An Empirical Study of Learners’ Acceptance of Open Learner Models in Malaysian Higher Education

A thesis submitted in fulfillment of the requirements for the degree of

Doctor of Philosophy

Sek Yong Wee

Bachelor of Science (Statistics)

Master of Science (Information Technology)

School of Business Information Technology and Logistics

College of Business

RMIT University, Melbourne, Australia

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Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

Sek Yong Wee

21 February 2017
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## List of Abbreviations

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<th>Abbreviation</th>
<th>Definition</th>
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<tbody>
<tr>
<td>AGFI:</td>
<td>Adjusted goodness of fit index</td>
</tr>
<tr>
<td>ANOVA:</td>
<td>One-way analysis of variance</td>
</tr>
<tr>
<td>ATT:</td>
<td>Attitude</td>
</tr>
<tr>
<td>AVE:</td>
<td>Average variance extracted</td>
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<tr>
<td>CFA:</td>
<td>Confirmatory factor analysis</td>
</tr>
<tr>
<td>CFI:</td>
<td>Comparative fit index</td>
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<tr>
<td>CSE:</td>
<td>Computer self-efficacy</td>
</tr>
<tr>
<td>DOI:</td>
<td>Theory of diffusion of innovations</td>
</tr>
<tr>
<td>EFA:</td>
<td>Exploratory factor analysis</td>
</tr>
<tr>
<td>GFI:</td>
<td>Goodness of fit index</td>
</tr>
<tr>
<td>ICT:</td>
<td>Information communication and technology</td>
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<tr>
<td>ISI:</td>
<td>Information sharing intention</td>
</tr>
<tr>
<td>KMO:</td>
<td>Kaiser-Meyer-Olkin</td>
</tr>
<tr>
<td>MO:</td>
<td>Motivation</td>
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<tr>
<td>MSB:</td>
<td>Mean square between</td>
</tr>
<tr>
<td>MSW:</td>
<td>Mean square within</td>
</tr>
<tr>
<td>NA:</td>
<td>Navigation</td>
</tr>
<tr>
<td>NFI:</td>
<td>Normed fit index</td>
</tr>
<tr>
<td>OLE:</td>
<td>Online learning experience</td>
</tr>
<tr>
<td>OLMs:</td>
<td>Open learner models</td>
</tr>
<tr>
<td>PEOU:</td>
<td>Perceived ease of use</td>
</tr>
<tr>
<td>PU:</td>
<td>Perceived usefulness</td>
</tr>
<tr>
<td>RMSEA:</td>
<td>Root mean square error of approximation</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>-------------</td>
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<tr>
<td>RMSR</td>
<td>Standardised root mean squared residual</td>
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<tr>
<td>SA</td>
<td>System adaptability</td>
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<tr>
<td>SCT</td>
<td>Social cognitive theory</td>
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<tr>
<td>SD</td>
<td>Screen design</td>
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<tr>
<td>SEM</td>
<td>Structural equation modeling</td>
</tr>
<tr>
<td>SI</td>
<td>System interactivity</td>
</tr>
<tr>
<td>TAM</td>
<td>Technology acceptance model</td>
</tr>
<tr>
<td>TBCL</td>
<td>Technology-based collaborative learning</td>
</tr>
<tr>
<td>TLI</td>
<td>Tucker-lewis index</td>
</tr>
<tr>
<td>TPB</td>
<td>Theory of planned behavior</td>
</tr>
<tr>
<td>TRA</td>
<td>Theory of reasoned action</td>
</tr>
<tr>
<td>VARK</td>
<td>Visual, aural, read/write, and kinaesthetic</td>
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Abstract

Technology-based collaborative learning (TBCL) is a pedagogical approach that involves groups of learners working together to share their learning information through the adoption of collaborative technologies in learning. It has numerous benefits including developing learners’ social skills, fostering interpersonal relationships, enhancing self-management skills, promoting cooperation, and encouraging collaboration. These benefits of TBCL motivate governments worldwide to develop and implement various strategies and policies to improve the adoption of collaborative technologies in teaching and learning.

Following the global trend, the government of Malaysia has introduced the Malaysia Education Blueprint 2013 - 2025 for improving the adoption of collaborative technologies. Numerous collaborative technologies including open learner models (OLMs) have been introduced for facilitating collaborative learning in Malaysian higher education. The tremendous benefits of OLMs in collaborative learning, however, have not been fully realized due to their low utilization. Existing studies try to address this issue with a focus on the technical aspects such as the presentation format and the type of interaction. Few studies have empirically investigated the adoption of OLMs from the perspective of learners, especially on learners’ attitudes and perceptions towards the adoption of OLMs in collaborative learning.

The objective of this research is to investigate learners’ attitudes and perceptions towards the adoption of OLMs in Malaysian higher education. Specifically, the research aims to (a) investigate the current adoption of OLMs in Malaysian higher
education, (b) identify the critical factors for the adoption of OLMs in Malaysian higher education, (c) explore the relationship between learning styles of learners and their attitudes towards the acceptance of OLMs in collaborative learning, (d) examine the gender difference in attitudes towards the acceptance of OLMs, and (e) provide specific recommendations to the government of Malaysia for improving the utilisation of OLMs in Malaysian higher education.

A quantitative methodology consisting of scenario-based prototyping design and online surveys of learners are adopted in this study. An extensive review of related literature has been conducted. This leads to the development of a conceptual framework for evaluating the adoption of OLMs in collaborative learning. With the use of the survey data collected in Malaysian higher education, the conceptual framework is tested and validated using structural equation modelling techniques and other statistical data analysis methods.

The study shows that there is a positive relationship between the motivation, computer self-efficacy, system design, system adaptability, navigation and the adoption of OLMs in Malaysian higher education. Furthermore it reveals that the perceived usefulness, the perceived ease of use, and trust have indirect positive influence in the adoption of OLMs by affecting the information sharing intention of learners. This leads to the development of a revised framework for better understanding the adoption of OLMs in collaborative learning.

This study has made a major contribution to the OLM research from both the theoretical and practical perspectives. Theoretically, the contributions are reflected in
(a) the development of a validated conceptual model for better understanding the adoption of OLMs in Malaysian higher education, (b) the provision of the empirical evidence of the relationship between learning styles of learners and their attitudes towards the adoption of OLMs in collaborative learning, and (c) the demonstration of the gender difference in attitudes towards the adoption of OLMs in collaborative learning. Practically, the contributions are demonstrated through the use of the research findings by various stakeholders in TBCL. Such findings can (a) help the Malaysian government develop specific strategies and policies for improving the adoption of OLMs in Malaysian higher education, (b) provide Malaysian higher education institutions with useful information for facilitating the implementation of OLMs, and (c) present useful information to individual instructional designers for developing user friendly OLMs to improve the adoption of OLMs.
Chapter 1

Introduction

1.1 Research Background

Technology-based collaborative learning (TBCL) is an educational approach that involves groups of learners working together to solve a problem, complete a task, or create a product through the adoption of information and communication technologies (ICT). It provides learners with an environment in which they can interact with instructional materials, instructors and peers through the use of collaboration technologies (Sridharan et al., 2010; Karunasena et al., 2012; Bhuasiri et al., 2012; Karunasena et al., 2012; Mbarek and Zaddem, 2013). The adoption of such an approach is becoming popular in collaborative learning due to its ability in improving the quality of education, providing better access to learning content, encouraging and facilitating active participation of learners in teaching and learning, bridging the digital divide, eradicating distance, as well as reducing the communication and information costs (Welsh et al., 2003; Zhang et al., 2004; Ruiz et al., 2006; Sridharan et al., 2011; Bhuasiri et al., 2012; Karunasena et al., 2013).

Following the global trend, the government of Malaysia in 2013 officially launched the Malaysia Education Blueprint 2013 - 2025 for improving the TBCL implementation. This blueprint highlights three waves of action which includes (a)
the first wave (2013 - 2015) on the enhancement of the ICT infrastructure, (b) the second wave (2015 - 2020) on the introduction of collaboration technologies, and (c) the third wave (2021 - 2025) on the full implementation of collaborative technologies (Malaysia Education Blueprint, 2013). Under this blueprint, numerous collaborative technologies including open learner models (OLMs) have been introduced for facilitating collaborative learning in Malaysian higher education.

An OLM is a visualization tool that displays a learner’s current level of understanding relating to the concept known, specific knowledge, and their misconceptions in a specific subject area (Bull and Kay, 2005). The adoption of OLMs can increase the awareness of learners’ knowledge and understanding in a specific domain. This increased awareness can assist with the development of meta-cognitive skills such as self-assessment and self-regulation. Adoption of OLMs further encourages learners’ autonomy which increases responsibilities for their learning processes (Mitrovic and Martin, 2007). The use of OLMs can increase a learner’s engagement in the learning process and provide them with better motivation (Bull, 2004; Mitrovic and Martin, 2007). Furthermore, the adoption of OLMs promotes reflective learning, which is critical for improving the effectiveness and efficiency of learning (Bull and Pain, 1995; Dimitrova et al., 2000).

The tremendous benefits of adopting OLMs in collaborative learning, however, have not been fully recognized. The utilization of these models is not encouraging (Barnard and Sandberg, 1996; Bull, 2004). There is plenty of research in the literature on how to improve the adoption of OLMs. Chen et al. (2007), for example,
portray an OLM as animal companions to encourage learners to engage in the learning process. Dimitrova et al. (2001) introduce an interactive OLM by engaging learners to negotiate with their learner models during the modelling process. Brusilovsky et al. (2004) propose additional navigation support to encourage learners to use OLMs. These studies, however, focus primarily on the technical issues such as the presentation format (Hochmeister et al., 2012) and the type of interactions (Bull and Kay, 2010). Little research has investigated the critical factors for the adoption of OLMs from the perspective of learners. Furthermore, few studies are available in investigating learners’ attitudes and perceptions towards the adoption of OLMs.

The development of OLMs in Malaysian higher education is still in its infancy stage. A better understanding of the critical factors for the adoption of OLMs would help improve the implementation of OLMs in the Malaysia higher education. Such a study not only helps the Malaysian government to better understand the value for their investment in TBCL. It can also facilitate the identification of the critical factors for the adoption of OLMs in Malaysian higher education.

### 1.2 Motivation of the Research

The motivation to undertake this research is due to three main reasons. Firstly, there is lack of research concerning the evaluation of the critical factors for the adoption of OLMs in Malaysian higher education (Sek et al., 2014). Although several studies exist in the literature for evaluating the adoption of collaborative technologies such as social networks, web-based learning, and learning management systems in Malaysian higher education, these studies are not applicable in adequately evaluating
the adoption of OLMs. Such inadequacy is due to (a) the different characteristics of individual collaborative learning technologies, (b) the context in which these studies are carried out (Sun and Jeyaraj 2013), and (c) the extent of learning information sharing between learners using individual collaborative technologies.

Secondly, there is a lack of empirical studies investigating the adoption of OLMs from the perspective of learners. A majority of existing literature related to the adoption of OLMs has focused primarily on the technical issues. Few studies have been conducted in investigating the adoption of OLMs from the learners’ perspective. Learners play a critical role in the adoption of OLMs in collaborative learning. Investigating the adoption of OLMs from the perspective of learners can lead to a better understanding of learners’ attitudes and perceptions towards the adoption of OLMs in collaborative learning. Such an investigation is important because the successful implementation of OLMs very much depends on learners’ willingness to adopt OLMs in collaborative learning.

Thirdly, there is a need for a new framework to adequately evaluate learners’ acceptance of OLMs in the pre-adoption of OLMs. Individuals’ initial perception of a technology in the pre-adoption of such a technology is important for the acceptance of the technology (Hameed et al. 2012; Sun and Jeyaraj 2013). A poorly managed pre-adoption of a specific collaborative technology may lead to the failure in implementation during post-adoption (Yang et al. 2015). Individual beliefs and motivations change over time. As a result, many determinants of the technology adoption often fail to predict the performance of the technology adoption in the post-
adoption. Failure is usually due to the little theoretical understanding of what initially brings potential adopters to adopt specific technologies and how educational institutions could leverage this understanding within a broad teaching and learning environment (Lee, 2014; Sek et al., 2015a). This shows that the development of an appropriate framework for adequately evaluating learners’ acceptance of OLMs during pre-adoption is desirable.

1.3 Research Objectives and Research Questions

The objective of this research is to investigate learners’ attitudes and perceptions towards the adoption of OLMs in Malaysian higher education. Specifically, the research aims to (a) investigate the current adoption of OLMs in Malaysian higher education, (b) identify the critical factors for the adoption of OLMs in Malaysian higher education, (c) explore the relationship between learning styles of learners and their attitudes towards the acceptance of OLMs in collaborative learning, and (d) examine the gender difference in attitudes towards the acceptance of OLMs.

