Probing a problem during a learning process can arouse motivation by linking the knowledge to a problem that learners may find relevant to themselves, interesting or challenging to solve, and by directly attracting learners' attention to what they are learning. This corresponds to Confirmed Fit and Visual Attractiveness in the motivation model. Each lesson used in the OGAMA slides presents a problem to learners to probe their thoughts about themselves and the relevant knowledge they already knew.

Attention Alarm

More attention may not mean more motivation, but a high level of motivation must indicate a high level of attention and engagement at the same time. Learners' attention must be drawn to make information be processed and learning take place. Attention alarms are evaluated as a motivational strategy in Lesson 3 in the experiment, which appears three times during learning process by inserting a page with messages to draw attention from learners to inform them about their learning progress. This strategy corresponds to Perceived Control and Visual Attractiveness in the motivation model.

Immediate Feedback

Immediate feedback appearing with rewarding mechanism or encouraging messages can help improve intrinsic motivation, as it is a positive reinforcement of learners' behaviour and engagement during the learning process. Feedback output by a virtual tutor can use various formats of such as sound or animation. It also motivates learners by improving their perception of being able to control the progress and being able to achieve a desirable goal or level of learning. The immediate feedback corresponds to Perceived Control, Attitudes Toward School and Visual Attractiveness. Informative feedback is used in each lesson to inform learners if an answer to a quiz is correct, and it is accompanied by encouraging feedback using text and emoji and explanatory feedback about why an answer is correct or not in Lesson 1 and Lesson 3, respectively, while Lesson 2 only has informative feedback. At the end of each lesson, encouragement is further provided for learners by displaying the badges and levels they have achieved.

As each lesson is embedded with the motivational strategies, to examine if there is an overall improvement on learners' self-reported motivation, related-samples Wilcoxon signed rank tests were performed for learners' motivational factors between Lesson 1 and Lesson 3. Significant increases were found in the following factors: Perceived Usefulness ($p=0.005$), Feedback ($p=0.002$), Learning Experience ($p=0.020$), Reading Experience ($p<0.001$) and quiz score ($p<0.001$), while there were no significant increases in the scores of Perceived Ease of Use, Visual Attractiveness, Confirmed fit and Continued Use Intention. The reason may be the fact that the three lessons used in the experiment are too short to make significant changes for those factors, and also the learning field, format and learning style and strategies used in the three lessons are roughly the same thus leading

to no significant changes in Perceived Ease of Use, Visual Attractiveness, Confirmed Fit and Continued Use Intention.

To study each motivational strategy applied in the learning courses, the effects of these strategies were evaluated on the change of learners' eye movements and brain activities from eye gaze and EEG data and on learners' self-report motivation (questionnaire scores) and learning performance (quiz score). 6 eye features (Pupil diameter, Fixation number, Fixation duration, Fixation/Saccade ratio, Saccade length and Regressions) were calculated, and each band power (including the overall mean, 4 brain regions and 2 hemisphere asymmetry) was calculated for EEG features from two 10-second windows "before" and "after" each strategy appeared. According to the Shapiro-Wilk normality test, except that the data of pupil diameter and fixation duration is normally distributed, the other eye gaze and EEG features are non-normally distributed, so paired samples t-test was used for the normally distributed data and related-samples Wilcoxon signed rank test was used for the non-normally distributed data. As described before, four motivational strategies were used in the learning materials, each appearing three times in total during the learning process. 123 statistical tests ($3 \text{ appearing times} \times (6 \text{ eye gaze features} + 35 \text{ EEG features})$) were run for each motivational strategy.

Significant effects of Introduction Page were found on the decrease and increase in the Pupil diameter ($p < 0.001$) and Regressions ($p < 0.001$), respectively, meaning that participants made less cognitive effort and less efficient learning after reading the introduction page. This may indicate the reduced interest of the participants, and the reason may be the fact that they found the learning materials were too easy, so they reduced cognitive effort after getting the information of the learning goal from introduction page.

For EEG features, significant differences were found before and after Introduction Page in high beta band power both in occipital brain region ($p = 0.020$) and in temporal region ($p = 0.008$), gamma band power in parietal region ($p = 0.011$) and gamma band intro-hemisphere asymmetry ($p = 0.044$). High beta brainwaves in occipital and temporal regions indicate new experience, complex thought and excitement, and visual, sensory input processing and language comprehension, and gamma waves relate to expanded consciousness and spiritual emergence. Some areas of the parietal lobe are important in

language processing and multi-modal sensory information processing. The reasons of the differences need further investigation.

Significant results were found for the effect of Problem Probing on the increase in fixation duration ($p=0.004$), suggesting that probing a problem can help engage the students more in learning process. Regarding EEG features, significant differences after Problem Probing appeared were found in theta band power in parietal region ($p=0.018$), indicating the existence of mental activities including learning, memory, and intuition, and integration of sensory information or language processing in parietal lobe.

Significant results were found for the effect of Attention Alarm on the increase in fixation duration ($p<0.001$) and decrease in saccade length ($p=0.023$) and regressions ($p<0.001$). As mentioned before, an increase in fixation duration indicates more engagement of the learners after the alarms, the decreases in saccade length and regressions indicate more focused attention, which makes it more efficient for the learners to extract information from the learning materials. Regarding EEG features, the only significant difference after Attention Alarm appeared was found in alpha band inter-hemisphere asymmetry ($p=0.020$), which was also commonly found as an indicator of emotional states [114].

For all the three lessons, Immediate Feedback was output from OGAMA as soon as learners click on an answer to a quiz, overall there were significant differences between “before Feedback” and “after Feedback” of pupil diameter ($p<0.001$), fixation number ($p=0.002$), fixation duration ($p<0.001$), saccade length ($p=0.019$) and regressions ($p<0.001$). Specifically, more regressions were detected after Feedback appeared, and this may indicate more self-reflection, as more regressive eye movements may come with the rumination over the information on the interface. Smaller pupils and less fixations detected after the Immediate Feedback indicate reduced cognitive effort and more efficient learning, and shorter fixation duration and saccade length suggest that the learners became more concentrated and extracted information more efficiently.

For EEG features, significant differences were found after Immediate Feedback appeared in mean power of theta band, alpha band, low/high beta band and gamma band (alpha: $p=0.009$; the others: $p<0.001$), and in each band power in occipital brain region (alpha: $p=0.014$; high beta: $p=0.002$; the others: $p<0.001$), parietal region (all $p<0.001$), temporal region (all $p<0.001$) and frontal region (theta/low beta: $p=0.001$; alpha: $p=0.020$;

high beta/gamma: $p < 0.001$) and in high beta intro-hemisphere asymmetry ($p = 0.050$). This indicates that the Immediate Feedback is the most effective motivating strategy amongst the four investigated in the present study, causing most features from sensor data to significantly change in such a short time period.

In addition, since different kinds of feedback were applied to different lessons as described before, the Friedman's ANOVA has also been employed to compare the changes of the eye features for the three kinds of feedback between the three lessons. No significant results have been found when the effects of three kinds of feedback were compared on the change of the sensor features, suggesting that more sample data and controlled studies will be required to draw conclusions on this.

6.3.3 Rule-based Reasoning Mechanism

The pre-conditions for motivation-based personalisation to be delivered in a learner-specific way can be defined in a set of logical expressions. Logical expressions are constructed based on logical operators such as variables representing learners' motivational states and self-reported service requests. Only when the pre-conditions expressed within these logical expressions are evaluated to be true, the personalisation consequence will be triggered. As the focus of the present research, the personalisation consequence is motivational strategies in the form of feedback output from e-learning systems to learners. This cause-effect relation is modelled as a set of rules between the system outputs and learners' motivational states, and then a reasoning engine uses learners' motivational states to reason against the rules to infer the personalised support to be provided for the learner.

Using SWRL and the ontological motivation model, the reasoning mechanism is described in this section that can perform production rule reasoning to derive personalised strategies based on specified requests. Last section has specified the present application domain knowledge to identify related core entities, and their interrelationships. This section will specify the use of SWRL to express and implement the rules for personalisation. Each rule defines a cause-effect relation among these entities, e.g. how personalised strategies are delivered under a specific condition with a specific user. The SWRL specifies a rule in the following format:

```

Example rule: Student(?Student1),
MotivationState(?StudMotiv1),isIn(?Student1, ?StudMotiv1)->
MotivationalStrategies(?feedback1), hasAudioType(?feedback1, ?audio1),
hasFeedbackContent(?feedback1, ?content1),
hasImage(?feedback1, ?image1), AudioType(?audio1), Image(?image1),
FeedbackContent(?content1)

```

Each rule is made up of an antecedent and a consequent [221]. All the possible personalisation scenarios should be covered by the rules, and each SWRL rule is designed with a specific condition for a specific personalisation outcome, stored as a series of OWL individuals in the ontological model [96]. The reasoning engine is required to decide if the pre-conditions of a rule are met to trigger a consequence. SWRL rule reasoning supports both forward chaining and backward chaining reasoning. The former type of reasoning generates consequences from factors and the rules that apply to the facts and then uses the generated consequences as new facts to activate other rules until no rules can be triggered, and the ultimate result is the consequence of the last triggered rule. In contrast, the latter type of reasoning uses a goal and the rules that apply to the goal until a conclusion is reached at the end.

The antecedent of the rule can be constructed to represent a conjunction of various user states or needs. For example, in the example rule, the first line constrains any individual from the **Student** class that has a motivational state (an instance in the **MotivationState** class). In this case, the variable name “Student1” is assigned to the class Student. In this rule, the student must be in the state “StudMotiv1”, where this individual name is assigned to the **isIn** object property. In the rule consequent, it specifies that if the individual meets the constraints, then the **MotivationalStrategies** class is affected to feed personalised strategies back to the student to address the motivational state. The individual name “feedback1” of the **MotivationalStrategies** class has three major properties. When the rule is triggered, the **AudioType** will be set to audio1, and the image1 and content1 will be used in the **Image** class and **FeedbackContent** class, respectively. The **hasAudioType**, **hasFeedbackContent** and **hasImage** properties are linked within the ontology to the feedback1 of the **MotivationalStrategies** class.

In the present research context, the motivation-based personalisation in e-learning environments are based on forward chaining reasoning, and the process can be described as follows. The personalisation takes as inputs: the rules from a rule base, motivational states from the classification models that assess the motivational state from a learner's sensor data using logistic regression, and self-reported requests from the front-end of e-learning systems. The reasoning engine has an in-memory working space within which a copy of rules and motivational states are imported. The inputs regarding learners' motivational states are dynamically captured and imported into the working space where logical operations of the forward chaining reasoning take place. When a learner makes a request through the front-end of the e-learning systems, the request is then used as a variable in the logical operation of the antecedent of rules. Meanwhile, the dynamic information within the e-learning environment is captured via sensors including an eye tracker and an EEG device, after the motivational states are inferred using the classification mechanism, it is then used in a way similar with the service requests as variables to be bound to the logic expressions of antecedents.

Following the rule design method mentioned before, the SWRL editor is used within Protégé to design a set of rules for the application scenario. When SWRL rules are created, they can be tested and checked for inconsistencies using Protégé. The rules are then reasoned where the results are shown as new individuals grouped into classes, or if the rules are inaccurate. Protégé will highlight where and why inconsistencies occur. Fig. 6.6 shows an extract of the rule creation process, where specific rules are associated with individual classes, instances of classes or object/data properties in the ontology.