To achieve these research objectives, the main research question for this study is formulated as follows:

How can the adoption of OLMs be improved in Malaysian higher education?

To answer this main research question, several subsidiary questions are developed as follows:

a) What are the current patterns and trends of the adoption of OLMs in Malaysian higher education?
b) What are the critical factors that influence the adoption of OLMs in Malaysian higher education?

c) What is the relationship between learning styles of learners and their attitudes towards the acceptance of OLMs in collaborative learning?

d) Are there any differences in attitudes between learners with different learning styles towards the acceptance of OLMs in collaborative learning?

e) What is the relationship between genders and attitudes towards the acceptance of OLMs in collaborative learning?

f) Are there any differences in attitudes between male and female learners towards the acceptance of OLMs in collaborative learning?

1.4 Research Methodology

The primary objective of this research is to investigate learners’ attitudes and perceptions towards the adoption of OLMs in Malaysian higher education. To fulfil the objective of this study, a quantitative research methodology is employed (Creswell, 2009). Such a quantitative methodology is used for evaluating specific hypotheses in order to answer specific research questions (Neuman, 2006; Creswell and Plano Clark, 2011). In particular, a quantitative methodology is useful for investigating how well-defined hypotheses are supported by numeric data representing the viewpoints of a population (Creswell and Plano Clark, 2011).

A quantitative research methodology is appropriate for meeting the objectives of this study due to two reasons. Firstly, the result obtained from the use of a quantitative methodology can be generalized to a large population (Creswell, 2009). The data collected through the use of a quantitative methodology can be used for drawing
strong inferences after undergoing statistical analysis. Secondly, a quantitative methodology allows the researcher to examine the relationship between various variables. The data can be used to look for cause and effect relationships. This can be used to make predictions of the adoption of OLMs in collaborative learning.

As indicated in Figure 1.1, this research follows seven stages to achieve the objective of the study using a quantitative methodology. The research begins with the formulation of the research objectives and the research questions in the first stage. During the second stage, the related literature is reviewed, leading to a better understanding of OLMs in facilitating collaborative learning. Such an understanding leads to the third stage of the research which focuses on the development of a conceptual framework for investigating the critical factor for the adoption of OLMs. This stage focuses on the development of several hypotheses based on the relationships between the theoretical constructs of the conceptual framework. In the fourth stage, two research instruments which include a questionnaire and OLMs scenario-based web-mediated prototype are developed to facilitate the collection of data. The fifth stage focuses on the collection of data from undergraduate students in the Malaysian higher education institutions using the developed research instruments.

In the sixth stage, various data analysis techniques are employed to address the research questions in this study including (a) chi-square test for independence for examining whether learners’ attitudes with respect to learners’ web-based learning experience, learners’ computer and web literacy, learners’ learning styles, and
leaners’ gender towards the adoption of OLMs are independent of each other, (b) correlation analysis for examining the strength and the direction of the relationship between learners’ attitudes and computer and web literacy, and between learners’ attitudes and web-based learning experiences, (c) structural equation modelling (SEM) techniques for validating the proposed conceptual framework, (d) one-way analysis of variances for examining whether there are differences in attitudes between learners with different learning styles towards the acceptance of OLMs in collaborative learning, and (e) independent t-test for determining whether there is a difference in attitudes between males and females towards the adoption of OLMs. Finally, in the seventh stage, the results of the data analysis are interpreted to draw specific conclusions that adequately answer the research questions.

**Figure 1.1  The Research Process**
1.5 Outline of the Thesis

Figure 1.2 presents an overview of the organization of this thesis. Chapter 1 introduces the study with a specific focus on the background and motivation of the research, the research objectives, the research question, and the research methodology. This chapter paves the way for the presentation of the whole thesis.

Chapter 2 provides a comprehensive review of the literature related to the development of TBCL in Malaysia, existing research in OLMs, the process of adopting collaborative technologies, and individual differences such as learning styles and genders towards the adoption of collaborative technologies. Such a review justifies the need for this study by pinpointing the shortcomings of existing research.

Chapter 3 develops a conceptual framework for evaluating the critical factors for the adoption of OLMs. The conceptual framework is grounded in the technology acceptance theory. Such a conceptual framework serves as a foundation for developing a specific hypothesis in this study to adequately answer the research questions in the study. It paves the way for the development of the research instrument required to test and validate the proposed conceptual framework.

Chapter 4 describes the research methodology in this study. This chapter presents an overview of the different approaches in this research. Chapter four explains how this research is designed to meet its objectives using the selected research approach. It explains the development of the research instrument, the data collection process, the
steps taken to enhance the reliability and the validity of the research instrument, and
the implementation of the data analysis process. Discussion in this section also
encompasses the actual implementation of the research methodology.

**Figure 1.2  An Overview of the Thesis**

**Chapter 5** provides the results of the survey in regards to the current patterns and
trends of the adoption of OLMs in Malaysian higher education. This chapter
highlights the emerging patterns and trends of the adoption of OLMs that facilitate collaborative learning in Malaysian higher education using a systematic analysis of the survey results consisting of the demographic analysis, pattern analysis, the chi-square test for independence, and correlation analysis.

Chapter 6 presents the results from the survey that pinpoints the critical factors for the adoption of OLMs in Malaysian higher education. It explains the process of SEM that is followed in this research to test and validate the conceptual framework. The chapter begins with an overview of the data analysis procedures carried out in this research, followed by details on the preparation of raw quantitative data for SEM analysis. The chapter then reveals techniques on the analysis of data with the use of confirmatory factor analysis and SEM.

Chapter 7 presents the results of the individual differences in the adoption of OLMs in collaborative learning. Various statistical methods including the chi-square test for independence, the t-test, and the one-way analysis of variance further assist in understanding the individual differences in learning styles of learners and genders in the adoption of OLMs.

Chapter 8 provides the conclusion for this study. It revisits the research question to confirm research accomplishment. The chapter presents a summary of the research findings and the contribution of the research and discusses the limitations of the research. It also highlights suggestions for further research.
Chapter 2

Literature Review

2.1 Introduction

TBCL has become an important educational approach for improving learners’ collaboration in collaborative learning (Sridharan et al., 2009; Hu and Hui, 2012). With the significant benefits that TBCL promises including developing learners’ interaction skills, establishing an environment of cooperation and collaboration, developing higher level thinking skills, enhancing self-management skills, and encouraging learners to exchange their learning information (Pituch and Lee, 2006), a tremendous amount of investment has been made worldwide in implementing various collaborative technologies to facilitate collaborative learning.

Malaysia is no exception to the global trend of rapidly introducing TBCL. In an effort to transform Malaysia from a production-based economy to a knowledge-based economy, the Malaysian government has invested millions of dollars to introduce collaborative technologies in its higher education. Various initiatives have been taken including the introduction of the Malaysia Education Blueprint 2013-2025 to further enhance the implementation of collaborative technologies for improving the effectiveness of TBCL (Malaysia Education Blueprint, 2013). In recognizing the importance of using collaboration technologies to facilitate
collaborative learning, universities in Malaysia have started to introduce OLMs in teaching and learning.

An OLM is a collaborative learning tool for representing a learner’s current level of knowledge and their misconceptions in a specific subject (Bull, 2004). It is becoming increasingly popular in TBCL (Bull and Kay, 2010). The introduction of OLMs in TBCL allows students to create a collaborative learning environment in which they can share learning resources, compare with each other’s work, and more importantly self-reflect and self-regulate on their learning (Bull and Kay, 2010).

Despite the usefulness of an OLM for improving the effectiveness of teaching and learning, the utilization of OLMs is not encouraging (Bull, 2004; Chen et al., 2007). Individuals’ decisions to adopt these models and their continuance of the intention are often influenced by various technological and individual differences and contextual factors (Sabherwal et al., 2006; Sun and Jeyaraj, 2013; Li, 2015; Sek et al., 2015a; Zhan et al., 2015). Existing studies try to address this issue mainly from the technical perspective through developing new modes of interactions between OLMs and learners (Bull and Kay, 2010) and employing different knowledge representation formats (Hochmeister et al., 2012). Few studies, however, have empirically investigated learners’ attitudes and perceptions towards the acceptance of OLMs from the perspective of learners (Sek et al., 2014b; Sek et al., 2015a).

The objective of this Chapter is to identify the research gaps in the adoption of OLMs in Malaysian higher education for justifying the need for conducting this
study by reviewing the related literature. To achieve this objective, the rest of the Chapter is organized as follows. Section 2.2 presents an overview of TBCL in Malaysia. Section 2.3 provides a comprehensive overview of OLMs, followed by the discussion of the technology adoption in Section 2.4. Section 2.5 investigates the relationship between learning styles of learners and attitudes towards the adoption of TBCL. Section 2.6 discusses the gender difference in attitudes towards the adoption of TBCL. Section 2.7 draws a conclusion for this Chapter.

2.2 An Overview of TBCL in Malaysia

TBCL is commonly referred to an environment in which learners’ interactions with instructional materials, instructors and peers are supported through the use of collaboration technologies (Hu and Hui, 2012; Balakrishnan, 2015). The integration of collaborative technologies in collaborative learning has a pivotal impact on the learner’s academic performance (Pituch and Lee, 2006). In recognizing the potential benefits of collaborative technologies in facilitating collaborative learning, the Malaysian government has introduced the Malaysia Education Blueprint 2013 – 2025 (Malaysia Education Blueprint, 2013).

Under the Malaysia Education Blueprint 2013 – 2025, three waves with different focuses are implemented from 2013 to 2025. The first wave is from 2013 to 2015. It focuses on ensuring that the basic ICT infrastructure is in place for the TBCL implementation. The main priorities include (a) ensuring that learners have sufficient access to ICT in collaborative learning, (b) providing the education system with a
learning platform and sufficient network bandwidth to use ICT services in collaborative learning, and (c) ensuring that academicians have basic competencies in ICT to facilitate collaborative learning. To achieve the objective in the implementation of the first wave, five focuses are put in place including (a) improving ICT network infrastructure, (b) delivering more collaborative technologies devices, (c) ensuring that academicians are well-trained for adopting collaborative technologies, (d) shifting towards more user-friendly contents to encourage learners’ participation in collaborative learning, and (e) integrating all data management for educational institutions and the ministry to facilitate collaboration among these institutions (Malaysia Education Blueprint, 2013).

The second wave is from 2015 to 2020. It concentrates on the introduction of collaborative technologies for collaborative learning. The potential collaborative technological solutions for facilitating collaborative learning are explored. This includes scaling up the best practices from all areas of excellence and innovation identified in the wave one.

The third wave is from 2021 to 2025. It focuses on the full implementation of collaborative technologies in collaborative learning. The third wave expects to fully embed collaborative technologies throughout the curriculum of the Malaysian education system. Various collaborative technologies would be introduced to improve learners’ collaboration in collaborative learning.
There is much research in the literature on the investigation of the adoption of collaborative technologies in the Malaysian higher education (Poon et al., 2004; Raman, Ryan, and Olfman, 2005; Matcha and Rambli, 2011; Omar, Embi, and Yunus, 2012; Al-rahmi et al., 2015; Balakrishnan, 2015). Poon et al. (2004), for example, propose a conceptual framework for measuring the acceptance of web-based collaborative technologies in Malaysian higher education while considering academicians’ characteristics, learners’ characteristics, interactivity, system characteristics, and institutional factors. The one-way analysis of variance is employed for analysing the influence of these factors in the adoption of web-based collaborative tools. The result reveals that all five factors have an impact on the adoption of web-based collaborative tools. Learners’ performances are highly correlated with learners’ positive attitudes in the adoption of web-based collaborative technologies. Learners are more willing to engage in a web-based collaborative learning environment if the learning contents are adapted for different learners.

Baleghi-Zadeh et al. (2014) develop a conceptual framework based on the task-technology fit model for examining learners’ adoption of collaborative learning management technologies. SEM is used to analysis the data collected from the survey. The finding indicates that the internet experience and the subject norm positively influence learners’ adoption of collaborative learning management technologies. This suggests that learners who have sufficient internet experiences are willing to adopt collaborative learning management technologies in collaborative learning.
Raman et al. (2005) propose a conceptual framework with respect to careful planning for implementation, familiarity with wiki technology, and motivation for evaluating learners’ adoption of the wiki for collaborative learning. Thematic analysis is performed on the data collected from the interview. The result indicates that the successful implementation of wiki-based collaborative learning mainly depends on learners’ familiarity with the wiki technology and careful planning for the wiki implementation and use. This suggests that the wiki technology can support collaborative knowledge creation and share learning information in an academic environment when learners are familiar with the wiki technology.

Al-rahmi et al. (2015) develop an assessment model based on the perceived usefulness, perceived ease of use, and engagement for examining learners’ adoption of social media in collaborative learning. The finding shows that the engagement, the perceived ease of use, and the perceived usefulness have a positive impact on learners’ intention to use social media in learning. Learners would have more motivation to engage in a social media based learning environment if the perceived usefulness and perceived ease of use of the social media tools are further enhanced.