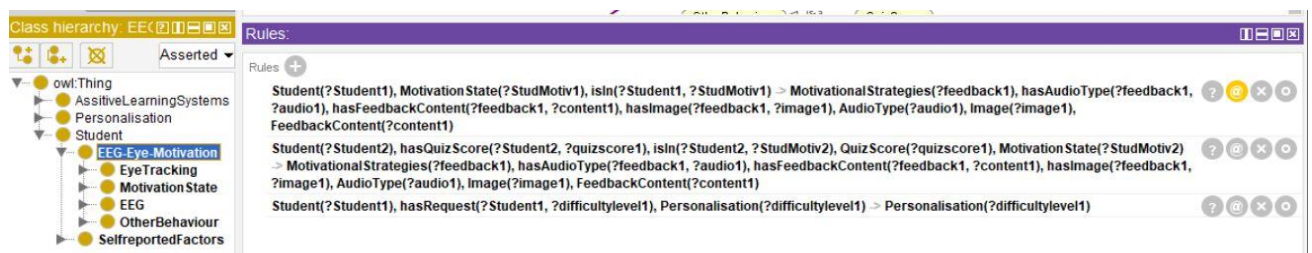


Fig. 6.6 Screenshot showing part of the SWRL rules within Protégé

Table 6.1 presents a subset of the SWRL rules developed in this study for the application scenario, based on the knowledge domain described in Section 6.3.1. Most

strategies are implemented in SWRL rules to be used for personalisation during the learning process, while some strategies are for system designers and developers to be complete before the system is put into use, such as the appropriate materials including appropriate formatting and difficulty levels of learning contents.

Table 6.1 Examples of SWRL rules

No.	SWRL Expression
1	<code>Student(?Student2), hasQuizScore(?Student2, ?quizscore1), isIn(?Student2, ?StudMotiv2), QuizScore(?quizscore1), MotivationState(?StudMotiv2) -> MotivationalStrategies(?feedback1), hasAudioType(?feedback1, ?audio1), hasFeedbackContent(?feedback1, ?content1), hasImage(?feedback1, ?image1), AudioType(?audio1), Image(?image1), FeedbackContent(?content1)</code>
2	<code>Student(?Student2), hasRequest(?Student1, difficultylevel1) -> MotivationalStrategies(?feedback1), hasAudioType(?feedback1, ?audio1), hasFeedbackContent(?feedback1, ?content1), hasImage(?feedback1, ?image1), AudioType(?audio1), Image(?image1), FeedbackContent(?content1)</code>
3	<code>Student(?Student1), MotivationState(?StudMotiv1), isIn(?Student1, ?StudMotiv1) -> MotivationalStrategies(?feedback1), hasAudioType(?feedback1, ?audio1), hasFeedbackContent(?feedback1, ?content1), hasImage(?feedback1, ?image1), AudioType(?audio1), Image(?image1), FeedbackContent(?content1)</code>

At this stage, the reasoning engine will check if the antecedent of any rule in the rule base is satisfied prior to firing the appropriate rule. The consequence of the fired rule is then used for firing other rules. In this way, the forward chaining reasoning can take into account a user's self-reported requests and dynamic information from sensor data to provide personalised strategies based on domain knowledge and heuristics.

Personalisation reasoning can be implemented with an existing open-source semantic reasoning engine called Pellet [222].

6.4 Conclusion

In this chapter, a sensor-based motivation assessment system architecture is introduced for motivation-based personalisation in e-learning environments. It combines ontological modelling, feature analysis and the classification mechanism to infer the levels of the motivational factors in a structure to illustrate the process of sensor-based motivation assessment. The EEG-Eye-Motivation Ontology is described to represent knowledge about the integrated features from EEG, eye tracking and other data in addition to the factors in the motivation model.

This chapter also details the knowledge base according to the motivation model to be used for personalisation of motivational strategies to address the motivational needs inferred from sensor data or self-reported request. Moreover, the evaluation of four typical motivational strategies has indicated that the effect of motivational strategies is in fact reflected in eye gaze and EEG data, suggesting that learners' long-term exposure to these motivational strategies during learning process in e-learning systems will probably contribute to more positive changes in their motivation. Furthermore, the rule-based reasoning mechanism is introduced to perform personalisation with the emphasis of the use of SWRL enabling the highly expressive personalisation components.

The next chapter will propose a system framework based on the motivation model and rule-based personalisation, while illustrating the diagnostic input and system reactions in motivationally personalised e-learning systems. The framework is partially implemented in a prototype of gaze-based learning application, to assess learners' motivational states during their interaction process with the system and to output personalised strategies from the system to address individual users' motivational needs.

Chapter 7 A Framework of Motivationally Personalised E-learning Systems

7.1 Introduction

The previous chapters have detailed the motivation modelling and computation as well as the rule-based personalisation to tailor motivational strategies in e-learning systems to users' dynamic motivational states. To apply the motivation model, classification mechanism and rule-based personalisation to e-learning systems in real world, this chapter introduces a framework of motivationally personalised e-learning systems to guide future application that attempts to take the learner's motivational states including various motivational dimensions into account and respond to them with personalised strategies dynamically. The framework abstracts the two essential, reusable functions, namely motivation assessment and rule-based personalisation. Based on the work described in previous chapters, the framework in this chapter is a generic one which is neither constrained by the use of ontology and SWRL to represent knowledge nor by the use of certain types of sensors such as eye trackers or EEG devices. The proposed framework aims to emphasise the functionality of motivationally personalised e-learning systems in the future with extendibility and reusability across applications.

Furthermore, in this chapter, a prototype of gaze-based learning application that incorporates an essential part of the framework is designed and implemented. The learning application uses an eye tracker to monitor a user's eye movements during the user's learning process. Based on both the real-time eye gaze data and user's self-input data, the application dynamically assesses the user's motivational states based on the classification models developed before to infer the motivational states, i.e., the levels of different motivational factors in the motivation model. The motivation states detected in real time are used to trigger relevant rules that lead to personalisation outcomes: the system responds to a user's motivational state by outputting personalised feedback from a pedagogic agent in the system to sustain or enhance the user's motivation and engagement during the interaction process. The learning application is an example of applying the motivation model, sensor-based motivation assessment, rule-based personalisation of motivational strategies described previously, and in a bigger picture,

applying user modelling and personalisation techniques to an e-learning system. It produces great insight into future work to apply the same approaches and research findings to practice in real-world applications across different domains.

7.2 The Proposed System Framework

Motivationally personalised e-learning systems focus on providing personalisation to maintain or enhance a learner's motivation and willingness to expand the learner's effort in learning [8]. As explained before, the motivation model includes both cognitive and affective aspects, and the concepts of motivation, cognition and affection themselves are highly intertwined, thus the framework based on the motivation model goes beyond both cognitively intelligent systems and affectively intelligent systems that aim at improving learners' knowledge and affective states, respectively. The present framework focuses on improving learners' motivation to engage in the e-learning system, but as a result of the satisfaction of multiple motivational dimensions, the learner's knowledge and skills as well as affective states will also be benefited.

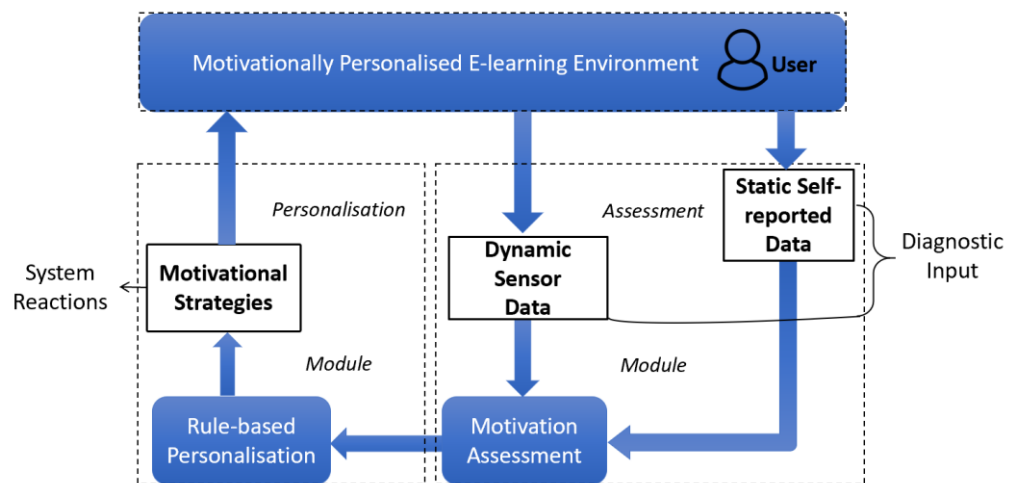


Fig. 7.1 The framework of motivationally personalised e-learning systems

The proposed system framework is presented in Fig. 7.1. It shows the working principles to perform data analysis from static self-reported data and dynamic sensor data for motivation assessment and rule-based personalisation. Combining the motivation model, the motivational states assessed by the classification models, and the

corresponding rules for personalised strategies to be provided, the system collects the data which will fit into with the motivation model and classification models to be used for inferring motivational states and further for personalisation of motivational strategies. In short, the motivationally personalised e-learning systems are those that implement the motivation model, classification models to assess motivational states, rules for personalisation, with the assistance of one or more sensors to capture real-time physiological or behavioural data to compute the level of the motivational factors.

The assessment module of the system deals with detecting and storing learners' motivational states. The diagnostic data input for assessing motivational states can be from a wide range of sources including a user's explicit self-reported data and implicit real-time data collected by the system or sensors during the user's learning process in the e-learning environment. The explicit, static data is based on user input which can take the form of registration forms, questionnaires or user provided feedback, whereas implicit, dynamic data is derived from the observation of user behaviour, which in computer systems can take the form of logs, databases, cookies or information from user choices, selections and browsing habits [91]. In the present context, the static self-reported data contains users' answers to questions related to intrinsic motivation or specific requests in the manner of a registration form at the beginning of learning, and users' answers to the self-assessment quizzes related to knowledge just learned at the end of learning. The dynamic data contains user's physiological or behavioural data captured in real time such as eye trackers and EEG devices.

After inferring the motivational states of learners, the personalisation module of the system enables the system to automatically provide personalised feedback to adapt to the motivational states, and it is responsible of accessing the information about learners' motivational states from the assessment module and trigger the pre-defined personalisation rules based on the motivational states. Personalised feedback using motivational strategies will be output through the e-learning system interface to the learners as system reactions towards different motivational states. In the proposed system framework, the initial personalisation can be performed based on a short motivation questionnaire and rules, and then the real-time behavioural or physiological data will be recorded and used to update users' motivation. A user's motivation is initially obtained from questionnaire score and then updated through the analysis of the user's learning

behaviour. According to the real-time motivational states, personalised strategies will be output to user to sustain and enhance users' motivation. The following two sections will detail diagnostic input and system reactions, respectively.

7.2.1 Diagnostic Input for Motivation Assessment

To realise motivationally personalised learning systems, the most essential theoretical and practical questions are: 1) what kinds of motivational states are to be distinguished, one from another? 2) What kinds of data are available as diagnostic input on which to make inferences about the motivational states of the learner? As described before, motivation is a multi-dimensional concept, and the factors determining the motivational consequence, i.e., continued use intention in an e-learning environment, have been identified in the motivation model, ranging from intrinsic motivation such as self-efficacy and attitudes toward school, extrinsic motivation such as visual attractiveness and perceived usefulness, and mediators such as learning experience. Each factor in the motivation model represent a dimension of motivation and thus should be addressed to sustain or enhance learners' motivation in e-learning environments.

As pointed out by prior research (e.g., [223]; [224]), there is an issue of reliability and accuracy about self-report data on which the majority of research on motivation is based, especially when the collection of self-reported data is interruptive to users' interacting process with a system. Means used for inferring a learner's motivational state include logic rules and data-driven models. For example, De Vincente and Pain [225] developed a set of rules based on human experts to infer motivational states from learners' pre-recorded interactions with the system, while Conati and her colleagues [226] used a dynamic Bayesian network to model a learner's emotional states as well as system actions towards the learner's states. However, using rules to infer motivational states usually relies on self-reported data, which has been criticised. In addition to self-report data, motivational states can be inferred from learners' interaction with the e-learning system and behavioural data such as mouse movements, use of help and learning speed and outcomes, as well as physiological data such as EEG and eye gaze.