Balakrishnan (2015) develop a conceptual framework to assess learners’ adoption of online computer supported collaborative technologies based on learners’ prior experience in using collaborative technologies, learners’ attitudes, and learners’ learning styles. The result indicates that learners’ prior experience in using collaborative technologies and learners’ attitudes have positively influence learners’ adoption of online computer supported collaborative technologies. The learners’
learning style does not have an impact on learners’ adoption of online computer supported collaborative technologies.

Many studies related to the adoption of collaborative technologies in higher education in Malaysia have been conducted as discussed above. A majority of these studies focus on the learning management system, web-based collaborative learning, social media, Wiki technology, and Facebook. There are, however, very limited studies that have been conducted on the adoption of OLMs from the perspective of learners in Malaysian higher education.

The evaluation of the learners’ attitudes and perceptions towards the acceptance of OLMs is necessary and important. This is because the development of OLMs in Malaysian higher education is still in its infancy stage. The investigation of learners’ acceptance of OLMs from the perspective of learners would provide a better understanding of the factors that influence learners’ adoption of OLMs for collaborative learning. Such an investigation not only helps the fulfilment of the second wave implementation of the Malaysia Education Blueprint 2013 - 2020. It also provides aid for educational institutions in implementing OLMs for collaborative learning.

2.3 An Overview of OLMs

A learner model refers to the model constructed from the observation of interaction between a learner and a learning system (Bull and Kay, 2010; Tashiro et al., 2016). A
learner model contains knowledge about a learner’s current level of understanding in a specific subject domain (Woolf, 2008; Tashiro et al., 2016). It maintains the record of a learner’s information including factual and historical data. This model shows the information about the current knowledge level of the learner, updated information related to their knowledge level and their misconceptions about the domain knowledge. This information is important because it can be used by an intelligent tutorial system to provide suitable learning materials to the learner (Tashiro et al., 2016). In the conventional intelligent tutoring system, the learner model is normally hidden from the learner.

There are various learner models that have been developed from different perspectives for improving the effectiveness of teaching and learning in the literature. The overlay model, for example, is the most popular learner model being used in learner modeling (Gaudioso et al., 2012). With the use of this model, the knowledge of a learner is seen as a subset of the experts’ knowledge. The drawback of this model is that it has the possibility of not representing the partial knowledge of a learner. It cannot predict what a learner knows based on the partial knowledge.

The perturbation model is an extension of the overlay model that represents a learner’s knowledge including possible misconceptions as well as a subset of the expert’s knowledge (Mayo, 2001). This model provides a more effective diagnosis than the overlay model does (Baschera and Gross, 2010). It, however, requires more resources to maintain the information about the incorrect concepts on the learner’s knowledge. The perturbation model adopts various types of formats to represent
learners’ knowledge including genetics graphs, Bayesian networks, and constraint-based models. The genetics graph is a type of semantic networks for representing rules and facts. The Bayesian network is a probabilistic graphical model that employs probability values to represent learners’ knowledge. The constraint-based model employs a partition method to represent learners’ knowledge about a domain.

The use of sophisticated techniques such as the overlay model (Gaudioso et al., 2012) and the perturbation model (Baschera and Gross, 2010) in the learner model representation can improve the accuracy of representing a learner’s information in learning. Such a practice, however, increases the complexity of learner modeling. To adequately address the issue of inaccuracy in the learner model representation, OLMs have been introduced (Self, 1990).

OLMs are a computer-based representation of a learner’s current understanding level relating to the concept known, specific knowledge, and their misconceptions in a specific subject area. They are inspectable by learners and peers, instructors, teachers, and even parents (Bull and Kay, 2005). The direct involvement of learners in engaging with the development of their learner models significantly contribute to the building of a comprehensive and accurate learner models. This produces numerous benefits for teaching and learning. For example, the adoption of OLMs can increase the awareness of learners’ knowledge and understanding in a specific domain. This increased awareness can assist with the development of meta-cognitive skills such as self-assessment and self-regulation and encourage learners’ autonomy with increased responsibilities for their learning processes (Mitrovic and Martin,
The use of OLMs can increase a learner’s engagement in the learning process and provide them with better motivation (Bull, 2004; Mitrovic and Martin, 2007). Furthermore, the adoption of OLMs promotes a learner’s reflective learning, which is critical for improving the effectiveness and efficiency of learning in the teaching and learning process (Bull and Pain, 1995; Dimitrova et al., 2000).

To increase the utilization of OLMs for collaborative learning, various approaches such as employing different representations of the same data and introducing different modes of interactions are proposed. Learners can have different presentations of information with different levels of focus (Van Labeke et al., 2007). There are a variety of representations commonly used in OLMs which range from simple textual descriptions (Mohanarajah et al., 2005) to complex three-dimensional network structures (Zapata-Rivera and Greer, 2004). Bull and Mabbott (2006), for example, propose five simple representation formats which include skill meters, graph, boxes, table and text for improving learners’ engagement with their OLMs application OLMlets. Xu and Bull (2010) introduce four different formats including example, index, function, and skill meter for encouraging learners’ participation in OLMs. Pérez-Marín (2007) suggests four representations formats including concept map, bar graph, table, and text summary for increasing the adoption of OLMs.

The above studies illustrate the variety of presentations used in OLMs to encourage learners’ engagement with OLMs in collaborative learning. These studies, however, do not encourage learners to have a direct interaction with the OLM. A further review of the literature on the adoption of OLMs suggests that learners’ engagement
with OLMs can be improved by allowing various types of interactions between learners and their learner models (Bull et al., 2005).

The availability of the different interaction modes between OLMs and learners can improve the adoption of OLMs in collaborative learning (Bull and Kay, 2010). Bull and McKay (2004), for example, introduce inspectable features in OLMs to allow learners to view the learner model to help the learner to identify the amount of knowledge possessed, the possibility of knowledge gaps and misconceptions. In addition, an inspectable OLM can help in raising learners’ awareness on their knowledge, prompting reflection, planning and formative assessment.

Bull and McEvoy (2003) integrate an editable function to allow learners to interact with their OLMs by modifying the content of the learner model. Learners are entirely responsible for their learner models and can directly update their learner models as soon as their knowledge changes. This feature allows learners to update their models manually by directly editing the percentage of knowledge acquired, deleting the list of problematic topics and misconceptions. The learner can proceed with the edit if the learning information represented on the OLM contraries to their belief.

Mabbott and Bull (2006) propose a persuasion method to improve learners’ engagement with OLMs. The persuasion type of interaction in OLMs provides an opportunity for learners to initiate the interaction between the learner and the model. Learners are allowed to change their learner models by showing to the system that their assessments of their skills are accurate. Reaffirmation of a learner’s knowledge
requires a learner to be evaluated by the system using a series of test questions. The demerit of this type of interaction is that the system has the full control to make the final decision about the learner’s knowledge. Such control would reduce the accuracy of a learner model in modeling the learner’s knowledge level.

Kerly et al. (2008) introduce a direct negotiation method to increase learners’ interaction with OLMs. The negotiation type of interaction in OLMs lets learners participate in a discussion with the system in an attempt to reach an agreement on the learner model’s content. The merit of this interaction is that the system allows a shared control over the learner’s beliefs and the system’s beliefs. Both parties are allowed to maintain their beliefs in the system (Bull and Pain, 1995). To allow the system to facilitate the interaction between a learner and the learner’s model, the system needs to maintain two distinct records of the learner’s and the system’s beliefs about the learner’s knowledge (Kerly et al., 2008). This can create potential conflicts between the learner and the system in viewing the learner’s model.

The majority of the literature and applications related to OLMs as discussed above have focused primarily on the technical issues such as the presentation format (Hochmeister et al., 2012) and the type of interactions (Bull and Kay, 2010). These studies show that learners’ engagement with OLMs can be affected by the presentation format and the type of interactions. There are, however, very limited studies that have been conducted in investigating learners’ attitudes and perceptions towards the adoption of OLMs from the perspective of learners (Sek et al., 2015a)
2.4 Collaborative Technology Adoption

Individual learners’ adoption of collaborative technologies involves a series of decisions and actions that reflect the different cognitive states that individuals move through when adopting a specific collaborative technology (Rogers, 1995; Karunasena et al., 2012; Sorgenfreii et al., 2014; Sek et al., 2015a). In the technology adoption process, individuals update, confirm, and change their initial decisions to accept or not to accept the technology. Overall there are three stages in collaborative technologies adoption including pre-adoption, adoption and post-adoption (Hameed et al., 2012; Sek et al., 2015a).

In the pre-adoption, individuals gain initial knowledge about a collaborative technology. Favourable or unfavourable attitudes would be formed towards the collaborative technology on which an adoption decision is to be made (Rogers, 1995; Sorgenfreii et al., 2014; Sek et al., 2015a). In the adoption process, individuals make a decision to accept or reject the collaborative technology based on the initial perception towards the adoption of the collaborative technology (Rogers, 1995; Sorgenfreii et al., 2014; Sek et al., 2015a). In the post-adoption, individuals seek confirmation for their initial decisions and may either reverse their adoption decision or continue to derive the benefits from the use of the collaborative technology (Rogers, 1995; Sorgenfreii et al., 2014; Sek et al., 2015a). Figure 2.1 show the stages of the collaborative technology adoption.
Individuals’ initial perception of a collaborative technology in the pre-adoption is important for the acceptance of the collaborative technology (Hameed et al., 2012; Sun and Jeyaraj, 2013). A poorly managed pre-adoption of a specific collaborative technology may lead to the failure of the implementation of the collaborative technology for collaborative learning in the post-adoption (Yang et al., 2015; Sek et al., 2015a). Courtois et al. (2014), for example, indicate that the critical factors for the adoption of tablets in collaborative learning vary from the pre-adoption stage to the post-adoption stage. Learners’ adoption decisions would be evolving through the phases of pre-adoption and post-adoption. This leads to the unsuccessful implementation of collaborative technologies in collaborative learning.
Chen et al. (2008) examine the critical factors that influence learners’ behavioural intentions towards the use of web-based collaborative technologies in a pre-adoption stage. The results show that there are differences on the critical factors that influence the adoption of web-based collaborative technology between the pre-adoption stage and the post-adoption stage.

Individual beliefs and motivations change over time. As a result, many determinants of the collaborative technology adoption often fail to predict the use and the performance of the collaborative technology adoption in the post-adoption (Yang et al., 2015; Sek et al., 2015a). This is usually due to the little theoretical understanding of what initially brings potential adopters to adopt specific collaborative technologies and how educational institutions could leverage this understanding for improving the adoption of collaborative technologies in collaborative learning (Tzeng, 2011; Lee, 2014). To increase the learners’ acceptance level, instructional technology designers should identify a wide range of learners’ preferences, intentions, and purpose for using collaborative technologies and should integrate these factors into the development process, preferably at the pre-adoption (Wetzel and Strudler, 2005; Tzeng, 2011; Lee, 2014; Sridharan et al., 2011). This shows that it is crucial to investigate the critical factors that influence learners’ adoption of OLMs at the pre-adoption stage. Such an investigation is able to provide a better understanding of the critical factors that affect learners’ adoption of OLMs before the actual implementation of OLMs in collaborative learning.
2.5 Learning Styles and the Adoption of Collaborative Technologies

A learning style refers to individuals’ characteristics on receiving, processing, evaluating, understanding, and utilizing learning information (Battaglia, 2008). It directly affects how a learner chooses and utilizes collaborative technologies in collaborative learning (Lee et al., 2009). This is because learners have their preferences in engaging with collaborative technologies to acquire learning information (Lee et al., 2009). An understanding of learners’ learning styles in the adoption of collaborative technologies in collaborative learning can provide information on which types of collaborative technologies are suitable to engage with for achieving a better engagement experience (Lee and Sidhu, 2015).

Learners’ learning styles play an important role in the adoption of collaborative technologies (Lee et al., 2009). Taylor (2004), for example, argues that learners’ learning styles have a significant effect on the adoption of knowledge management systems. Li (2015) shows that there is a difference between learners with different learning styles towards the adoption of the Wikis in collaborative learning. Cheng (2014) reveals that some learners would have more advantages on the utilization of collaborative technologies in exchanging information in collaborative learning.

Learners have substantial differences in their sensitivities and abilities to process stimuli. Such differences cause learners to react differently to the stimuli afforded by the different functionalities of individual collaborative technologies. Individual
learners have a tendency to constantly prefer one sensory input such as visual, verbal, or tactile over another when dealing with various collaborative technologies (Lee et al., 2009). Learners’ preferred sensory receivers can be used to determine an individual’s dominant learning style. This dominant learning style describes the most effective manner for learners to receive and learn information using certain modalities or affordances of the collaborative technologies.