Motivation assessments based on sensor data is a good alternative to that merely relying on self-reported data by avoiding the interruptions to the learning process. Therefore, in the proposed framework, dynamic sensor data is monitored and captured instead of or in

addition to learners' self-reported data to infer the motivational states, using data-driven classification models such as the logistic regression models developed in Chapter 5.

7.2.2 System Reactions from Repertoire of Motivational Strategies

After the different motivational states are distinguished based on the diagnostic input and classification models, the system needs to select from its repertoire of motivational strategies as described in Section 6.3.1 to behave towards a specific motivational state by outputting personalised strategies to the learner in order to maintain or improve the learner's motivational state. Pedagogic agents have the potential to support learners by engaging them through social interaction as mentioned before, which can be implemented as instructors or learning companions within the e-learning environments to output the motivation-based personalisation.

The reactive behaviour of systems can be based on rules inspired by motivation models or by linking learners' dynamic data to motivational states and learning performance empirically via statistical approach or machine learning techniques. The present framework for motivationally personalised e-learning systems has benefited from both the abovementioned two approaches and has also gone beyond them. It aims at maintaining or enhancing motivation in the e-learning environment and base the rules of system reactions on the motivation model developed in e-learning context with target learners.

The system proposed by the framework analyses both self-input registration data and real-time data from sensors during a learning process, the motivational states are assessed dynamically using the classification models for the factors in the motivation model, then the system outputs personalised feedback using motivational strategies to maintain or enhance learners' motivation. The system reacts with comments, encouragement, information and explanation. These reactions are determined based on a set of pre-defined production rules that are fired in response to the values of the relevant motivational factors. The rules have been developed based on the motivation model to address each motivational dimension in the model, as described in Chapter 6.

Practically in real-world e-learning systems, one strategy may work for multiple dimensions of motivation, as it has been found in the motivation model that the

motivational factors are highly intertwined; therefore, the motivational strategies also work in a collaborating manner. Specifically in the present system framework, system reactions to learner's motivational states, in form of personalised feedback, include but are not limited to information or explanation about performance, praise, encouragement, empathy, help and support, intrinsic and extrinsic rewards, suggestions such as pause and breathing exercise and difficulty level of the learning materials.

7.3 A Prototype of Gaze-based Learning Application

This section will introduce a prototype that takes the example of an eye tracker as the sensor to capture dynamic gaze data for motivation assessment and personalised learning. Eye gaze data can shed light on human's various cognitive process including problem solving and reasoning, and eye gaze features like pupil dilation and pupil invisibility have been used as indicators of human emotional states. However, learning motivation involving both emotional and cognitive aspects has been rarely directly modelled and measured using eye-tracking data. As mentioned in Chapter 5, eye-tracking data for motivation computation are firstly analysed after the experiment, and it has been found that gaze features such as average pupil diameter and fixation number can play significant roles in assessing motivation in an e-learning environment with a prediction accuracy up to 81.3% [206], and learners' motivational states can be assessed based on gaze data in real time in a unobtrusive manner, to output tailored motivational strategies automatically in e-learning environments to enhance motivation and learning for people with dyslexia and for all.

To implement a prototype of the proposed framework of motivationally personalised e-learning systems, a Windows desktop application is designed and implemented with a Tobii EyeX tracker. It is more flexible than the existing learning management system like Moodle environment, as Tobii provides developers with a driver and SDK to be used directly for their applications while there is no straightforward method to use eye trackers in Moodle. As a result, it will be much less meaningful if Moodle environment is only used to present the learning materials to user. Therefore, a brand-new learning application called GazeMotive is developed instead of an extension based on existing learning systems [227].

The learning application has implemented part of the classification models for assessing the level of the motivational factors, including Confirmed Fit, Reading Experience and Perceived Ease of Use, based on gaze features computed from real-time eye-tracking data. The feedback output from the system is personalised to dynamically adapt the system responses to user's motivational states using the motivational strategies to address the corresponding motivational needs. The feedback output to users provides them with assistance to improve the motivational states by addressing their individual motivational needs. For example, in terms of Visual Attractiveness, when the user is detected not to be visually attracted by the system, a pedagogic agent in the system will output feedback to re-attract users' attention including encouragement and a meta-cognitive information to help improve the level of Visual Attractiveness: "We have finished 1/3 of this course. Try to pay more attention, as the more we concentrate, the more effectively we learn!".

7.3.1 Design and Implementation

This section specifies the functionality of the application. This involves specifying what the users should do with the application and what the users want to do with the application. Therefore, it can be defined about which user tasks the application should support and the possible scenarios for particular user tasks. A use case diagram is drawn in the Enterprise Architect 14.0 [228]. Unified Modelling Language (UML) is employed to describe the use cases of the system, shown in Fig. 7.2.

The application is designed for two kinds of users, the expert and the learner. Any learning materials can be added to the system in front-end by expert users in the format of pictures, and it uses materials adapted from a free e-learning course from OpenLearn University [229], the frozen planet, as an example. Verdana fonts, 16-40pt, bullet points, and dark fonts on light yellow background are adopted as well as visual elements like images and badges with references to the principles of e-learning design for users with learning difficulties [230], [231].

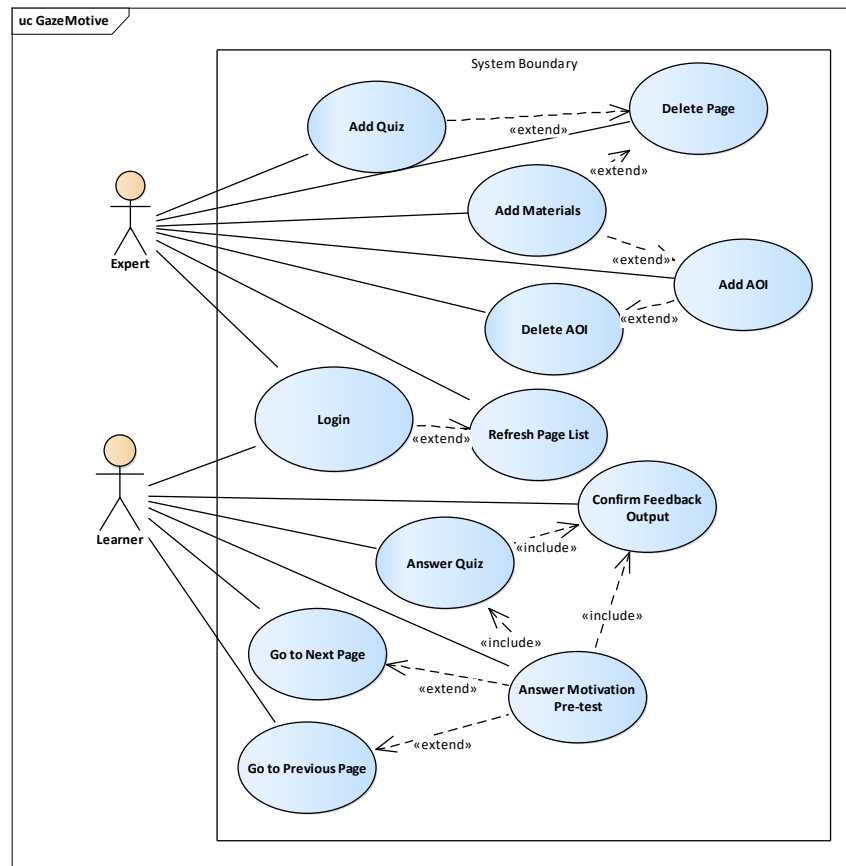


Fig. 7.2 Use case diagram of GazeMotive

As the application assesses learners' motivational states from eye gaze features collected or computed from the eye tracker, it does not matter much what learning materials are used in the system. However, some gaze features are related to the AOIs in a learning page, such as fixation number in AOI, so different learning materials and different learning pages can have different AOIs. Therefore, in the application, the AOIs can be set by expert users after adding the learning pages.

Motivation assessment involves the use of an eye tracker and the collection of real-time data and classification of motivational states during user's interaction process with the learning application. Different motivational factors that determines motivation in e-learning environment were assessed based on different gaze features with different parameters using the logistic regression models resulted from the experiment [206]. For example, Confirmed Fit is determined by average saccade velocity and samples out of monitor, whereas Learning Experience is computed with fixation spatial density, average saccade length and fixation number in AOI. In addition to gaze data collected by the eye

tracker, learners' self-input data has also been used to assess certain motivational factors such as Attitudes Toward School at the beginning of a learning process, and in the quiz stage, feedback will also be adapted to the correctness of a user's answer submitted.

Finally, a cartoon image representing a pedagogic agent plays the role of a learning companion to provide learners with personalised feedback. The inference rules and dynamic feedback that were adapted to user's motivational states and implemented in the system prototype are mostly in format of text and pictures. This is an example of future work where more comprehensive personalisation rules and diverse formats of feedback and interventions can also be implemented such as speech and animation. The feedback messages addressing specific motivational needs will be output to users, when the motivational factor is assessed based on the real-time eye gaze data and the corresponding rule is triggered. Additionally, the output can also be based on user's self-input data, for example, when a user submits an answer to a quiz, the feedback will be output to user based on both the submitted answer in addition to the fixation number.

The development techniques used to build the system include Windows OS, Visual Studio, Windows Forms, C# and Tobii SDKs. Windows Forms (WinForms), a graphic class library of Microsoft .NET Framework, provide developers with convenient ways to develop rich applications. Tobii provides developers with the SDKs to integrate eye trackers into their applications. Fig. 7.3 shows a class diagram that illustrates the classes of the primary business functions in GazeMotive. In Fig. 7.3, "SWF" stands for "System.Windows.Forms"; "..." and "...(...)" represent that there are many other attributes and methods of the classes. Specifically, the following forms are created.

A) "Entrance" form: this is used to login users. After successfully logging in a user, this form will become invisible, and corresponding forms will be initialised and shown for different users including learners and experts.

B) "Expert" form: this has a set of Winform controls and methods to realise use cases of expert users.

C) "Question" form: this has a set of Winform controls and methods to allow expert users to add questions as materials.

D) "SelfReported" form: this is initialised and shown to learner users before they start learning. Learner users do the motivation pretests with the form. With the answers to the

questions, this form will check the states of “Attitude Toward School” and “Self-efficacy”, and for different states, this form will show corresponding notifications. Afterwards, this form will initialise and show a “Learner” form.

E) “Learner” form: this has a set of Winform controls and methods to realise use cases of learner users. The form initialises a “MotivationalState” and a “EyeTrackingDevice”, and this form has a function to invoke the methods of checking motivational states at set intervals. This form will display notification when learner users are in certain states.

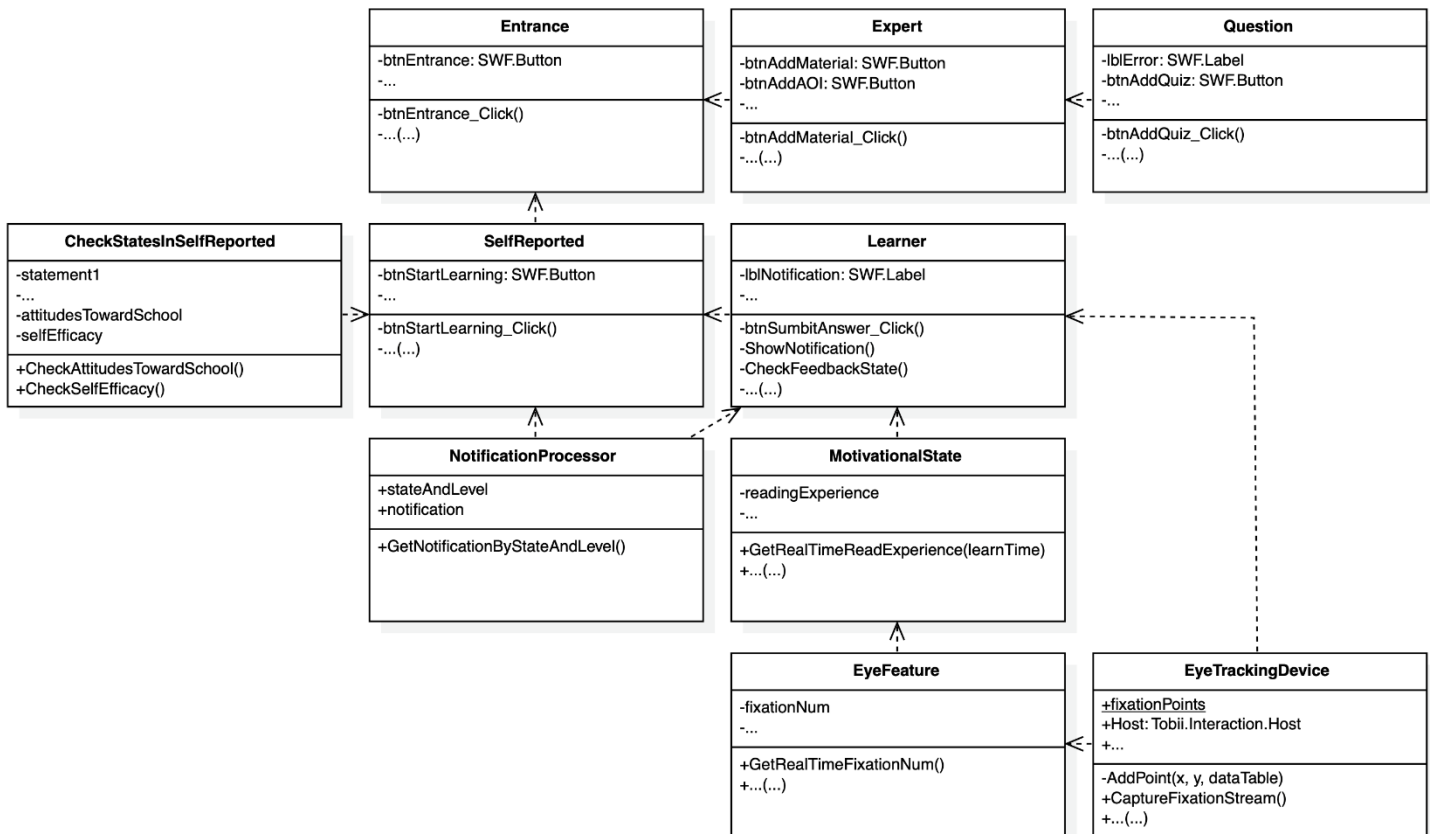


Fig. 7.3 Class diagram of GazeMotive

The following components are used in the aforementioned forms: Label, Text, Button, PictureBox, ComboBox, Panel, MessageBox, RadioButton, Timer, etc. PictureBox control is used to display picture materials. MessageBox is used to show the notifications. Timer is used to invoke the methods of checking the states at set intervals. In addition, the other classes shown in Fig. 7.3 are explained as follows.

A) “CheckStatesInSelfReported” class: this is defined to describe and check the states of learner users of the pretests.

B) “NotificationProcessor” class: this is defined to describe the hard-coded notifications of the states.

C) “EyeTrackingDevice” class: this is defined to control the device, capture eye movement data, and process the data into fixations, etc.

D) “EyeFeature” class: this is defined to describe the eye gaze features, such as fixation number, and process the data captured from the device into the eye gaze features.

E) “MotivationalState” class: this is defined to describe the motivational states and check the states based on the eye gaze features.

7.3.2 GazeMotive Walkthrough

When a user logs on with a username and a password (see Fig. 7.4(a)), GazeMotive will redirect the user to either the expert interface or the learner interface. The expert interface allows an expert user to add or delete learning materials, page by page, and one lesson can consist of any number of pages. The expert user can then input self-assessment quizzes after each lesson (see Fig. 7.4(b)). For each page, expert users need to select one or more AOIs by clicking on the points at the corners of the polygons to enable relevant gaze features in AOIs to be computed during a learner’s interaction process with the system, and an AOI can also be selected for review or deleted by the expert users (see Fig. 7.5).

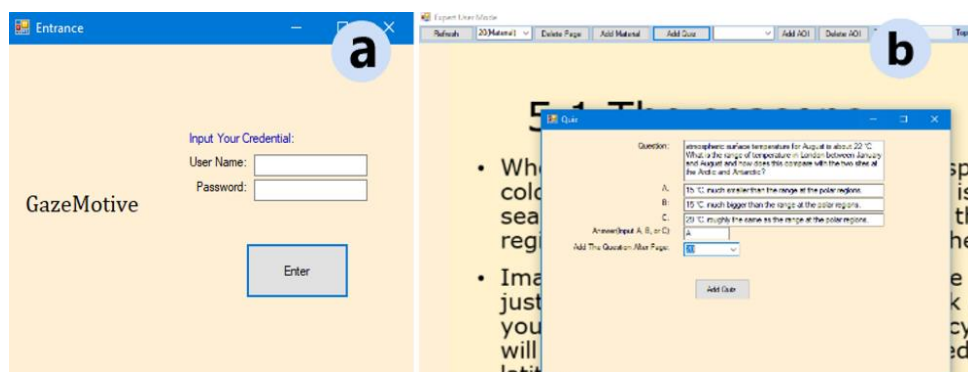


Fig. 7.4 Screenshots of expert interface for (a): login; and (b): adding a quiz

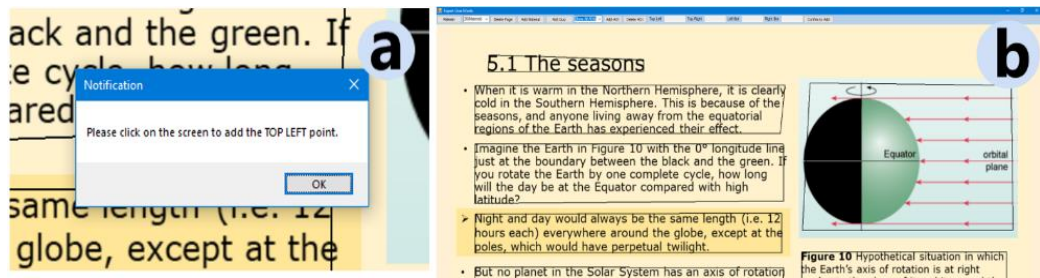


Fig. 7.5 Screenshots of expert interface showing (a): the process of adding an AOI, and (b): an example of the AOIs added

The learner user interface is similar with the expert one, the main differences focuses on the dynamic feedback output from the system to user dependent on the motivational states detected from eye-tracking data based on the classification models described in Chapter 5. The system also adopts a user's self-reported data before the user starts learning to measure some motivational factors related to intrinsic motivation that usually remains stable in a short time period compared to other factors.

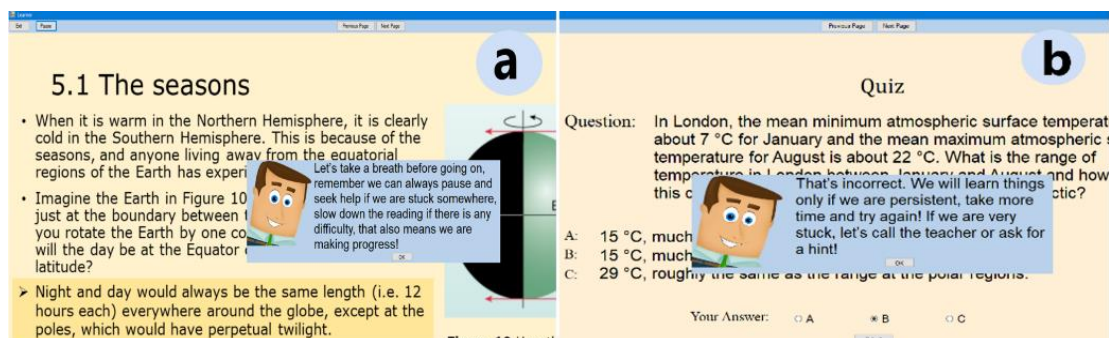


Fig. 7.6 Screenshots of user interface showing the examples of personalised feedback to provide motivational help

(a): when the system detects a user to have negative reading experience from eye-tracking data in a learning page; (b): when the user submits an incorrect answer to a quiz and is meanwhile detected from the eye-tracking data as having not put enough effort

During the learning process, a pedagogic agent representing a virtual tutor will output personalised feedback to the user to address specific motivational needs when necessary. For example, in the learning stage, if the motivational factor, Reading Experience, of a user is classified in low level, the system will output corresponding messages: "Let's take

a breath before going on, remember we can always pause and seek help if we are stuck somewhere, slow down the reading if there is any difficulty, that also means we are making progress!” (see Fig. 7.6(a)); in the quiz stage, if the system detects the user’s answer to be wrong and the fixation data indicates that the user did not pay enough attention to the quiz, the system will output “That’s incorrect. We will learn things only if we are persistent, take more time and try again! If we are very stuck, let’s call the teacher or ask for a hint!” (see Fig. 7.6(b)).

7.4 Evaluation Study

The prototype “GazeMotive” is designed for people with learning difficulties such as dyslexia who usually suffer from low level of motivation. The system can detect the users’ motivational states and needs from real-time gaze data and self-reported data and output personalised feedback dynamically to improve their experience during the learning process and thus enhance their overall motivation and learning as a whole in the long run. Evaluation on long-term effects requires years of time for longitudinal studies and exceeds the scope of this project.

The aim of the present evaluation study is to collect users’ first-hand experience after they interact with this prototype of a gaze-based e-learning system compared to the non-gaze-based one, using a series of mixed methods for triangulation to generate robust results from multiple perspectives.

Overall, compared with a usability method, it is still in debate about what is a coherent and reliable set of user experience (UX) evaluation methods, though it is revealed in a workshop that most of the presented methods evaluate UX by recruiting participants to perform observation, interviews and collect self-reporting experience [232]. In the evaluation for GazeMotive, multiple methods were used measuring qualitative and quantitative data to generate reliable results. Firstly, three experts in usability were invited to perform heuristic evaluation to identify and fix basic usability problem. Secondly, potential student users were recruited to complete pre-defined tasks individually, and they were asked to think aloud to find usability issues while observation was being performed. Moreover, System Usability Scale (SUS) questionnaire and follow-up interviews were

utilized to allow UX in various aspects to be captured in both qualitative and quantitative ways.

Additionally, the evaluation of a user's overall motivation is specified as an assessment of whether the user intends to continue the usage of the prototype through open-ended questions in interviews. Similarly, the evaluation of UX on the personalised feedback output from the pedagogic agent and the overall learning is narrowed down to a measure of whether the user perceives the personalised feedback and the system prototype overall as helpful to enhance learning experience.

All the evaluations were conducted in a quiet neutral room with good lighting, temperature and ventilation and minimal distraction where tables and chairs were well placed. Heuristic evaluation was performed when implementation was not completed; then, student participants were recruited for the evaluation studies. Firstly, they were asked to complete pre-defined tasks while observation and data recording was being performed. Secondly, subjective ratings were collected about participants' perceived accuracy of the personalised feedback they received. Thirdly, the System Usability Scale (SUS) was employed to collect quantitative data about usability of the system prototype; finally, a follow-up interview is conducted individually with each participant. The ethical approval for the evaluation studies was obtained in the Faculty of Computing, Engineering and Media at De Montfort University.