Learners with different learning styles would exercise different preferences in their selection of collaborative technologies in collaborative learning. These preferences may be related to matching their preferred sensory dimensions with the affordances of the respective collaborative technologies in collaborative learning. There are various learning styles including visual, aural, read/write, and kinaesthetic (VARK) learning styles that have been proposed for helping the categorization of learners into different learning styles. The VARK model is able to classify learners based on their sensory preference in obtaining learning information. Four sensory modalities of learning have been identified based on the VARK model including visual learners, aural learners, read/write learners, and kinaesthetic learners (Fleming, 2008).

Visual learners learn more effectively and efficiently when learning materials are presented in a visual form (Fleming, 2008). They usually prefer to engage in a collaborative learning environment which equips with electronic media such as a forum, wiki, animation, simulation and videos (El Bachari et al., 2012; Marković et al., 2013). In contrast, auditory learners prefer to work independently with their learning materials presented in an audio and video form (Pamela, 2011). They are
willing to participate in a collaborative learning environment with the help of audio recording and podcast to facilitate the interaction between peers (Fleming, 2008; El Bachari et al., 2012; Marković et al., 2013).

Kinaesthetic learners learn more efficiently through experience by involving the adoption of a hands-on approach to problem-solving. They prefer working in social interaction (Battalio, 2009). They prefer physical movement activities in their learning environments such as experimenting and practicing which involve multisensory experiences. Kinaesthetic learners would feel demotivated if their learning environments only allow them to listen and watch in a class passively. They prefer a collaborative learning environment which can provide an opportunity for them to discuss and exchange information and interact with each other through the use of forum, wiki, weblog, and animation (El Bachari et al., 2012; Marković et al., 2013).

In term of read/write learners, they learn best through written and spoken words. They are more motivated to engage with collaborative technology in collaborative learning where the learning materials are in the form of printed text. Read/write learners would be motivated to engage with the collaborative technologies if they can utilize email, weblog, wiki, instant messaging and e-book for interacting with peers (Fleming, 2008; El Bachari et al., 2012; Marković et al., 2013).

The VARK model focuses on individual learner’s sensory preferences. It uses different sensory receivers including visual, audio, read, and kinaesthetic to determine the dominant learning style of an individual. The VARK model has been
widely applied in many collaborative web-based learning environments for investigating learners’ sensory preferences in receiving, interpreting, and disseminating learning information (Drago and Wagner, 2004; Zapalska and Brozik, 2006; Becker et al., 2007; Peter et al., 2010; Ocepek et al., 2013). Ocepek et al. (2013), for example, use the VARK model to identify learners’ sensory preferences in designing collaborative multimedia learning systems. Peter et al. (2010) employ the VARK model to determine learners’ sensory preferences to enhance the adoption of collaborative e-learning technologies. Becker et al. (2007) adopt the VARK model to classify learners into different categories for accommodating the instructional design in collaborative learning.

An appropriate consideration of learners’ sensory learning styles when introducing collaborative technologies in collaborative learning can improve the adoption of these collaborative technologies (Lee et al., 2009; Huang et al., 2012). This is because different functionalities offered by the collaborative technologies would attract different types of sensory learners to engage with collaborative technologies (Mayer, 2003; Becker, 2007; Akkoynulu and Soylu, 2008; Bolliger and Supanakorn, 2011). For designing a better OLM-based collaborative learning environment, the investigation of the relationship between learners’ sensory learning styles and their attitudes towards the adoption of OLMs is desirable. This is because such an investigation would help instructional technology designers to adopt suitable design strategies for accommodating different types of sensory learners to improve the adoption of OLMs in collaborative learning.
2.6 Gender and the Adoption of Collaborative Technologies

There are some studies about the gender difference in the adoption of collaborative technologies in collaborative learning (Chan et al., 2013; Felnhofer et al., 2014; Zhan et al., 2015). Such studies show that there are gender differences in the adoption of a specific collaboration technology between males and females (Wood and Rhodes, 1992; Shi et al., 2009; Chan et al., 2013). Such a difference is partly because females are more expressive and prefer to engage in social-oriented activities, whereas males tend to be more task-oriented (Wood and Rhodes, 1992; Shi et al., 2009; Felnhofer et al., 2014; Zhan et al., 2015).

The exploration of the impact of the gender difference in learners’ acceptance of collaborative technologies is increasingly becoming important (Huang et al., 2013; Kimbrough et al., 2013). This is because gender differences have a major role to play in determining the successful implementation of collaborative technologies. There are several important attempts at investigating the gender differences towards the acceptance of collaborative technologies in various collaborative learning environments. Huang et al (2013), for example, reveal that females feel more anxious about using Web 2.0 applications than males. Ding et al (2011) point out that females seem to profit more from single-gender collaboration than from mixed-genders in computer-supported collaborative learning. Chan et al (2013) find that females engage more actively than males in online communications. Kimbrough et al (2013) conclude that females adopt computer-mediated communication tools more frequently than males for social interaction and communication. Table 2.1
summarizes the study of the gender differences in the adoption of various collaborative technologies for collaborative learning.

Table 2.1  A Summary of Gender Differences in the Adoption of Collaborative Technologies

<table>
<thead>
<tr>
<th>References</th>
<th>Contexts</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ding et al. (2011)</td>
<td>Computer-supported collaborative learning</td>
<td>Females seem to profit more from single-gender collaboration than from mixed-gender collaboration.</td>
</tr>
<tr>
<td>Fu et al. (2012)</td>
<td>Blogs</td>
<td>Females produced significantly more posts than males did, and they regarded gender difference as a significant factor affecting knowledge sharing.</td>
</tr>
<tr>
<td>Chan et al. (2013)</td>
<td>Online social network collaborative learning</td>
<td>Females engage significantly more actively in online communications.</td>
</tr>
<tr>
<td>Huang et al. (2013)</td>
<td>Collaborative Web 2.0 applications</td>
<td>Males and females perceived Web 2.0 application differently when considering them for learning tasks. Overall females felt more anxious about using Web 2.0 applications than males.</td>
</tr>
<tr>
<td>Kimbrough et al. (2013)</td>
<td>Computer -mediated communication</td>
<td>Females are more frequent computer-mediated-communication users than males. Females prefer to use technologies more frequently than males for social interaction and communication such as text messaging, social media, and online video calls.</td>
</tr>
<tr>
<td>Felnhofer et al. (2014)</td>
<td>Collaborative virtual environments</td>
<td>Males experience more spatial presence, involvement and a higher sense of being than females.</td>
</tr>
<tr>
<td>Zhan et al. (2015)</td>
<td>Online learning community</td>
<td>Females in this study experienced significantly greater satisfaction than the male. Females would achieve better individual learning outcomes than males.</td>
</tr>
</tbody>
</table>

The studies as discussed above, however, show inconsistent findings on the impact of the gender differences in the adoption of collaborative technologies. These studies show that the willingness of males and females in adopting collaborative technologies is influenced by the features and functionalities of collaboration technologies (Huang et al., 2013; Sek et al., 2015a). Various collaborative technologies have their own characteristics. As a result, the effect of gender on the adoption of different collaborative technologies would be different (Brown et al.,
2010; Huang et al., 2013; Sun and Jeyaraj, 2013; Sek et al., 2015a). The impact of gender on the adoption of OLMs is still unclear. An investigation of the impact of the gender differences in the adoption of OLMs is important because appropriate assistance can be provided to learners in a more targeted manner.

2.7 Concluding Remarks

This chapter reviews the related literature on the development of TBCL in Malaysian higher education for better understanding the adoption of collaborative technologies in collaborative learning. Such a review highlights the need to explore the adoption of OLMs from the learners’ perspective. The review of the importance of pre-adoption stage in the adoption of collaborative technologies demonstrates the importance of investigating learners’ adoption of OLMs at the pre-adoption stage. The review of the existing studies on learning styles of learners and the adoption of collaborative technologies highlights the importance of considering learners’ learning styles in improving the adoption of OLMs. The review of the gender and the adoption of collaborative technologies highlights the importance of considering the gender difference in the adoption of OLMs in collaborative learning.
Chapter 3

A Conceptual Framework

3.1 Introduction

A theory is a set of interrelated concepts for predicting, explaining or understanding specific phenomena such as relationships, events, or behaviours (Popper, 2002). The main purpose of using a theory in a study is to help (a) describe the phenomenon of interest and their relationships, (b) explain how, why and when the phenomenon happens, (c) predict what will happen in the future, and (d) provide a basic foundation for intervention and operations (Gregor, 2006).

A conceptual framework shows how one makes logical sense of the relationships among the critical factors identified as important to the problem (Sekaran, 2013). It can hold or support a theory of a study. The development of a conceptual framework helps to hypothesize and empirically test certain relationships for producing specific outcomes to the phenomenon under the investigation (Zikmund, 2003). A sound conceptual framework in this study is critical for facilitating the identification of the critical factors in the adoption of OLMs in Malaysian higher education, thus providing the foundation for guiding the development of the questionnaire for answering the research question in the study.
The objective of this chapter is to select an appropriate theory for guiding the development of a conceptual framework for investigating the critical factors that influence the adoption of OLMs in Malaysian higher education. Within the conceptual framework, the individual factors that may influence the adoption of OLMs in Malaysian higher education are hypothesized to be tested.

The content in this chapter is organized into five sections. Section 3.2 presents a review of the existing theories for the adoption of technologies, leading to the identification of the TAM as the appropriate theory for this research study. Section 3.3 discusses the critical factors for the adoption of OLMs grounded in a TAM based framework. Section 3.4 ends the chapter with some concluding remarks.

### 3.2 Theoretical Foundations

There are several prominent theories available for facilitating the investigation of technology adoption from various perspectives (Sabherwal et al., 2006; Jeyaraj et al., 2006). These theories include (a) the theory of diffusion of innovations (DOI), (b) the social cognitive theory (SCT), (c) the motivational theory, (d) the theory of reasoned action (TRA) (Fishbein and Ajzen, 1975), (e) the theory of planned behavior (TPB) (Ajzen, 1985, 1991), and (f) the TAM (Davis, 1989). They have been developed to understand the behavior of individuals in the adoption of a specific technology. Each of these theories has its specific characteristics in explaining the adoption of an individual technology (Jeyaraj et al., 2006).
Table 3.1 provides a summary of existing theories on technology adoption. To pave the way for the selection of an appropriate theory as the foundation for guiding the development of a conceptual framework in this study, these theories are discussed in details in the following.

**Table 3.1 An Overview of the Theories in Technology Adoption**

<table>
<thead>
<tr>
<th>Theory</th>
<th>Focus of the Theory</th>
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<tbody>
<tr>
<td>DOI</td>
<td>Focus on the technology characteristics in the adoption of technology</td>
</tr>
<tr>
<td>SCT</td>
<td>Focus on the concept of social learning and self-efficacy in the adoption of technology</td>
</tr>
<tr>
<td>Motivational theory</td>
<td>Focus on intrinsic and extrinsic motivations in predicting the adoption of technology</td>
</tr>
<tr>
<td>TRA</td>
<td>Focus on the attitude, subjective norm, and intention of an individual in the adoption of technology</td>
</tr>
<tr>
<td>TPB</td>
<td>Emphasis on the perceived behavioral control, attitude, subjective norm, and intention of an individual in the adoption of technology</td>
</tr>
<tr>
<td>TAM</td>
<td>Concentrate on the perceived usefulness and perceived ease of use in predicting the adoption of technology</td>
</tr>
</tbody>
</table>

DOI is a dominant theory for explaining how, why, and at what rate the technology is adopted by an individual (Rogers, 2003). It contributes to the understanding of the adoption of technology from two perspectives, namely, (a) the technology adoption decision process and (b) a set of critical factors for the adoption of technology. There are five stages in the technology adoption decision process including (a) the knowledge stage, (b) the persuasion stages, (c) the decision stage, (d) the implementation stage, and (e) the confirmation stage. In the knowledge stage, an individual gain the initial understanding of the technology. In the persuasion stage, an individual actively seeks related information about the technology. In the decision stage, an individual’s adoption decision on to reject or to adopt the technology is reached. In the implementation stage, an individual begins to utilize the technology.
Finally, in the confirmation stage, an individual finalizes his or her decision to continue adopting the technology.

DOI identifies five critical factors that influence the adoption of a technology by an individual, namely, (a) relative advantages, (b) compatibility, (c) complexity, (d) trialability, and (e) observability (Rogers, 1995). The relative advantage refers to the degree to which a technology is seen as better than the product it replaces. The compatibility is about how consistent the technology is with the values, experiences, and needs of the potential adopter. The complexity refers to which the technology is perceived as difficult to understand and use. The trialability relates to the extent to which the technology can be experimented with before a commitment to adopt is made. The observability refers to the extent to which the results of the technology are visible for the potential adopters (Rogers, 1995).