7.4.1 Heuristic Evaluation

Heuristic evaluation was conducted with three experts in the fields of computer science, education and intelligent systems. The experts were invited to go through the prototype twice or more times with a critical eye independently to ensure unbiased evaluation.

Throughout the evaluation process, the following recognised heuristics from Nielsen [233] were adjusted to the present context as principles to examine the usability aspects of the overall system prototype and interfaces: visibility of system status, match between the personalised feedback of system and the real situation of user, user control and freedom, consistency and standards, error prevention, recognition rather than recall, flexibility and efficiency of use, aesthetic and minimalist design, help users recognise, diagnose and recover from errors, help and support.

During the process, the evaluators were also encouraged to comment on other usability principles or relevant aspects. Notes were taken by observers. The notes taken were then marked and coded to identify main themes from the qualitative data inductively. The heuristic evaluation has led to the identified usability issues which is summarised as follows:

Visibility of System Status

Situation: The system does not output any information to show the system status.

Suggestion: When logging a user to the interface, the system could be added with a status bar to show some status information such as “Logging in”. When experts are adding points of an area of interest, the system could be added a status bar to show the pixels information such as “X: 1920, Y:1080”.

Match Between System and Real World

Not received.

User Control and Freedom

Situation 1: The experts can only add the points of an area of interest one by one, from the top left point to right bottom point.

Suggestion 1: The system enables the modification of any points of an area of interest.

Situation 2: The points of areas of interest are dedicated for the monitor. The information should be changed when the monitor is changed to another with different resolution.

Suggestion 2: The system may consider the relative pixels information of the materials, so that the experts does not need to modify the information for different monitors.

Consistency and Standards

Not received.

Help Users Recognise, Diagnose, Recover from Errors

Situation: The system can output appropriate notifications when the experts are doing the tasks such as adding points of areas of interest.

Suggestion: No suggestion.

Error Prevention

Not received.

Recognition rather than Recall

Situation: When an expert adds a wrong point of an area of interest, the system does not provide function to undo it. The expert only can complete the adding with the wrong point and then deleting the wrong area.

Suggestion: The system could enable the undo function of adding points of an area of interest.

Flexibility and Efficiency of Use

Situation: If an experienced expert user comes back and utilises this system again, he or she will do the same thing as the novice user, e.g., adding the materials one by one.

Suggestion: The system could provide shortcuts for the experienced expert users. For example, the system could record the previous materials or questions added by an expert user. In the next time, the expert user then can select them to add again.

Aesthetic and Minimalist Design

Situation: All the controls, such as points information and page information, are listed under the title bar.

Suggestion: The controls could be classified into different categories, and the UI could be improved to be more good-looking.

Help and Documentation

Situation: The users cannot obtain any guidance of how to use the system.

Suggestion: The system could provide some instructions of how to use the system for different kinds of users.

7.4.2 Pre-defined Tasks

Four university students were recruited to participate in the evaluation study, and a within-subject design is adopted for evaluating the UX about the gaze-aware personalised feedback based on the motivation assessment using gaze data. Each participant was asked to complete two learning tasks with the gaze-based personalised feedback output from the virtual agent in the system and the other one as control version without the gaze-based feedback (only feedback about the correctness of the answer to a quiz was remained).

Each learning task includes a lesson about transferable skills or geographic science about the poles followed by self-assessment quiz of three multiple-choice questions. All

participants did not learn the same knowledge before the evaluation study. Two of the participants were asked to do the task with the lesson of transferable skills with gaze-based feedback and do the geographic lessons with traditional quiz feedback without gaze-based assessment and personalisation. The other two participants did two lessons on geographic science with gaze-based version of the learning application and the two lesson about transferable skills with the control version.

Due to the difficulty of recruiting students with dyslexia, generic students without dyslexia were recruited as participants. To simulate one of the typical learning difficulties experienced by dyslexic students, the participants were told the fact at the beginning of the study that the text of the learning materials have been processed using an online tool in advance to create similar reading experience of dyslexic students so that they would recognise the text in a lower speed than they usually do. For example, “Contrary to popular belief, not every person with dyslexia will reverse letters while reading and writing” is presented as “Cntorray to poaulpr bileef, not eervy peosrn wtih dislexya will rsvreee ltertes wihle radnieg and wrniitg”.

After the introduction of the study, a short warm-up and the presentation of ethical forms, the tasks were then carried out while the participants were being observed. The observation focused on user’s perceived effectiveness of the personalised system reactions that were triggered by rules based on the real-time motivation assessment along with user’s behaviour during the learning process in the system prototype. The researcher, i.e., I, took notes about all “think aloud” of participants, and their quiz scores were recorded as learning performance. The eye gaze data collected by a Tobii eye tracker will be cleared automatically every 10 seconds during users’ learning process, so no eye gaze data will be stored for any participants.

Table 7.1 shows the averaged quiz performance for the participants for each task. It can be seen from the table that all participants performed better on the quiz scores with GazeMotive, except one participant who got the same high score from both versions of the system. It is highly possible that the tasks were too easy for that participant, but it may also be due to coincidence because the sample is too small to allow for statistical analysis. Therefore, the evaluation mainly focused on qualitative data, but the quantitative data in the table has provided a direct impression that learners using GazeMotive that

incorporates the classification models and rules developed in the present project are likely to perform better on learning performance than those using the control version.

Table 7.1 Quiz performance

	GazeMotive system	Non-gaze version
Participant 1	50	16.7
Participant 2	66.7	16.7
Participant 3	83.3	83.3
Participant 4	100	66.7

Most importantly, during the observation, the rule-based personalised feedback (i.e., system reactions) that each participant encountered during the learning process in the gaze-based version of the system has been recorded. After each learning task with the gaze-based system, the user is asked to provide subjective ratings for the system reactions they have just met in the learning process. This is not performed during the learning process to avoid interruptions.

As each lesson just last about 5 minutes, it can be assumed that user can easily recall the feedback to motivate them in the lesson when they are asked to rate the effectiveness and accuracy. Users were asked to self-rate the personalised feedback using motivational strategies that they have seen in the learning process to address their motivational needs and enhance learning experience. Users had to rate the feedback from 1 to 5 depending on the effect those feedback would have on them to maintain or enhance the motivation to continue learning. They also could provide a 0 rating if the feedback did not fit their situations, i.e., inaccurate).

As mentioned before, the personalised feedback uses motivational strategies linked to the motivational factors in the conceptual model. Once the motivational factor is detected by gaze data or self-reported data to meet the precondition of the rule, the corresponding feedback was triggered and output by the system to user.

Table 7.2 provides descriptions of the strategies that were mapped to the motivational factors (which have been explained in detail before) and the corresponding example feedback used in the system. The times each strategy was triggered and the average rating

is also shown in the table, from which it can be seen that the motivational factors and the corresponding to the strategies used in the system have all achieved the rating of over 4 in total of 5 point, except perceived ease of use and reading experience. The reason is explored in detail in the interviews explained in Section 7.4.4.

Table 7.2 Motivational strategies implemented in GazeMotive, times appearing and average ratings in the evaluation study

Factors	Strategies	Example Feedback	Times	Ratings
Attitudes Toward School	Achievement Highlight; Goal Setting	We can all enjoy learning and achieve the goal if we try. Let's start from defining the goal: I want to complete the Lesson 1 first, which will take just around 10 minutes!	12	4 (SD=1)
Self-efficacy	Empathy; Support	Give a try and make a difference! If we are very stuck, let's call the teacher, or ask for a hint! The teacher is always there for you.	12	4.5 (SD=0.5)
Confirmed Fit	Linkage Instruction; Problem Probing; Attention Alarm	Learning the knowledge is useful and fun, isn't it? The materials were specifically designed for learners of your age, if you have learned relevant knowledge, go through the slides and see if you can find anything new, remember, as the more we concentrate, the more effectively we learn!"	18	4.25 (SD=0.83)
Reading Experience	Suggestion; Achievement Highlight; Progress Notification	Let's take a breath before going on, remember we can always pause and seek help if we are stuck somewhere, slow down the reading if there is any difficulty, that also means we are making progress!	12	3.75 (SD=0.83)
Perceived Ease of Use	Help and Support; Effort Encouragement	Keep in mind that we can all enjoy the learning process and achieve the goal if we try. If we have any concerns or questions that inhibit your learning, let's call a teacher for help!	14	3.25 (SD=0.83)
Feedback	Informative, Explanatory, and Encouraging Feedback	That was too easy for you. Let's hope the next one is more challenging so that we can learn something.	24	4.25 (SD=0.43)

7.4.3 System Usability Scale

The System Usability Scale (SUS) [234] is a recognised reliable, simple evaluation tool consisting of ten Likert-scale items. It provides a comprehensive view for subjective evaluation of usability and allowing reliable differentiation between usable and unusable systems to be obtained from small sample size. The scale was used after the participants completed the learning tasks with the system prototype, but before any debriefing or discussion occurred. Participants were indicated to rate each item on the scale immediately without pondering over it, and they were allowed to mark the item they are unsure about.

Again, the sample size is too small for statistical analysis, but the results can provide an at-a-glance impression of the system usability. The SUS-results showed that participants rated the system prototype highly in terms of usability and overall satisfaction. The SUS mean score (in the overall range of 0-100) was 87.5 for all the four participants, where a SUS score of 70 is considered as the overall average, so over 70 is usually considered to represent a user-friendly system. All the individual ratings was 75 or above, and the lowest-scored item has the same score of 75 for all the four participants, which is “I think that I would need the support of a technical person to be able to use this system”. The reason can be revealed from the interviews detailed in the next section, though it should not be seen as a low score.

7.4.4 Interviews

A follow-up semi-structured interview for each participant was conducted for about 20-30 minutes after the previous procedures primarily to explore their experience using the system prototype. i.e., GazeMotive, and the reason behind their UX including their subjective ratings of the personalised feedback and usability aspects, as well as their suggestions of future improvement of the system.

The interview follows the six stages: introduction, warm-up, general issues, deep focus, retrospective and wrap-up. The introduction aims to clarify the objectives of the research and interview, where researcher and the participant also introduce themselves and confidentiality is highlighted to state how the data collected will be used and the rights of participants. Then the researcher starts a short warm-up talk focusing on the system

prototype to draw the participant's attention. For the GazeMotive system that they just experienced, it is emphasised again that the system is designed for students with learning difficulties such as dyslexia for which one of the common characteristics is the difficulty of processing text, so when answering the following questions, the participants should not take into account the special processing of the text, which is to simulate the reading difficulties of dyslexics.

Several open-ended, non-directed questions were carefully organised from general to specific to make them feel comfortable and promote an unbiased creative stream of ideas. To start with, general open-ended questions were firstly asked about the previous experience of e-learning systems. Then the questions related to the GazeMotive system they just used were talked about to acquire user's overall perceptions and preference about the system. Gradually, the questions with deep focus were presented concerning the user's experience on specific motivational feedback they met in the system and the usability issues when doing the learning tasks, and they were encouraged to give reasons of liking or disliking any elements and the ratings of the SUS items along with suggestions. Notes were taken during the interviews. Then the researcher tried to summarise and bridge different answers to make them connected. Essential questions are listed below:

- A) Have you experienced with the similar learning system before?*
- B) Have you learned the knowledge in the learning tasks before?*
- C) Talk about your overall impression and feelings about the system.*
- D) At the beginning, how do you find the message output (if you have received) –e.g. helpful/inaccurate?*
- E) During learning process, what messages have you received? Discuss the reason of your ratings one by one when you were asked to rate their accuracy in the last stage.*
- F) At the quiz stage, how do you find the message output, e.g., informative/helpful/ or possibly annoying?*
- G) What is your learning and reading experience with the gaze-based e-learning system compared with the non-gaze-based one? Which one is more useful and effective to help with your learning?*
- H) Why would you like to continue/discontinue to use the system for your learning?*
- I) What features do you like and dislike? Why?*

J) Any bugs/technical problems experienced? We will keep improving the system.