DOI is widely used for explaining the adoption of specific technologies in the past two decades (Tarhini et al., 2015). The advantage of DOI is its capability in providing a strong theoretical foundation for studying the adoption of a technology by proposing (a) a comprehensive framework for understanding the technology adoption by individual, (b) a series of the technology adoption stages by individual, and (c) the critical factors for examining the technology adoption by an individual.

DOI considers the adoption of a technology as driven primarily by the technology characteristics. It tends to ignore the influence of individual factors in the adoption of the technology (MacVaugh and Schiavone, 2010). The use of such theory assumes
that the adoption of a technology is a rationalistic decision with a focus on the improvement of the technical efficiency (Kristian Häggman, 2009). The adoption of a technology, however, may be influenced by the individual difference. The individual difference consists of learners’ technologies learning experiences (Hartley and Bendixen, 2001), computer self-efficacy (Tan and Teo, 2000), and motivation (Rubin, 2002; Park, Lee, and Cheong, 2007).

SCT is a theory for explaining the adoption of a technology with respect to the self-efficacy (Bandura, 1997). The self-efficacy is about an individual’s belief in his or her capability in engaging with a technology (Bandura, 2001). It focuses on understanding how people engage in certain behaviour as a result of interacting with personal and environmental stimuli as shown in Figure 3.1 (Compeau et al., 1999). The environmental stimulus is related to the influence of family and friends. The personal stimulus is about the individual’s cognitive ability (Compeau et al., 1999; Straub, 2009; Tarhini et al., 2015).

![Diagram of the Social Cognitive Theory](image_url)

**Figure 3.1** The Social Cognitive Theory
SCT has been utilized in investigating the adoption of a technology by individuals due to its dynamic nature. It considers individual behaviours to constantly changes (Straub, 2009). SCT emphasizes that the adoption process of a technology involves encouraging individuals to ensure that they have the requisite skills to use a new technology (Straub, 2009). The advantage of SCT for examining the adoption of a technology is that SCT (a) highlights the importance of an individual’s ability to engage with a technology in the adoption of a technology (Tarhini et al., 2015) and (b) pinpoints that an individual’s behaviour towards the adoption of a technology can be improved through the influence of others (Straub, 2009).

SCT emphasizes on the individual’s characteristics for explaining the adoption of a technology. It does not examine the technological characteristic of a technology (Ramayah and Lee, 2012; Chen et al., 2013). The technology characteristic plays an important role in facilitating the adoption of a new technology by an individual. This is because different technologies have their unique characteristics which would affect the adoption of these technologies. For this reason, SCT is not sufficiently enough to explain the adoption of a technology.

The motivation theory is introduced to investigate the adoption of a technology based on an individual’s extrinsic and intrinsic motivations (Davis et al., 1992). The extrinsic motivation refers to an individual’s goal of action being governed by the outcome of an activity. It often comes from external rewards or fears. The external is a tangible recognition of one’s endeavor. The external fear relates to a feeling of anxiety caused by the imminence of the failure. Extrinsic motivators can be used
successfully to boost intrinsic motivations. The intrinsic motivation refers to individual’s perception of pleasure and satisfaction from performing the behavior (Davis et al., 1992). The advantage of motivation theory for investigating the adoption of technology is that motivation theory (a) highlights the importance of the consideration of individual’s intrinsic motivation in the adoption of technology and (b) proposes the inclusion of extrinsic motivation of learners in the adoption of technology (Stafford and Stern, 2002; Vandenbroeck et al., 2008; Yoo et al., 2012).

The motivational theory emphasizes on the individual’s intrinsic and extrinsic motivations for explaining the adoption of a technology. It does not examine the system and design aspects of a technology (Yoo et al., 2012). The system and design aspects play an important role in facilitating the adoption of a technology. This is because different technologies would have different functionalities and designs. The difference in functionalities and designs would influence individual’s adoption decisions. For this reason, the motivation theory is not sufficient to explain the adoption of a technology.

TRA is developed for investigating the relationship between the attitude and the behaviour of an individual in the adoption of a technology (Fishbein and Ajzen, 1975). There are four main components in the TRA framework including the behaviour, the intention, the attitude and the subjective norm. The behavioural intention indicates how much effort that an individual is likely to dedicate for performing such behaviour. The attitude toward behaviours refers to the favourable or unfavourable perception of an individual towards specific behaviours (Werner,
The subjective norm refers to the subjective judgment of an individual with regards to the preference for behaviours from others (Werner, 2004). An individual’s behavioural intention determines his or her actual behaviours. The behavioural intention is in turn determined by individual’s attitudes toward this behaviours and subjective norms in regard to the performance of this behaviour (Fishbein and Ajzen, 1975). Figure 3.2 shows the TRA framework.

![Figure 3.2 The Theory of Reasoned Action](image)

TRA is extensively used in predicting and explaining the behaviour of an individual towards the adoption of technologies. It is, however, criticized for ignoring the ability of an individual in adopting the technology (Grandon et al., 2011). To overcome the weakness of TRA, Azjen (1991) proposes an additional factor called the perceived behavioural control for determining the behavioural of an individual in TPB. The perceived behavioural control is the perception of an individual on how
easily a specific behaviour could be performance (Azjen, 1991). It indirectly influences the behaviour via the intention of an individual in the adoption of technologies. Figure 3.3 shows the TPB model.

![The Theory of Planned Behaviour](image)

**Figure 3.3  The Theory of Planned Behaviour**

Both TRA and TPB have some limitations in predicting the behaviour of an individual in the adoption of technologies (Werner, 2004). The first limitation is that the determinants proposed for predicting the actual behaviour of an individual in the adoption of technologies are not sufficient enough in producing reliable results. There might be other factors that influence the behaviour of an individual in the adoption of specific technologies. Existing research shows that only 40 per cent of the variance of behaviour could be explained using either TRA or TPB (Ajzen, 1991; Werner, 2004). The second limitation is the assumption that human beings are rational and make systematic decisions based on available information. Unconscious
motives are not considered (Werner, 2004). The third limitation is that both TRA and TPB are predictive models that predict the behaviour of an individual based on certain criteria. The individual, however, does not always behave as predicted by these criteria (Werner, 2004; Grandon et al., 2011).

To overcome the limitation of TPB and TRA in predicting the adoption of technologies, TAM is proposed (Davis, 1989). TAM provides a set of measurements scales which are capable of explaining an individual’s adoption behaviors. Two main determinants including the perceive ease of use (PEOU) and the perceived usefulness (PU) are suggested as the critical factors that influence the adoption of a technology by individuals (Davis, 1989). The PEOU defines as the degree to which the person believes that using the particular technology would be free of efforts (Davis, 1989). The PU refers to the degree to which the individual believes that using the particular technology would enhance his or her job performance (Davis, 1989). TAM posits that the intention of an individual in using a technology is jointly influenced by PEOU and PU (Davis, 1989). Figure 3.4 shows the TAM model.

TAM is a well-validated model for explaining and predicting the adoption of a technology by individuals (Venkatesh and Davis, 2000; Mueller and Strohmeier, 2011). The usefulness of TAM in investigating the adoption of a technology by individuals is well demonstrated in the existing research (Adams et al., 1992; Subramanian, 1994; Lau and Woods, 2008; Al-rahmi and Othman, 2013). Adams et al. (1992), for example, employ the TAM framework for examining individual user’s intention to adopt computer applications, leading to the identification of PU, PEOU,
and attitudes as the critical factors for the adoption of these computer applications. Subramanian (1994) applies the TAM framework for exploring individual user’s intention to adopt voice mails and dial-up communication systems for communication, leading to the identification of PEOU and PU as the critical factors for the adoption of these mail communication systems. Lau and Woods (2008) adopt a TAM framework for investigating learners’ intentions to use learning objects in an e-learning environment, leading to the identification of PEOU, PU, and attitude as the determinants of the adoption of learning objects. Al-rahmi and Othman (2013) employ a TAM framework for examining the adoption of social media for collaborative learning, leading to the identification of PU and PEOU as the critical factors for the adoption of social media in facilitating collaborative learning. The above studies indicate that learners’ adoption of a technology would improve if they perceive that the technology is easy to use and useful.

![The Technology Acceptance Model](image)

**Figure 3.4** The Technology Acceptance Model
TAM is widely recognized as a robust and powerful model for predicting the acceptance of technology by individuals (Huang et al., 2012; Terzis et al., 2013; Pai and Yeh, 2013). Two main determinants including the PEOU and the PU in the TAM model, however, are often insufficient to fully explain the relationship inherent in the adoption of a technology (Ma et al., 2005, Padilla-Meléndez et al., 2008; Duan et al., 2012; Cheung and Vogel, 2013). Chen et al. (2002), for example, show that using a generic TAM model might result in inconsistent outcomes due to the lack of possible explanatory constructs in a given context. Legris et al. (2003) reveal that the original TAM model explains only 40 per cent of system use. There are other significant determinants that influence the PEOU and the PU in the adoption of technologies.

To overcome the weaknesses of the original TAM framework in predicting individual learner’s adoption intention of a technology, Davis et al. (1989) suggest that additional external constructs need to be included in the original TAM framework to improve its explanatory power of the user acceptance of a technology. The proposed additional constructs have to align with the technology, users, and the context (Sabherwal et al., 2006; Sun and Jeyaraj, 2013; Abdullah and Ward, 2016). These additional variables need to cover human, technology and design factors (Lucas and Spitler, 2000; Legris et al., 2003; Venkatesh et al., 2003; Jeyaraj et al., 2006; Šumak et al., 2011; Abdullah and Ward, 2016). Different collaborative technologies have their unique characteristics and functionalities. These unique characteristics of collaborative technologies warrant the need of different determinants for a better understanding of the adoption of collaborative technologies (Marangunić and Granić, 2015; Abdullah and Ward, 2016).
There are numerous studies in extending the TAM framework to investigate the adoption of collaborative technologies in collaborative learning from the perspective of individuals, systems, interfaces, and designs. Table 3.2 provides an overview of the employment of the TAM framework by incorporating four dimensions with various critical factors for studying the adoption of collaborative technologies in collaborative learning. Thong et al. (2002), for example, adopt the TAM framework for assessing learners’ adoption of digital libraries for facilitating collaborative learning in Hong Kong higher education institutions. A telephone interview is employed to gather 397 learners’ perceptions of the adoption of digital libraries in collaborative learning. SEM is used for the data analysis, leading to the identification of screen design, navigation, computer self-efficacy, computer experience, system accessibility, and system visibility as the critical factors that impact the adoption of digital libraries in collaborative learning.

Lee (2006) employs the TAM framework for evaluating the adoption of web-based collaborative technologies. The data is collected from 1085 undergraduate students in the universities in Taiwan. The collected data is analysed using SEM, leading to the identification of computer self-efficacy, subjective norms, perceived network externality, and course attribute as the critical factors in the adoption of web-based collaborative technologies in collaborative learning.

Pituch and Lee (2006) adopt the TAM framework for examining the determinants that influence the adoption of collaborative technologies. The study is conducted in a Taiwan University through an online survey with a total of 321 participants. The
collected data is analysed using SEM, leading to the identification of system functionality, system interactivity, system response, self-efficacy, and internet experience as critical to the adoption of collaborative technologies.

Fu et al. (2007) utilize the TAM framework for investigating the adoption of e-collaboration applications in a Taiwanese university using an online survey with 451 students. SEM is used for analysing the impact of these dimensions on learners’ adoption intentions, resulting in the identification of PU, PEOU, enjoyment, pedagogic, and content as the critical factors for adopting e-collaborative application.

Nov and Ye (2008) employ the TAM framework for investigating the adoption of web-based digital libraries for collaborative learning. This study is conducted in the university in United Stated with 170 respondents. The collected data is analysed using regression analysis, leading to the identification of computer self-efficacy, computer anxiety, resistance to change, screen design, and relevance as the critical factors in the adoption of web-based digital libraries for collaborative learning.

Chang and Tung (2008) use the TAM framework for assessing the adoption of collaborative technologies. The data is collected from 212 students in the universities in Taiwan. SEM is adopted for the data analysis leading to the identification of compatibility, perceived usefulness, perceived ease of use, perceived system quality and computer self-efficacy as the critical factors in the adoption of collaborative technologies in collaborative learning.
Wu et al. (2008) utilize the TAM framework for examining the adoption of collaborative technologies. The data is collected from 212 undergraduate students through an online survey in Taiwan. The partial least squares method is applied for the data analysis, leading to the identification of computer self-efficacy, perceived behavioural control, and system functionality as the important factors that influence the adoption of collaborative technologies for collaborative learning.

Cheung and Vogel (2013) employ the TAM framework for investigating the adoption of Google applications in collaborative learning. The data is collected through an online survey distributed in Hong Kong higher education institutions. A total of 136 students participated in this study. SEM is employed for the data analysis leading to the identification of information sharing, perceived resource, compatibility, subject norms, and self-efficacy as the critical factors in the adoption of Google Applications in collaborative learning.