K) Discuss the lowest rated item in SUS. Do you have any suggestions about future improvement?

All the questions were presented as neutral and non-leading as possible. After the interviews, the notes were coded, grouped and reviewed to identify main categories described as below.

In subjective accuracy of the personalised feedback, all participants find them useful and encouraging, but three of them mentioned they appeared a bit frequently during the learning process. It is explained to them that the time interval is set to be 10 seconds for the purpose of testing their accuracy. In real-world scenarios, it should be different with the time interval of one minute or longer, or this should not be set to a fixed value. All of them feel the feedback messages are useful to maintain their motivation or “refreshing” to motivate them most times, but there were also a couple of times they feel confused to see them, “probably because sometimes they appeared more frequently than expected”.

Regarding the ratings of the feedback during learning process, although they found all of them useful, but the feedback for perceived ease of use is less accurate, which is consistent with the accuracy of the logistic regression model for predicting the level of this factor. Also, one of the participants mentioned that it’s better that some information in the feedback is better adjusted after the first time to make sure the participant gets no or less repeating feedback. Regarding the feedback related to self-reported attitudes toward school and self-efficacy, all participants feel it is nice to see the message at the beginning, as it either makes them feel encouraged, supported or makes the goal clear prior to the learning. At the quiz stage, the comments for the feedback after each answer is submitted are all positive, probably because of the combination of user’s input answer to a quiz and gaze data for personalisation of the feedback; for example, a user commented that “it was quite impressive to see the system knows not only the correctness of my answer but also my concentration and effort for answering the quiz and provides me with the accurate feedback accordingly.”

In terms of overall experience, all participants agreed that compared to the traditional non-gaze-based one, the gaze-based system is more useful to help with learning. Some of them think it may also be interesting to visualise the gaze pattern during the learning

process, but whether this will be distractive or helpful to engage learners needs further research and validation.

In terms of lack of system features, more functions should be implemented to allow more options of system settings for user preference. For example, some participants mentioned they wanted to tailor the interface including colour and visibility of the progress or past user's achievements. Also, help and support is stated in the feedback output to user, which, however, is only available in a blend learning environment which combines the use of the system and the availability of a teacher for assistance for the current system prototype, but it would be better to enable a chat room or discussion forum or an online connection with teachers for seeking help when needed.

In terms of usability issues, the lowest rated item in SUS is "I think that I would need the support of a technical person to be able to use this system". This is mainly due to the eye tracker calibration, and it is not fixed to or embedded the laptop in the current prototype of the system which caused inconvenience about adjusting its position. For improvement of the interfaces, all of them mentioned that it would be better if the picture of the learning companion can move or talk when delivering feedback messages, so animation and audio features should be implemented as part of the personalised feedback.

7.5 Conclusion

In this chapter, a framework of motivationally personalised e-learning systems is described for personalisation in e-learning environments based on learners' motivational states. The framework is designed to sustain or improve learners' motivation and willingness to expand effort in learning, and their cognitive abilities and emotional states will also be benefited using systems developed from the framework. The diagnostic input for assessing learners' motivational states is explained along with the system reactions being personalised feedback from motivational strategies. The framework, including motivation model and classification models as well as the rule-based personalisation can be incorporated into different learning applications, and the system can also be adapted to cater for users with other special learning difficulties or needs.

Then it is demonstrated how the motivation model and corresponding personalisation rules are applied to real-world scenarios for motivation-based enhanced learning. By

implementing part of the classification models to assess certain factors in the motivation model along with the inference rules and motivational strategies, the prototype GazeMotive realised the idea of enabling an e-learning environment to detect and respond to a user's motivational states in real time including different dimensions of motivation such as reading experience and visual attractiveness. The system prototype assesses motivational states with the classification models by monitoring eye gaze features and self-input data during the users' interaction process with the system, and this motivation-sensitive system demonstrates a way of implementing e-learning systems that can dynamically output personalised feedback to address users' motivational needs detected from real-time eye gaze data.

Finally, the evaluation of the system prototype is described in detail using multiple methods including heuristic evaluation, pre-defined tasks and observation, usability scale and interviews to consolidate the results and to facilitate deep understanding of user experience and usability of the system. The results show that using the gaze-based system prototype yields better self-reported motivation and learning experience compared to traditional non-gaze-based version of the system. The system is expected to enhance motivation and learning performance of students with dyslexia over the long term, which requires large-scale longitudinal studies in future. The next section will summarise the research conducted and contributions to knowledge in the thesis, followed by potential future work in the research area, and conclusions of highlights in the present project.

Chapter 8 Discussions and Conclusions

8.1 Summary of Research

The research presented in this thesis includes many achievements, and this section will summarise the work. In the heart of this PhD project, different approaches to motivation modelling and computation have been employed, such as the qualitative approach to the conceptual motivation modelling, ontology-based approach to computational motivation modelling, the quantitative approach to quantifying the relationships between the motivational factors, as well as the sensor-based approach to assessing the level of the motivational factors.

In summary, this thesis has described:

A) a conceptual motivation model developed for people with dyslexia incorporating motivational factors that influence their continued intention to use e-learning systems based on both an empirical study with dyslexic students and prior research from technology acceptance and psychological perspectives [3], [220];

B) a computational motivation model using ontology in which the conceptual motivation model is structured as a hierarchy of classes [137];

C) a multi-item questionnaire that was designed to measure the factors in the motivation model and the structural equation modelling process to further explore and confirm the statistical effects of the motivational factors on continued use intention and quantify the relationships between the motivational factors in the model [220];

D) an experiment conducted to collect EEG and eye-tracking data, and classification models using logistic regression for motivation computation to assess the motivational states in real time based on eye gaze data [206] and EEG data [235];

E) an approach to motivation-based personalisation that emphasises the use of ontologies for knowledge representation of both the motivation model and sensor features for motivation assessment [235], and the semantic rule-based reasoning mechanism for personalisation of motivational strategies;

F) a framework of motivationally personalised e-learning systems based on the abovementioned research, which is partly implemented in a prototype of learning

application [227]. The prototype implemented can output personalised strategies in the application to adapt to users' motivational states based on both self-reported data and the eye-tracking data during the learning process. A mix of evaluation studies have also been conducted with both experts and learners and proved the advantage of the prototype over the traditional system without motivationally personalised strategies.

8.2 Summary of Contributions to Knowledge

This thesis aims to address the research gap described in Chapter 1 by:

A) conducting a series of research studies using a hybrid approach to motivation modelling for people with dyslexia to identify the most relevant and important factors representing multiple motivational dimensions and their motivational needs in e-learning environments;

B) investigating the dynamic data captured by sensors and the extracted features as indicators for motivation computation and applying classification algorithms for the real-time motivation assessment including the multiple dimensions of motivation.

This section will summarise the reflections on the contributions that this thesis has made to knowledge. To deepen the understanding about the factors that motivate or inhibit a dyslexic learner's continued intention to learn in an e-learning environment, the motivation model has been developed combining different perspectives from the extensive literature review on psychological theories, technology acceptance theories and dyslexics characteristics, as well as from a qualitative empirical study with dyslexic learners.

To measure the factors identified in the motivation model quantitatively and to further explore how they work together and how they relate to each other to impact on continued intention of using e-learning systems, a multi-item questionnaire has been designed which has been tested for its reliability and validity. This questionnaire is reusable as an instrument for measuring motivation based on learners' self-reported data. The motivation model in the present work outweighs previous models, as it contains a much more comprehensive view of learners' motivational needs, and it is developed using both qualitative and quantitative approaches, involving empirical studies for validation in the e-learning context directly with target users. The deep understanding about the factors

and their interrelationships specified in the motivation model can facilitate designers of e-learning systems and educators of dyslexic learners to reprioritise the design and education considerations to satisfy the learners' motivational needs, and it can also help uncover the potential usability issues of systems that may inhibit their motivation to engage in learning.

To explore the possibility of computing the motivational factors while learners are interacting with e-learning systems without interruption to their learning, a novel approach has been proposed combining the use of an eye tracker and a wearable EEG device for motivation computation, and the approach is validated with an empirical experiment with dyslexic participants to capture the dynamic sensor data and produced logistic regression models for assessing the high or low levels of the motivational factors. The high prediction accuracies of the research results have proved the possibility of real-time assessment of learners' motivational states based on sensor data instead of self-reported data that may be interruptive, allowing learners' different motivational needs implied by the factors in the motivation model to be detected during the learning process.

To apply the motivation model and computation method to e-learning systems to enable personalised motivational strategies to be provided for users in real time, an architecture has been proposed using ontologies for representing relevant knowledge in a structured, machine-readable way, including the factors in the motivation model and the sensor features to assess learners' motivational states, i.e., compute the level of each motivational factor, and the personalisation of motivational strategies corresponding to the motivational states. The use of SWRL has also been specified to provide explicit definition of the personalisation rules, i.e., the causal relationships between the motivational states and the personalised strategies. A reasoning engine is in charge of checking if users' motivational states will trigger the corresponding rules to generate personalised strategies for the users. The proposed method of knowledge representation using ontologies enriched with semantic rules facilitates the reusability and modifiability of the represented knowledge and rules. It ensures the independence of the reasoning engine, self-contained motivation model and personalised strategies, which promotes its reusability and modifiability across different applications and knowledge domains.

To provide guidance for future design and development of e-learning systems that incorporates the motivation model, computation method and personalised strategies a

real-world scenario, a framework of motivationally personalised e-learning systems has been presented which is partially implemented into a prototype of gaze-based learning application. The application can assess learners' motivational states pertaining to multiple motivational dimensions and provide personalised strategies for the learners dynamically to adapt to their motivational states in real time. Evaluation results from both learners and experts have provided evidence on the superiority of the gaze-based learning application over traditional one without the personalisation to adapt to learners' motivation states, while highlighting the strength and usability of the proposed motivation model, computation method and personalisation mechanism for motivation-based, personalised, enhanced learning in real world.

In addition, as the motivational strategies used are extracted from domain knowledge, and there is little research investigating their effectiveness in the present context. To investigate whether they really work on learners during the learning process in e-learning environments, four typical strategies have been applied when the experiment was conducted with dyslexic participants and sensor data were captured during their learning process. The changes of sensor data including eye gaze and EEG data of learners after the motivational strategies were applied have been proved to have statistical significance, which contributes to the knowledge from both methodological and empirical perspectives. These two perspectives of contribution are further elaborated below in detail.

From methodological perspective, this research has led to a comprehensive view of the methodology for motivation modelling, computation and personalisation of motivational strategies to be applied to e-learning environment for people with dyslexia, which is reusable across domains, e.g., the modelling and personalisation focusing on users' other surrounding information, behaviour or mental states. Motivation modelling and computation consists of multidisciplinary collaboration. Specifically, in order to develop such a motivation model for people with dyslexia in e-learning environments, both the qualitative approaches from multiple perspectives (i.e., psychological theories, technology acceptance and dyslexia) and quantitative approaches have been employed in order to explore and identify the statistical impact of motivational factors on continued use intention and their interrelationships. In particular, both CB-SEM and PLS-SEM have been employed and the results have been compared, which produces great insights on how the two SEM approaches perform in the present research context.