Rani et al. (2014) adopt the TAM framework for evaluating learners’ adoption of learning management system. This study is conducted in Malaysian universities through printed questionnaires distributed to 145 undergraduates. Regression analysis is adopted for the data analysis, leading to the identification of design, security, privacy, and internet connection as the critical factors in the adoption of learning management system for collaborative learning.

Lee et al. (2014) use the TAM framework for evaluating learners’ adoption of web-based learning management system. This study is conducted in Indonesian higher
institutions through online survey with a total of 326 respondents. The collected data is analysed using SEM, leading to the identification of computer self-efficacy, internet self-efficacy, technology accessibility, and learning content as the important determinants of the adoption of web-based learning management system.

Kwon et al. (2014) adopt the TAM framework for assessing the adoption of social networking in facilitating collaborative learning. The data is collected through online social networking services’ forums in eight different nations with a total of 2214 participants participate in this study. The collected data is analysed using SEM, leading to the identification of perceived mobility, security, connectedness, system and service quality, and flow experience as the critical factors that influence the adoption of social networking for collaborative learning.

Cheng (2015) investigates learners’ adoption intention of mobile collaboration technology for collaborative learning by using TAM framework. The investigation is conducted in Taiwan through a survey of 486 mobile users. SEM is adopted for the data analysis, leading to the identification of navigation, convenience, PU, PEOU, and perceived enjoyment as important to the adoption of mobile collaboration technology for collaborative learning.

Tuğba et al. (2016) apply the TAM framework for examining the adoption of mobile education information systems in collaborative learning. The data is obtained from 227 undergraduate management students in Turkey through an online survey. SEM is used for the data analysis leading to the identification of context and trust as the
critical factors that influence the adoption of mobile education information system in facilitating collaborative learning.

The studies above show that the applicability of the TAM framework for investigating the adoption of various collaborative technologies in different collaborative learning environments. OLMs are developed to support collaboration among learners in the collaborative learning environment. The TAM framework suitable for investigating the adoption of various collaborative technologies in a different collaborative learning environment is therefore applicable to study of the adoption of OLMs in collaborative learning.

### 3.3 A Conceptual Framework and Hypotheses

This section presents a conceptual framework for facilitating the investigation of the adoption of OLMs in Malaysian higher education. Five dimensions including individuals, systems, interfaces, designs, and information sharing are included for extending the TAM framework in this study. The proposed five dimensions for investigating the adoption of OLMs focus on the aspects related to the interface design, the system features, as well as the information sharing intention.
### Table 3.2  
A Summary of the Extension of TAM with Various Critical Factors in the Adoption of Collaborative Technologies

<table>
<thead>
<tr>
<th>Study</th>
<th>Applications</th>
<th>Individuals</th>
<th>Systems</th>
<th>Interfaces</th>
<th>Designs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hong et al. (2002)</td>
<td>Digital Library</td>
<td>Computer self-efficacy, computer experience</td>
<td>System accessibility, system visibility</td>
<td>Screen design, navigation</td>
<td>Perceived usefulness, perceived ease of use</td>
</tr>
<tr>
<td>Fu et al. (2007)</td>
<td>E-collaboration Technology</td>
<td>Enjoyment</td>
<td>Functionality, pedagogy</td>
<td>Interface design, content</td>
<td>perceived ease of use</td>
</tr>
<tr>
<td>Chang and Tung (2008)</td>
<td>E-learning collaborative technology</td>
<td>Computer self-efficacy</td>
<td>Compatibility, perceived system quality</td>
<td>Consistency of interface design</td>
<td>Perceived usefulness, perceived ease of use</td>
</tr>
<tr>
<td>Wu et al. (2008)</td>
<td>E-learning System</td>
<td>Computer self-efficacy, perceived behavioral control, social interaction</td>
<td>System functionality</td>
<td>Content feature</td>
<td>perceived ease of use</td>
</tr>
<tr>
<td>Cheung and Vogel (2013)</td>
<td>Google Applications</td>
<td>Self-efficacy, subjective norms</td>
<td>Compatibility</td>
<td>Perceived resource</td>
<td>Perceived usefulness, perceived ease of use</td>
</tr>
<tr>
<td>Rani et al. (2014)</td>
<td>Learning Management System</td>
<td>Enjoyment</td>
<td>Privacy, security, internet connection</td>
<td>Design features</td>
<td>Perceived usefulness, perceived ease of use</td>
</tr>
<tr>
<td>Lee et al. (2014)</td>
<td>E-learning System</td>
<td>Computer self-efficacy, internet self-efficacy</td>
<td>Technology accessibility</td>
<td>Learning content</td>
<td>Perceived usefulness, perceived ease of use</td>
</tr>
<tr>
<td>Kwon et al. (2014)</td>
<td>Social networking services</td>
<td>Flow experience, perceived mobility</td>
<td>System quality, service quality, perceived security</td>
<td>Connectedness</td>
<td>Perceived usefulness</td>
</tr>
<tr>
<td>Tugba et al. (2016)</td>
<td>Mobile Education Information System</td>
<td>Personal initiative, personal characteristics</td>
<td>Trust</td>
<td>context</td>
<td>Perceived usefulness, perceived ease of use</td>
</tr>
</tbody>
</table>
To effectively evaluate learners’ adoption of OLMs, five dimensions consisting of twelve factors have been proposed as shown in Figure 3.5. These five dimensions are individual characteristics, system characteristics, interface characteristics, trust, and information sharing intention. The detailed discussion of the twelve factors for assessing learners’ adoption of OLMs including motivation, computer self-efficacy, online learning experience, system interactivity, system adaptability, screen design, navigation, trust, and information sharing intention, perceived usefulness, perceived ease of use, and attitude is presented in the following.

### 3.3.1 Individual Characteristics

There are always differences existent between individuals in cognitive styles, belief, perceptions, motivation, and learning experience (Chen et al., 2000; Waite et al., 2007). These differences can have an important effect towards the acceptance of OLMs (Sun et al., 2008; Bull and Kay, 2010; Sek et al., 2015a). Learners’ impressions towards the adoption of OLMs determine the successful implementation of these collaborative technologies in teaching and learning processes.

Individual characteristics are critical for the successful implementation of OLMs (Bull and Kay, 2010; Lee, Hsiao, and Purnomo, 2014; Sek et al., 2015a). They play a significant role in determining learners’ adoption of OLMs in collaborative learning (Lee et al., 2009; Bull and Kay, 2010; Sek et al., 2015a). Such characteristics including learners’ motivation (Rubin, 2002; Park et al., 2007), computer self-efficacy (Tan and Teo, 2000), and online learning experience (Hartley and Bendixen, 2001) are included in assessing the adoption of OLMs from the learners’ perspective.
Motivation (MO) refers as a learner’s desire to adopt OLMs in collaborative learning. Individual differences in MO to use OLMs in collaborative learning are found to be the important factor in the successful implementation of OLMs in collaborative learning (Roca and Gagné, 2008; Bull and Kay, 2010; Chen and Tseng, 2012; Sek et al., 2015a). Learners’ motivation to engage with collaborative technologies would increase if they are able to improve their academic performances with the adoption of these collaborative technologies (Chen and Tseng, 2012). Park, Lee, and Cheong (2007), for example, reveal that motivation has a significant positive effect on both the PU and the PEOU in the adoption of collaborative technologies. Learners’ motivation to engage with the OLM would increase if they can improve their academic performance with the adoption of OLMs. Furthermore, learners would have the interest to engage with OLMs if they can use the OLM without difficulties. This discussion leads to the following hypotheses:

**H1a**: MO positively influences the PU in the adoption of OLMs.

**H2a**: MO positively influences the PEOU in the adoption of OLMs.
Figure 3.5 A Conceptual Framework for Evaluating the Adoption of OLMs
Computer Self-Efficacy

Computer self-efficacy (CSE) defines as an individual’s judgment of his or her ability to perform learning tasks with the adoption of OLMs (Pituch and Lee, 2006; Sek et al., 2015a). Learners with adequate levels of CSE are more likely to participate in OLM-based collaborative learning. Conversely, for learners with low levels of CSE, it can be problematic for them to have the interest to engage with OLMs (Sánchez and Hueros, 2010). CSE indicates the confidence of learners in the ability to utilise OLMs which possibly influences the acceptance of OLMs for collaborative learning (Tan and Teo, 2000; Pituch and Lee, 2006). Gong et al. (2004), for example, assert that CSE has a positive effect on PEOU on the adoption of collaborative technology. Wang and Newlin (2002) conclude that students with higher CSE are more willing to adopt technologies in teaching and learning processes for improving their learning performance. Learners’ perceptions on their ability to adopt OLMs in collaborative learning would directly affect their intentions to adopt the OLM. Based on the discussed above, the following hypotheses have been proposed:

H1b: CSE positively influences the PU in the adoption of OLMs.

H2b: CSE positively influences the PEOU in the adoption of OLMs.

Online Learning Experience

Online learning experience (OLE) refers to an individual’s previous web-based collaborative learning experience (Pituch and Lee, 2006; Liu et al., 2010). Individuals who have a previous learning experience in dealing with collaboration technologies in collaborative learning are much more willing to perform learning
tasks with the adoption of OLMs (Hartley and Bendixen, 2001; Song et al., 2004). This means that when learners acquire learning experience with web-based collaboration technologies, their acceptance of OLMs in collaborative learning would increase (Pérez Cereijo, Young, and Wilhelm, 2001). Liu et al. (2010), for example, suggest that previous OLE with collaborative technologies would have a direct impact on both the PU and the PEOU of the collaborative technologies. Song et al. (2004) indicate that learners’ previous OLE in using collaboration technologies would affect the adoption of other new collaboration technologies. Learners’ previous OLE with other collaboration technologies would affect them in the adoption of OLMs in collaborative learning. The above argument leads to the following hypotheses:

\[ H1c: \text{OLE positively influences the PU in the adoption of OLMs.} \]

\[ H2c: \text{OLE positively influences the PEOU in the adoption of OLMs.} \]

### 3.3.2 System Characteristics

System characteristics refer to the interaction between the system and its organizational learning context (Ramayah and Lee, 2012; Chen et al., 2013). It is an important element to be considered for improving learners’ acceptance of collaboration technologies (Pituch and Lee, 2006; Jeong, 2011). Two system characteristics including system adaptability and system interactivity are the main variables which have a significant influence on the PU and the PEOU in the adoption of collaboration technologies (Pituch and Lee, 2006; Martínez-Torres et al., 2008; Tobing et al., 2008; Mueller and Strohmeier, 2011).
**System Adaptability**

System adaptability (SA) refers to the feature of a system that provides adaptation of learning content to the learner based on his or her current levels of knowledge level (Del Puerto Paule Ruiz et al., 2008). The personalisation of learning materials in OLMs-based collaborative learning environments on the learners’ preferences and understanding levels would attract learners’ engagement of OLMs in collaborative learning (Van Velsen et al., 2008). This is because the integration of different learning contents with respect to diverse needs of learners can avoid the cognitive overload. As a result, learners’ intentions to adopt OLMs would increase.

SA is an important system feature that can increase learners’ adoption of collaborative technologies (Zaina et al., 2011). Tobing et al. (2008), for example, point out that SA would positively influence the PU and the PEOU in the adoption of web-based collaborative technologies. Zaina et al. (2011) show that adaptation features available on the collaborative technology would increase learners’ participation in using the collaboration technologies. If learners are able to obtain learning materials based on their current levels of understanding in an OLM-based collaborative learning environment, learners’ willingness to adopt OLMs would increase. This discussion leads to the following hypotheses:

*H3b: SA positively influences the PU in the adoption of OLMs.*

*H4b: SA positively influences the PEOU in the adoption of OLMs.*
System Interactivity

System interactivity (SI) refers to the interactions among peers, instructors or parents in exchanging learning information through OLMs (Johnston, Killion, and Oomen, 2005; Pituch and Lee, 2006). The integration of interaction functionality in OLMs can create opportunities to facilitate learners’ social interaction in the OLM-based collaborative learning environment (Bull and Kay, 2010; Ke et al., 2012). The establishment of positive interactive relationships among peers and instructors not only play an essential role in fostering learners’ positive perceptions of the adoption of OLMs. It also facilitates the creation of comfortable collaborative learning environment (Chen et al., 2013).

SI can have an impact on the acceptance of collaboration technologies. Chen et al. (2013), for example, argue that SI has a direct positive effect on both the PU and the PEOU in the adoption of web-based collaborative technologies. Pituch and Lee (2006) indicate that SI positively influences the PU and the PEOU in the adoption of the collaborative technologies. In a OLM-based collaborative learning environment, if learners are able to interact with their peers and instructors in exchanging opinion, ideas and learning information easily, learners’ willingness to adopt OLMs would improve. This discussion leads to the following hypotheses:

\( H3b: SI \) positively influences the PU in the adoption of OLMs.

\( H4b: SI \) positively influences the PEOU in the adoption of OLMs.
3.3.3 Interface Characteristics

Interface characteristics refer to the feature of a system in providing interactive functionality to facilitate the interaction activities between collaborative technologies and its users in the collaborative learning environment (Liu et al., 2010). A good user interface design of OLMs not only can help learners to operate the OLM more easily. It can help learners to reduce cognitive load as well as encourage active participation of learners in OLM-based collaborative learning environment (Cho et al., 2009). Interface characteristics play an important in encouraging learners’ engagement with OLMs in collaborative learning (Saade and Otrakji, 2007; Bull and Kay, 2010). The quality of interface characteristics significantly contributes to the usability of OLMs (Liu et al., 2010). A good quality in the interface design of OLMs can encourage learners’ participation in adopting OLMs. Conversely, bad interface design can reduce learners’ intentions to adopt OLMs (Hasan and Ahmed, 2007; Cho et al., 2009). Two interface characteristics including screen design and navigation are important for predicting the PU and the PEOU of the adoption of OLMs in collaborative learning (Lindgaard, 1994; Sek et al., 2015a).

Screen Design

Screen design (SD) is the visual appearance of OLMs’ interface (Lim et al., 1996; Hasan and Ahmed, 2007; Sek et al., 2015a). It can help to improve the interaction between learners and OLMs in collaborative learning. A good menu design which allows learners to access their learning information easily by using the available functions on the OLMs would increase the PU of the OLM (Liu et al., 2010). Furthermore, a well-organised and carefully designed screen of OLMs can help
learners scan and identify relevant learning information more easily. A simple and flexible user interface not only can reduce learners’ cognitive loads, but it also can improve the acceptance of the OLM (Lim et al., 1996; Sek et al., 2015a). Liu et al. (2010), for example, show that user interface design and features would affect learners’ PU and PEOU of the collaborative technology. Cho, Cheng and Lai (2009), reveal that a good screen design of collaborative technologies would enhance learners’ acceptance of collaborative technologies. Learners’ engagement with OLMs would increase if the screen design of OLMs is able to attract learners’ attention to participate in OLM-based collaborative learning. The above argument leads to the following hypotheses:

**H5a**: SD positively influences the PU in the adoption of OLMs.

**H6a**: SD positively influences the PEOU in the adoption of OLMs.

**Navigation**

Navigation (NA) refers to the way of learners discovering the location of relevant learning information within OLMs (Lindgaard, 1994). It offers the learner to access all the relevant learning information more easily as well as the ability to move around within the OLM (Jeong, 2011; Sek et al., 2015a). The inappropriate design of NA can impede learners from adopting the OLM (Bull and Kay, 2010; Cheng, 2015). This is because learners can easily become lost when they are required to have a heavy cognitive load in obtaining the relevant learning information in OLMs. A good design of NA in the OLM would increase learners’ acceptance of OLMs in collaborative learning (Webster and Ahuja, 2006; Bull and Kay, 2010; Sek et al., 2015a). Jeong (2011), for example, postulate that NA would directly affect learners’
PU and PEOU of the collaborative technology. Cheng (2015) demonstrates that NA has a positive influence on the PU and the PEOU in the adoption of mobile collaborative learning environment. Learners’ motivation to adopt OLMs for collaborative learning would increase if they can have a good design of NA in OLMs. Based on the above argument, the following hypotheses are proposed:

\[ H5b: \text{NA positively influences the PU in the adoption of OLMs.} \]

\[ H6b: \text{NA positively influences the PEOU in the adoption of OLMs.} \]

### 3.3.4 Design Characteristics

Design characteristics focus on the design issues of the collaborative technologies which are related to the easiness and the usefulness of adopting collaborative technologies. Design characteristics are important to the enhancement of the design of users’ interface. A good design users’ interface would significantly influence the adoption of collaborative technologies (Jeong, 2011). This is because learners would be motivated to engage with the collaborative technology if they can use the collaborative technology with minimum cognitive load. Furthermore, learners’ engagement with collaborative technology would further enhance if they can obtain benefits from adopting the collaborative technology. Design characteristics comprising of PEOU and PU are considered as important factors in influencing the adoption of collaborative technologies (Sun et al., 2008).
Perceived Ease of Use

PEOU is the degree to which an individual learner believes that the use of OLMs would be free of effort (Davis, 1989; Padilla-Meléndez, Garrido-Moreno, and Del Aguila-Obra, 2008; Huang, 2015; Sek et al., 2015a). The improvement of PEOU of OLMs can enhance learners’ active participation in OLM-based collaborative learning environment (Hung and Cheng, 2013; Sek et al., 2015a). When learners can easily engage with the OLM, their motivation to continue using OLMs would increase. Learners’ PEOU of the OLM would directly influence their acceptance of OLMs for collaborative learning. Padilla-Meléndez, Garrido-Moreno, and Del Aguila-Obra (2008), reveal that the PEOU has a direct positive effect on the PU of the collaborative technology. Huang (2015) suggests that learners’ PEOU of collaborative technology would directly influence their PU of the collaborative technology. Learners’ PEOU of OLMs would directly impact their PU of OLMs in the adoption of OLMs for collaborative learning. Based on the above argument, the following hypothesis is proposed:

H7: PEOU positively influences the PU in the adoption of OLMs.

PEOU also has an effect on learners’ information sharing intentions in OLM-based collaborative learning (Hung and Cheng, 2013; Sek et al., 2015a). Learners are willing to share their learning information in OLM-based collaborative learning environment if they can use the OLM without difficulties (Su et al., 2010; Cheung and Vogel, 2013; Sek et al., 2015a). Cheung and Vogel (2013), for example, reveal that the PEOU has a significant positive impact on the learners’ willingness to share their learning information. Learners’ willingness to share their learning information
would increase in an OLM-based collaborative learning environment if the learners can adopt OLMs without difficulties. Thus, the following hypothesis is presented.

\[ H8: \text{PEOU positively influences the information sharing intention of learners in the adoption of OLMs.} \]

**Perceived Usefulness**

PU is the degree to which an individual learner believes that using OLMs would enhance his or her academic performance (Davis, 1989; Hung and Cheng, 2013; Sek et al., 2015a). Learners’ intentions to share their learning information through the adoption of OLMs would increase if learners perceived that OLMs are able to help them to improve their academic performance (Brown et al., 2010; Huang, 2015). Cheung and Vogel (2013), for example, indicate that learners’ PU of collaborative technology has a positive effect on the learners’ willingness to share their learning information. Learners’ PU of OLMs would have a positive impact on learners’ willingness to participant in sharing their learning information. If learners believe that the adoption of OLMs for sharing their learning information can enhance their academic performance, their willingness to share learning information would improve. Based on this discussion, the following hypothesis is proposed.

\[ H9: \text{PU positively influences the information sharing intention of learners in the adoption of OLMs.} \]

PU is an important factor that influences learners’ intentions to adopt OLMs for collaborative learning (Brown et al., 2010; Hung and Cheng, 2013; Sek et al., 2015a). Learners’ intentions of using OLMs would increase if OLMs can help them
to improve their academic performances. Dasgupta, Granger, and McGarry (2002), for example, show that the PU of the collaborative technology has a significant positive impact on learners’ intentions to adopt the collaborative technology. Brown, Dennis, and Venkatesh (2010) suggest that learners’ intentions to use the collaboration technology would depend on the PU of the collaboration technology itself. Learners’ intentions to adopt the OLM would increase if they believe that OLMs can help them in achieving good academic performances. Based on this discussion, the following hypothesis is proposed.

\( H10: \text{PU positively influences the intention to adopt the OLM.} \)

### 3.3.5 Information Sharing Characteristics

Information sharing characteristics refer as the intention of learners to share their learning information in collaborative technology learning environment (Cheung and Vogel, 2013; Liu et al., 2014). They play a significant role in determining learners’ willingness to participate in sharing their learning information in collaborative learning environment. Two factors including learners’ information sharing intentions and trust are important to facilitate the sharing of learning information in a collaborative learning environment (Hung and Cheng, 2013; Liu et al., 2014).

**Trust**

Trust is about an individual learner’s willingness in dealing with risks which come from actions conducted by others in OLM-based collaborative learning environment (Hwang, 2008; Sek et al., 2015a). Trust not only plays a critical role in promoting the
dissemination and sharing of learning information and knowledge among learners. It also influences learners’ intentions for actively participate in OLM-based collaborative learning environment (Liu et al., 2014; Sek et al., 2015a).

Trust helps facilitate the formation of interpersonal relationships in learning, leading to effective knowledge creation and sharing (Limerick et al, 1993; Tamjidyaracholo et al. 2013; Liu et al., 2014). It allows learners to exchange learning information more effectively and efficiently in OLM-based collaborative learning environment. The successful implementation of OLMS in facilitating the sharing of learning information is built on trust (Liou et al., 2015). Tamjidyaracholo et al. (2013), for example, reveal that trust is essential for creating a successful knowledge sharing atmosphere in collaborative learning environment. Liu et al. (2014) point out that trust has a significant positive effect on learners’ willingness to share their learning information for supporting the acquisition of learning information. Learners’ willingness to share their learning information in OLM-based collaborative learning environment would increase if a trust relationship among learners is built. The above discussion leads to the following hypothesis:

\[ H11: \text{Trust positively influences the information sharing intention of learners in the adoption of OLMS.} \]

**Information Sharing Intention**

Information sharing intention (ISI) refers to the willingness of learners to transmit or disseminate knowledge to others in the OLM-based collaborative learning environment (Lee, 2001; Hung and Cheng, 2013; Sek et al., 2015a). Learners’
willingness to share their learning information through the adoption of OLMs would increase when they feel that OLMs are reliable and safe to be used for sharing their learning information (Chai and Kim, 2010; Cheung and Vogel, 2013; Liu et al., 2014). This directly influences learners’ attitudes towards the adoption of OLMs for collaborative learning. Cheung and Vogel (2013), for example, point out that learners’ information sharing intention has a positive impact on the learners’ attitudes towards the adoption of collaborative technologies. Learners’ would have a positive attitude towards the adoption of OLMs for collaborative learning if they have an intention to share their learning information in OLM-based collaborative learning environment. Based on the argument above, the following hypotheses have been proposed:

\[ H12: \text{Information sharing intention positively influences the attitude of learners in the adoption of OLMs.} \]

**Attitude**

Attitude defines as an individual learner’s favourable or unfavourable feeling towards the adoption of OLMs for collaborative learning (Fishbein and Azjen, 1975; Davis 1989; Cheung and Vogel, 2013; Sek et al., 2015a). If learners have a positive attitude towards the adoption of OLMs, their intentions to adopt OLMs would increase. Huang (2015), for example, demonstrates that learners’ attitudes have a direct positive influence on the learners’ intentions to adopt the collaborative technology in collaborative learning. Learners’ attitudes would have a positive influence towards their intentions to adopt OLMs for collaborative learning. The above discussion leads to the following hypothesis:
**H13:** Attitude positively influences the intention to adopt OLMs.

### 3.4 Concluding Remarks

This chapter presents a comprehensive review of existing theories for the adoption of a technology. After carefully evaluating the appropriateness of each theory, the TAM framework is chosen as the foundation theoretical basis in this study for guiding the development of a conceptual framework due to the ability in predicting the adoption of a technology by individuals. A conceptual framework is proposed consisting of five dimensions including individuals, systems, interfaces, designs, and information sharing for investigating the adoption of OLMs in Malaysian higher education. Such a framework forms the basis for the development of the survey instrument as described in the subsequent chapters, thus facilitates in answering the research question 2: *What are the critical factors that influence the adoption of OLMs in Malaysian higher education?* The measurement items for the identified factors in the conceptual framework will be discussed in chapter 4.
Chapter 4

Research Methodology

4.1 Introduction

A research methodology is a procedural framework for guiding the researcher to systematically and scientifically solving a research problem (Saunders et al., 2009; Sekaran and Bougie, 2010). The objective of the research methodology is to address the research activities including collecting, analyzing, interpreting, and reporting data in research studies for answering the research question (Creswell, 2009). The selection of an appropriate research methodology is important in a research project because it helps guide the selection of the research method that researchers must make during their studies and set the logic by which they make the interpretation of the collected data at the end. This shows that a proper design of a research methodology in addressing the research problem not only can provide the correct way of conducting a research study. It also influences the quality of the research findings (Creswell and Plano Clark, 2011).

Selecting an appropriate research methodology for a research project is a challenging process. This is due to (a) the nature of a specific research project including descriptive, analytical, applied, fundamental, quantitative, qualitative, conceptual, empirical, explanatory, and exploratory (Kothari, 2008; Sekaran and Bougie, 2010)
and (b) the existence of various research methods and techniques such as interview, survey, observation, experiment, case study, mathematical models, and experience (Marczyk et al., 2005; Kotheri, 2008; Mertens, 2009).