For the purpose of real-time assessment of learners' motivational states, dynamic sensor data including eye-tracking data and EEG data has been captured, and more importantly, the procedure of feature extraction and selection is described in details resulting in the combination of eye gaze and EEG features for the production of a logistic regression model for the computation of each motivational factor in the motivation model. The integration of EEG and eye-tracking data has achieved high prediction accuracies for motivation assessment, and the feature extraction and selection process are highly applicable for future research and different domains.

Furthermore, an ontology-based motivation model with personalisation components has been developed, which can be adapted to many scenarios. Ontology is also used for structuring complex information of sensor features used for motivation assessment. The architecture is provided showing a holistic picture for sensor-based motivation assessment including the use of ontology to represent the abovementioned knowledge, feature analysis and the classification models using logistic regression. The use of SWRL further increases the personalisation capabilities of the component by expressing additional concepts that cannot be directly inferred from the ontology language.

Finally, the proposed framework of motivationally personalised e-learning systems that is implemented partly has led to technological insights by providing a feasible approach to future design and development of such systems in the real world. Additionally, the evaluation methods and criteria provide a context for developing, evaluating and comparing alternative solutions in the future.

From empirical perspective, empirical research findings have been provided from both the qualitative study and quantitative one with dyslexic learners about their views on the factors influencing their motivation, along with the statistical significance of each factor and the quantified relationships between factors in the motivation model. Empirical data has also been obtained from an experiment with dyslexic learners and proved the feasibility of exploiting dynamic sensor data to compute motivation in real time.

Empirical evidence was obtained regarding the effectiveness of the proposed solutions to motivation-based enhanced learning in e-learning systems: the prototype of the gaze-based learning application has been proved to be more advantageous than the traditional learning application from user studies involving both experts and learners. The application implements the logistic regression models for assessing the motivational

states mainly based on eye gaze features and addresses learners' multiple motivational needs by providing personalised feedback according to the motivational states detected in real time. In addition, the motivational strategies implemented as interventions output by systems in real time has been proved by experiments with the target users to have the ability to make significant differences of learners' eye gaze or EEG activities after being applied to the e-learning environment, which implies that the long-term use of e-learning systems that incorporate the models and strategies for motivation assessment and personalised learning is useful at facilitating confounding positive changes of learners' motivation and learning behaviour further.

8.3 Future Work

The present research has conceived a hybrid approach to motivation modelling for people with dyslexia in e-learning environments, but the degrees of dyslexia and the types of e-learning systems were not differentiated in both qualitative and quantitative studies. Therefore, future work for motivation modelling needs to involve larger sample size and different learning context to allow for comparative studies between different samples with different conditions or between e-learning systems with competing features.

When exploring sensor-based approach to motivation computation, multinomial logistic regression or other machine learning techniques can be employed to allow more than two classes of the outcomes to be distinguished from each other, which is particularly meaningful when the difficulty of learning tasks is considered, as Yerkes-Dodson law has implied that different tasks require different levels of arousal to optimise learning performance. Moreover, the performance of different machine learning algorithms for motivation computation can be compared. It is also worth introducing more kinds of sensor data other than eye gaze and EEG data as predictors aiming at improving the prediction power.

The present work focuses on motivation modelling and computation, and the motivation-based personalisation employs only inference rules from domain knowledge, and the system prototype implemented personalised feedback from motivational strategies in text format. The evaluation of motivational strategies does not cover the personalisation rules of the motivational strategies based on different motivational states.

Therefore, future studies should be conducted to validate the rules for personalising strategies in e-learning environment based on learners' different motivational states.

In addition, personalised feedback output by system should involve more formats, more channels to stimulate the information processing. More types of services in e-learning environments, such as the difficulty levels and interfaces, etc., can be personalised. For example, the output can be different quantities of course materials along with feedback to users as mentioned in Chapter 3. Semantic density (SD) can be employed representing the complexity and semantic quantity of learning objects adopted by prior research [137], [154]. For example, each learning object can be assigned to a semantic density between 1 and 5, the learning objects with SD value ≤ 2 can be presented to students with low motivation, and those with moderate motivation can be assigned to the learning objects with SD ≤ 4 totally, and highly motivated students can have learning objects with semantic density value 5.

Facial expression can be applied to the pedagogic agent embedded in the system along with the words for providing personalised feedback for their ability of conveying social emotions. Specifically, If the user's motivation is high, the facial expression of the emoticon providing feedback will be happy, else it will be worried. The emoticon can provide feedback before and after a learning course. All these also should be evaluated with larger representative sample in a strict experiment setting with comparative study design. Finally, future personalised systems can implement the ontological motivation model and SWRL rules described in Chapter 6. This can be realised using the OWL-API as described [236] and used before for context-aware help-on-demand services [96].

In addition, the long-term task to evaluate the effectiveness of the proposed motivation model and the approach to motivation computation and personalisation in real-world scenarios should be addressed in future by conducting longitudinal comparative studies.

8.4 Conclusions

Motivation is essential to learning behaviour and learning effectiveness of dyslexic learners, but there is a distinct lack of research investigating the factors impacting on their motivation to engage in e-learning systems; needless to say, no research has targeted at developing a motivation model or proposing an approach to real-time assessment of their

motivational states and applying personalised strategies to e-learning systems to respond to their dynamic motivational states. This thesis aims to fill the research gap of motivation modelling and computation for people with dyslexia in e-learning systems, and the hybrid approach used is inspired by and based upon the work of many others in different domains. The presented research contributes to the state of the art by being one of the first investigating the topic.

The motivation model developed from both the qualitative and quantitative approaches, the computation method that exploits sensor monitoring including both eye tracking and EEG for real-time motivation assessment, and the semantic rule-based approach to knowledge representation of motivation model, sensor features for motivation computation and the personalisation rules as well as the framework of motivationally personalised e-learning systems are all applicable to different designs with reusability, modifiability and extendibility across different domains.

This ground-breaking work in this thesis includes both the methodologies and the knowledge obtained from empirical research and can be of future use. It will inspire other researchers to continue the research in the field of motivation modelling, real-time motivation computation and motivationally personalised e-learning systems for people with dyslexia as well as for more generic user groups.

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Appendices

Appendix 1 mYouTime Learning Materials in the Qualitative Study

- _Nat 4.14 Hvittlys (Elev2)
- _Nat 2.6 Regnskogen
- _Nat 4.6 Påvisningsreaksjoner
- _Nat 4.12 Arbeid
- _Nat 4.14 Hvittlys (Elev1)
- _Nat 3.4 Tobakk
- _Nat 3.3 Abort
- _Nat 4.13 Bilbelte
- _Nat 3.1 Puberteten
- _Nat 3.2 Fosterutvikling★
- _Nat 2.3 Celledeling★
- _Nat 2.2 Dyrecelle★

There are two versions of each material. One has the text slides (and quizzes) with text that can be read aloud by pushing a button on the slide. The other set only shows the slides without this button. The last three (marked by ★) are control, they do not have text slides, but are mostly videos followed by a quiz.

Appendix 2 Interview Probing Questions in the Qualitative Study

General questions about daily learning experience:

- 1. What kinds of problems or barriers do you encounter when you are studying?*
- 2. What type of assistive technology do you use to support your learning as someone who has dyslexia?*
- 3. How do you use this?*
- 4. How long have you used this?*
- 5. How does this help you in your studies?*
- 6. What sort of problems have you had using these resources?*
- 7. Do these resources motivate you to continue in your studies?*

If the participant uses NO technology, ask these questions instead:

- 1. Why don't you use any of the other resources?*
- 2. What makes you want to continue your studies?*

Then ask the questions about the actual experience using the learning application:

- 1. How informative was the text on the slides?*
- 2. What did you think about the length of each lesson?*
- 3. What kind of problems did you have with the text slides? How did you deal with these problems?*
- 4. What do you think about the instant feedback when answering questions in the quiz?*
- 5. Is there anything you would like to see or hear in the application that you did not?*
- 6. What do you think are the good points of this learning application that would mean you would use it?*
- 7. What makes you feel the application is enjoyable or pleasant to use (if any)?*
- 8. What do you think about this change of feedback?*
- 9. Would you prefer this version of the quiz feedback or the original version?*

Appendix 3 Measurement Scales

*** = removed after EFA

Latent Variables	Measured Variables
Perceived Usefulness [66] Mean (SD) = 3.90 (1.082)	(1) Using the learning tool improves my learning effectiveness. (2) Using the learning tool makes learning easier for me. (3) Using the learning tool does NOT improve my learning performance. (reverse) (4) The learning tool is a useful tool for me.
Perceived Ease of Use [66] Mean (SD) = 3.60 (1.010)	(1) Learning how to use the learning tool is easy for me. (2) My interaction with the learning tool is clear and understandable. (3) It is NOT easy for me to become skilful at using the learning tool. (reverse) (4) Overall, I find the learning tool easy to use.
Perceived Enjoyment [67] ***	(1) When I learn things via the learning tool, I feel time passes quickly. (2) Learning things via the learning tool is enjoyable to me. (3) Using the learning tool makes me feel FRUSTRATED. (reverse) (4) Using the learning tool is a very comfortable experience for me.
Perceived Convenience [147] ***	(1) I can learn at any time via the learning tool. (2) I can learn at any place via the learning tool. (3) The learning tool is NOT convenient for me to engage in learning. (reverse) (4) Overall, I feel that the learning tool is convenient for me to learn knowledge.

Satisfaction [237] ***	<p>(1) Based on my experience with the learning tool, I am very content with using it.</p> <p>(2) Based on my experience with the learning tool, I am very DISSATISFIED with using it.</p> <p>(reverse)</p> <p>(3) Based on my experience with the learning tool, I am delighted with using it.</p>
Confirmation [63] Mean (SD) = 3.45 (1.118)	<p>(1) My experience with using the learning tool was better than what I expected.</p> <p>(2) The service level provided by the learning tool was better than what I expected.</p> <p>(3) Overall, most expectations for using the learning tool were confirmed.</p>
Perceived Fit [237] Mean (SD) = 3.46 (1.195)	<p>(1) Using the learning tool fits with the way I learn.</p> <p>(2) Using the learning tool does NOT fit with my learning preference. (reverse)</p> <p>(3) Overall, using the learning tool fits with my learning needs.</p>
Feedback [238] Mean (SD) = 3.06 (0.964)	<p>(1) The learning tool provides positive feedback.</p> <p>(2) I did NOT receive compliments in the learning tool. (reverse)</p> <p>(3) The feedback I received in the learning tool is informative.</p> <p>(4) The feedback I received in the learning tool is in time.</p>
Visual Attractiveness [169], [65] Mean (SD)= 3.36 (0.909)	<p>(1) The way things are displayed in the learning tool is attractive.</p> <p>(2) I do NOT like the way the content looks in the learning tool.</p> <p>(3) Overall, I find that the learning tool looks attractive.</p>
Utilization [63]	<p>(1) I utilized the main functions in the tool I used.</p> <p>(2) I utilized the most functions in the tool I used.</p>

Mean (SD) = 3.18 (0.895)	(3) I completed the learning tasks in the learning tool I used. (4) I took the self-assessment test/quiz in the learning tool I used.
Technology Self-efficacy [68] Mean (SD) = 3.70 (0.830)	(1) I could complete the learning tasks using a mobile or web-based learning tool, if there was no one around to tell me what to do. (2) I could complete the learning tasks using a mobile or web-based learning tool, if I had never used a tool like that before. (3) I could complete the learning tasks using a mobile or web-based learning tool, if I had only the instruction manuals for reference. (4) I could complete the learning tasks using a mobile or web-based learning tool, if I could call someone for help if I got stuck. (5) I could complete the learning tasks using a mobile or web-based learning tool, if I had a lot of time to complete the learning tasks for which the system was provided. (6) I could complete the learning tasks using a mobile or web-based learning tool, if someone showed me how to use it first
Attitudes toward School [148] Mean (SD) = 3.71 (1.078)	(1) I really like school. (2) School is BORING. (reverse) (3) I would NOT like to work in a school when I grow up. (reverse) *** (4) I am learning a lot in school.
Perceived Control Mean (SD) = 3.14 (1.013)	(1) I felt I was able to control the progress as I wanted when using the learning tool. *** (2) I felt it was easy to undo or cancel when unpredicted things happen in the learning tool I used. (3) I felt I was able to control the learning progress to adapt to my own learning pace when using the learning tool.

	(4) I felt I could manipulate the learning tool I used in the way I like. ***
	(5) When I used the learning tool, I felt the progress in the tools was OUT OF MY CONTROL. (reverse)***
Perceived Privacy Mean (SD) = 3.74 (0.900)	<p>(1) When using the learning tool, I knew my personal information could be only identified by myself unless I gave permissions.</p> <p>(2) When using the learning tool, I knew how my personal information would be stored and used. ***</p> <p>(3) When using the learning tool, I felt other people could not have access to my learning progress or any other personal information unless I gave permission.</p> <p>(4) When using the learning tool, I felt UNSAFE about my personal information overall. (reverse)</p>
Learning Experience Mean (SD) = 3.26 (0.780)	<p>(1) The learning materials used in the learning tool are clear and understandable.</p> <p>(2) The learning materials used in the learning tool are interesting and fun.</p> <p>(3) I felt the self-assessment test/quiz in the learning tool helpful to my learning. ***</p> <p>(4) I often needed additional help in either technical or learning aspects when using the learning tool. (reverse) ***</p> <p>(5) The way the learning material is presented is suitable for me.</p> <p>(6) The difficulty level of the learning material fits me well.</p> <p>(7) Overall I felt FRUSTRATED using the learning tool for my learning. (reverse) ***</p>
Reading Experience	<p>(1) I had less difficulties of reading hen using the learning tool.</p> <p>(2) The functions provided in the learning tool helped a lot with my reading.</p>

Mean (SD) = 3.43 (1.096)	(3) The text length and format of the learning materials in the learning tool fits me well. (4) Overall my reading experience is positive using the learning tool.
Continued Use Intention [66]	(1) In the next few weeks, assuming I have access to the learning tool, I would like to use/continue to use it.
Mean (SD) = 3.74 (1.019)	(2) If I could, I would like to DISCONTINUE my use of the learning tool in the next few weeks. (reverse) (3) My intentions are to continue using the learning tool in the next few weeks, at least as active as today.

Appendix 4 The Significant EEG and Eye Tracking Features ($p < 0.05$) According to Spearman Correlation

Motivational Factors	Significant Features	Category
Perceived Usefulness	Gamma-max; Theta-IntroAsymmetry; HighBeta-IntroAsymmetry	EEG
Perceived Ease of Use	LessonDuration	Other-Behaviour
	Gamma-mean; HighBeta-occipital; Gamma-occipital; HighBeta-temporal; Gamma-temporal; HighBeta-frontal	EEG
	FixationNumber-overall; FixationSpatialDensity-overall; Regressions-overall	Eye
Visual Attractiveness	PupilDiameter-average; FixationSpatialDensity-overall	Eye
Feedback	Gamma-max; Theta-InterAsymmetry	EEG
Attitudes Toward School	LowBeta-max; HighBeta-temporal; Gamma-temporal; HighBeta-frontal; Theta-InterAsymmetry	EEG
	FixationNumber-AOI; FixationSpatialDensity-overall	Eye
Self-Efficacy	LowBeta-frontal; HighBeta-frontal; Gamma-frontal; Theta-IntroAsymmetry; LowBeta-IntroAsymmetry; HighBeta-IntroAsymmetry	EEG
	FixationNumber-AOI; FixationSaccadeRatio; SamplesOutOfMonitor; AverageSaccadeVelocity; PathVelocity	Eye
Reading Experience	LessonDuration; QuizPerformance	Other-Behaviour
	Theta-max	EEG
	FixationConnectionLength-overall; FixationSpatialDensity-overall; FixationNumber-overall; Regressions-overall	Eye
Learning Experience	Theta-occipital; LowBeta-occipital	EEG
	PupilDiameter-average; PupilDiameter-max; FixationSpatialDensity-overall	Eye
Confirmed Fit	Alpha-max; HighBeta-max; Gamma-max	EEG

	SaccadeLength-overall; SamplesOutOfMonitor; PupilDiameter-average; PupilDiameter-max; FixationConnectionLength-overall	Eye
Continued Use Intention	Theta-min; Alpha-max; Alpha-min; LowBeta-min; HighBeta-min; Theta- mean; Theta-IntroAsymmetry; Gamma-IntroAsymmetry	EEG
	FixationDuration-AOI; FixationNumber-10s; SamplesOutOfMonitor; PathVelocity	Eye

Appendix 5 The Significant EEG and Eye Tracking Features ($p < 0.05$) According to One-way ANOVA/Kruskal Wallis Test

Motivational Factors	Test	Significant Features	Category
Perceived Usefulness	Kruskal-Wallis Test	QuizPerformance	Other-Behaviour
		HighBeta-IntroAsymmetry	EEG
Perceived Ease of Use	One-way ANOVA	FixationNumber-overall	Eye
	Kruskal-Wallis Test	LessonDuration	Other-Behaviour
		Gamma-mean; HighBeta-mean, Gamma-occipital, HighBeta-occipital, Gamma-temporal, HighBeta-temporal, Gamma-parietal, HighBeta-frontal, Alpha-IntroAsymmetry	EEG
		FixationSpatialDensity-overall	Eye
Visual Attractiveness	Kruskal-Wallis Test	Theta-max, Alpha-max, Gamma-max, Theta-parietal, Theta-InterAsymmetry	EEG
		FixationSpatialDensity-overall	Eye
Feedback	One-way ANOVA	FixationNumber-overall	Eye
	Kruskal-Wallis Test	SamplesOutofMonitor	Eye
		Theta-max; Gamma-max; Theta-occipital; LowBeta-occipital; HighBeta-occipital; Gamma-occipital; HighBeta-temporal; Gamma-temporal; HighBeta-frontal	EEG
Attitudes Toward School	One-way ANOVA	Theta-min	EEG
		FixationNumber-AOI, FixationNumber-overall, FixationConnectionLength-overall	Eye
	Kruskal-Wallis Test	Alpha-InterAsymmetry	EEG
		FixationSpatialDensity-overall, FixationSaccadeRatio, PupilDiameter-average	Eye

Self-Efficacy	Kruskal-Wallis Test	Gamma-mean, Gamma-occipital, HighBeta-parietal, Gamma-parietal, LowBeta-temporal, Gamma-temporal, Alpha-frontal, LowBeta-frontal, HighBeta-frontal, Gamma-frontal, Theta-IntroAsymmetry	EEG
		FixationSaccadeRatio, SamplesOutOfMonitor	Eye
Reading Experience	Kruskal-Wallis Test	LessonDuration, QuizPerformance	Other-Behaviour
		Theta-max, Alpha-max, HighBeta-min	EEG
		AverageSaccadeLength-10s, FixationSpatialDensity-overall	Eye
Learning Experience	Kruskal-Wallis Test	Theta-max, Theta-occipital, LowBeta-occipital, HighBeta-occipital, Gamma-occipital	EEG
		PupilDiameter-average, PupilDiameter-max, FixationSpatialDensity-overall	Eye
Confirmed Fit	One-way ANOVA	Theta-min	EEG
		FixationConnectionLength-overall	Eye
	Kruskal-Wallis Test	Alpha-max, HighBeta-max, Gamma-max	EEG
		SamplesOutOfMonitor	Eye
Continued Use Intention	One-way ANOVA	Theta-min, Alpha-min, LowBeta-min	EEG
	Kruskal-Wallis Test	Alpha-max, HighBeta-min, Theta-mean, HighBeta-temporal	EEG
		FixationNumber-10s	Eye

Appendix 6 Classification Tables

Perceived Usefulness cut value = 0.6 (0.5)		predicted		
		Group 1 (low level)	Group 2 (high level)	Percentage Correct
observed	Group 1 (low level)	19 (14)	7 (12)	73.1 (53.8)
	Group 2 (high level)	9 (7)	34 (36)	79.1 (83.7)
	Overall Percentage			76.8 (72.5)
Visual Attractiveness The cut value = 0.348 (0.5)		predicted		
		Group 1 (low level)	Group 2 (high level)	Percentage Correct
observed	Group 1 (low level)	34 (36)	7 (5)	82.9 (87.8)
	Group 2 (high level)	3 (6)	25 (22)	89.3 (78.6)
	Overall Percentage			85.5 (84.1)
Perceived Ease of Use The cut value = 0.416 (0.5)		predicted		
		Group 1 (low level)	Group 2 (high level)	Percentage Correct
observed	Group 1 (low level)	23 (26)	15 (12)	60.5 (68.4)
	Group 2 (high level)	7 (14)	24 (17)	77.4 (54.8)
	Overall Percentage			68.1 (62.3)
Feedback The cut value = 0.371 (0.5)		predicted		
		Group 1 (low level)	Group 2 (high level)	Percentage Correct
observed	Group 1 (low level)	34 (34)	10 (10)	77.3 (77.3)
	Group 2 (high level)	4 (9)	21 (16)	84.0 (64.0)
	Overall Percentage			79.7 (72.5)
Self-efficacy The cut value = 0.481 (0.5)		predicted		
		Group 1 (low level)	Group 2 (high level)	Percentage Correct
observed	Group 1 (low level)	23 (23)	4 (4)	85.2 (85.2)
	Group 2 (high level)	1 (1)	41 (41)	97.6 (97.6)
	Overall Percentage			92.8 (92.8)

Attitudes toward school The cut value = 0.496 (0.5)		predicted		
		Group 1 (low level)	Group 2 (high level)	Percentage Correct
observed	Group 1 (low level)	34 (34)	8 (8)	81.0 (81.0)
	Group 2 (high level)	8 (8)	19 (19)	70.4 (70.4)
	Overall Percentage			76.8 (76.8)
Learning Experience The cut value = 0.53 (0.5)		predicted		
		Group 1 (low level)	Group 2 (high level)	Percentage Correct
observed	Group 1 (low level)	30 (30)	6 (6)	83.3 (83.3)
	Group 2 (high level)	7 (7)	26 (26)	78.8 (76.8)
	Overall Percentage			81.2 (81.2)
Reading Experience The cut value = 0.536 (0.5)		predicted		
		Group 1 (low level)	Group 2 (high level)	Percentage Correct
observed	Group 1 (low level)	29 (29)	4 (4)	87.9 (87.9)
	Group 2 (high level)	4 (4)	32 (32)	88.9 (88.9)
	Overall Percentage			88.4 (88.4)
Confirmed Fit The cut value = 0.64 (0.5)		predicted		
		Group 1 (low level)	Group 2 (high level)	Percentage Correct
observed	Group 1 (low level)	25 (17)	5 (13)	83.3 (56.7)
	Group 2 (high level)	13 (9)	26 (30)	66.7 (76.9)
	Overall Percentage			73.9 (68.1)
Continued Use Intention The cut value = 0.438 (0.5)		predicted		
		Group 1 (low level)	Group 2 (high level)	Percentage Correct
observed	Group 1 (low level)	20 (20)	9 (9)	69.0 (69.0)
	Group 2 (high level)	3 (8)	37 (32)	92.5 (80.0)
	Overall Percentage			82.6 (75.4)