There are four stages in the selection of a research methodology in a research project including the research paradigm, the research methodology, the research design, and the use of specific research methods in the research design (Creswell and Plano Clark, 2011). The research paradigm provides the underlying philosophical principle for guiding the selection of the research methodology, which in turn determines the research design (Marczyk et al., 2005). An appropriate consideration of these four stages is essential for the successful selection of the most suitable research methodology in a research project (Sekaran and Bougie, 2010).

This chapter aims at discussing the selection and implementation of an appropriate methodology for achieving the objective of the research. It first presents an overview of various research methodologies, leading to the selection of a quantitative research methodology for this study. It then discusses the implementation of the quantitative research methodology with a focus on issues such as how the selection of a research sample is conducted, what data is collected, how the collection of data is carried out, how data will be used for the research and what are statistical data analysis methods used for analysing the data in the research.

To effectively accomplish the objective of this chapter, Section 4.2 explains the research paradigm for guiding the selection of an appropriate research methodology
in this study. Section 4.3 describes two popular research methodologies, followed by
the presentation of the research design and the research method in section 4.4.
Section 4.5 and section 4.6 discuss the development of research instruments and how
the research methodology followed in this research is implemented to meet the
research objectives respectively. Section 4.7 explains the data analysis methods in
this study. Section 4.8 ends the chapter with some conclusion remarks.

4.2 Research Paradigms

A research paradigm is a set of beliefs for guiding the implementation of a research
project (Chen and Hirschheim, 2004; Morgan, 2007). The purposes of a research
paradigm are to describe (a) how the world works, (b) how the knowledge is
excerpted from the world, (c) what types of questions are to be asked, and (d) what
methodologies are to be adopted in answering these questions (Saunders et al., 2012).

The research paradigm is intrinsically associated with three dimensions including
ontology, epistemology, and methodology (Saunders et al., 2012; Antwi and Hamza,
2015). An ontology is concerned with articulating the nature and structure of the
phenomenon. It refers to whether the phenomenon is objective and external to the
researcher or the phenomenon is created by the consciousness of the researcher
(Lincoln et al., 2011). An epistemology is related to the nature of knowledge
(Saunders et al., 2012; Antwi and Hamza, 2015). It refers to whether the knowledge
is formulated and evaluated by empirically verifying the theory or the knowledge is
formulated by engaging with the researcher in a social context (Chen and
Hirschheim, 2004; Saunders et al., 2012; Antwi and Hamza, 2015). A methodology
is associated with the methods of gathering and analyzing the research data for generating valid conclusions. It concerns about whether qualitative methods or quantitative methods are adopted for gathering and analyzing the research data (Chen and Hirschheim, 2004; Lincoln et al., 2011; Saunders et al., 2012).

Positivism and interpretivism are two major research paradigms in the social science and business research (Chen and Hirschheim, 2004; Saunders et al., 2012). They differ by ontologies, epistemologies, and methodologies, as displayed in Table 4.1.

Positivism is a deterministic philosophy stating that causes probably determine effects or outcomes (Crewell, 2009). Research under the positivist paradigm therefore requires the identification and assessment of the cause that influences the outcome (Chen and Hirschheim, 2004; Marczyk et al., 2005; Mertens, 2009). It is mostly represented through (a) the formulation of hypotheses, models, or causal relationships among constructs, (b) the use of quantitative methods to test theories or hypotheses, and (c) the objective and value-free interpretation of the research data, (Chen and Hirschheim, 2004; Saunders et al., 2012).

Interpretivism is a philosophy of social sciences based on the view that the social world can only be fully understood through the subjective interpretation of the reality and the associated intervention (Chen and Hirschheim, 2004; Bryman and Bell, 2007; Saunders et al., 2012). It is mostly depicted through (a) the subjective interpretation of the research data, (b) the engagement of the researcher in the specific social and cultural setting in the investigation, and (c) the use of qualitative
methods for obtaining and analysing participants’ viewpoints (Chen and Hirschheim, 2004; Bryman and Bell, 2007; Saunders et al., 2012).

### Table 4.1  An Overview of Research Paradigms

<table>
<thead>
<tr>
<th>Assumptions</th>
<th>Explanations</th>
<th>Research Paradigms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td><strong>Positivism</strong></td>
</tr>
<tr>
<td>Ontology</td>
<td>The researcher’s view of the nature of reality</td>
<td>Real-world phenomena and relationships exist independently of the individual’s perceptions</td>
</tr>
<tr>
<td>Epistemology</td>
<td>The researcher’s view regarding what constitutes acceptable knowledge</td>
<td>Concerned with the hypothetic deductive testability of theories</td>
</tr>
<tr>
<td>Methodology</td>
<td>The data collection methods often used for gaining the knowledge about the world.</td>
<td>Researchers derive generalizable models or theories of behaviour through the analysis of small-scope findings from large samples and use objective measurement to obtain research evidence using quantitative method</td>
</tr>
</tbody>
</table>

|             |              | **Interpretivism**   |
|             |              | Emphasizes the subjective meaning of the reality constructed and reconstructed through a researcher and social interaction process |
|             |              | Scientific knowledge should be obtained through the understanding of human and social interaction by which the subjective meaning of the reality is constructed |
|             |              | Researchers have to deal with the investigated social setting and learn how the interaction takes place from respondents’ perspective using qualitative method |

### 4.3 Research Methodology

A research methodology is a strategic blueprint which involves the collection, organization, and integration of the research data for producing the research outcomes (Neuman, 2006; Creswell, 2009). There are four main problems that need to be addressed in the selection of a research methodology including (a) what the questions to be answered are, (b) what the relevant data are, (c) how to collect the data, and (d) how to analyze the data (Sekaran and Bougie, 2010). A research methodology can help the researcher to complete the research project with proper planning.
guidance by (a) providing an execution plan for the researcher to effectively fulfill the research objective and (b) helping the researcher to complete the research project within the limited resources and time (Creswell and Plano Clark, 2011).

Qualitative and quantitative research methodologies are commonly used in a research project (Creswell and Plano Clark, 2011). A qualitative methodology follows the interpretivist paradigm for discovering and understanding how individuals respond to a social phenomenon in details (Saunders et al., 2012). It focuses more on the description of a scenario using words rather than the quantification of a phenomenon in the collection and analysis of the research data (Sekaran and Bougie, 2010). The collected data is analyzed to identify the patterns and to interpret those patterns (Creswell and Plano Clark, 2011). The interpretations made in this manner lead to the generation of a theory (Crewell, 2009). Examples of qualitative methods include interview, case study, action research, and the ground theory (Saunders et al., 2012).

A quantitative research methodology follows a positivist paradigm for confirming the theory proposed by the researcher on a certain phenomenon (Saunders et al., 2012). It focuses more on the quantification in the collection and analysis of the research data (Sekaran and Bougie, 2010). Such a method normally adopts inference analysis and statistical analysis for drawing meaningful conclusions from the research (Creswell and Plano Clark, 2011). Typical examples of quantitative methods include surveys, scenario-based prototyping simulations, laboratory experiments, field experiments, and forecasting.
4.4 Research Design

A quantitative research methodology is adopted in this research to meet its objectives. This research follows a confirmatory approach to validate a set of a priori hypotheses developed on OLMs-based collaborative learning. The quantitative research methodology is suitable for this research due to two main reasons. Firstly, a quantitative method is capable of assessing the validity of the proposed hypotheses on OLMs-based collaborative learning by collecting and analysing collected numerical data. Secondly, a quantitative method is useful for increasing the generalizability of the hypotheses being proposed on OLMs-based collaborative learning in this research, since these hypotheses are based on the perceptions of a larger population (Creswell, 2009; Saunders et al., 2012). In this study, two quantitative methods including surveys and scenario-based prototyping are employed for addressing the research problem.

Survey

A survey is commonly used for investigating the cause of a phenomenon as well as the attitudes and behaviors of individuals with empirical evidence (Carroll, 2000; Creswell, 2009; Sekaran and Bougie, 2010). It is suitable to be adopted in this study because it employs direct questioning to gather respondents’ opinions on a specific topic. Such opinions can facilitate (a) the investigation of the current pattern of OLMs adoption in Malaysia higher education institutions, (b) the validation of the conceptual framework in regards to the critical factors for the adoption of OLMs in collaborative learning empirically while generalizing the research findings to a large population, (c) the examination of the impact of learners with different learning
styles towards the acceptance of OLMs in collaborative learning, and (d) the investigation of the difference between males and females towards the acceptance of OLMs in collaborative learning.

**Scenario-based prototyping**

Scenario-based prototyping design considers scenarios as a central artifact in the system design (Hertzum, 2003; Sek et al., 2015b). It is used for envisaging and developing new technology-based systems (Carroll, 2000; McCabe, Sharples, and Foster, 2012; Persson et al., 2014). Such a design is frequently used in human-computer interaction research for describing the design specifications and the functionality of a prototype (Carroll, 2000; Persson et al., 2014; Sek et al., 2015b). It is practical in the initial development of an information system where the feedback from learners would put into consideration (Carroll, 2000; Persson et al., 2014; Sek et al., 2015a). In this study as shown in Figure 4.1, the description of the pedagogical features of OLMs such as the functionalities and interaction tools for facilitating collaborative learning are made available for each participant in the research project. This transparency affords the participant to become aware of the adaptable features available in OLMs for collaborative learning.
4.5 The Development of the Research Instrument

A quantitative research methodology is adopted in this research to achieve its objectives. Two quantitative methods including survey and scenario-based prototyping design are employed for facilitating the investigation of learners’ attitudes and perceptions towards the acceptance of OLMs. This section describes the development of these two research instruments in this study.

4.5.1 Survey Instrument Development

The survey is developed using a four-stage development process proposed by Straub (1989) and Moore and Benbasat (1991) to ensure the reliability and validity of the research findings. As illustrated in Figure 4.2, there are two main processes in the
The survey instrument development procedure includes both the development and refinement of the survey instrument. The development phase consists of specifying the domain of constructs and generating items for each. This is achieved by comprehensively reviewing the related literature on the adoption of collaborative technologies, as presented in Chapter 2 and Chapter 3.

**Figure 4.2 Survey Instrument Development Procedures**
The literature review leads to the identification of motivation, computer self-efficacy, online learning experience, system adaptability, system interactivity, screen design, navigation, PU, PEOU, information sharing intention, and attitude as the key factors that could influence the adoption of OLMs in collaborative learning. The item generation for each construct is done on the basis of the literature review. Table 4.2 illustrates the constructs, the associated items for measuring the individual constructs, and the sources of the items.

### Table 4.2  OLMs Adoption Constructs, Items and Origins

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Items</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motivation</td>
<td>I would enjoy learning using OLMs</td>
<td>Lin,(1998); Stafford and Stern,(2002); Vandenbroeck, Verschelden, and Boonaert, (2008)</td>
</tr>
<tr>
<td></td>
<td>I find OLMs to be useful in studies</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OLMs would help learners to do better in studies</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OLMs would increase academic performance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>It is easy to learn more using OLMs</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OLMs can effectively enhance learning</td>
<td></td>
</tr>
<tr>
<td>Computer Self-Efficacy</td>
<td>I can easily access contents of OLMs</td>
<td>Compeau et al. (1999); Murphy et al. (1989); Hsu and Chiu (2004)</td>
</tr>
<tr>
<td></td>
<td>I can freely navigate contents of OLMs</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I can use OLMs without the help from others</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I can use OLMs if there are user manuals available</td>
<td></td>
</tr>
<tr>
<td>Online Learning Experience</td>
<td>I have previous experience in using online collaboration technologies</td>
<td>Cereijo, Young, and Wilhelm, (1999); Hartley and Bendixen, (2001); Liu et al.(2010)</td>
</tr>
<tr>
<td></td>
<td>I have online learning experience</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I know how to use online learning collaboration technologies</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I have experience in adopting collaborative technologies for collaborative learning</td>
<td></td>
</tr>
<tr>
<td>System Interactivity</td>
<td>OLMs would enable interactive communication between instructors and learners</td>
<td>Martínez-Torres et al., (2008); Pituch and Lee, (2006)</td>
</tr>
<tr>
<td></td>
<td>OLMs can control the rhythm of learning</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OLM can control learning sequence</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OLM can select appropriate learning contents</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OLM can enable interactive communication between learners</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OLM can select learning materials based on current level of knowledge</td>
<td></td>
</tr>
<tr>
<td>System Adaptability</td>
<td>OLMs provide learning content which is suited to current level of knowledge</td>
<td>Tobing et al., (2008)</td>
</tr>
<tr>
<td></td>
<td>Learning content presented with respect to current level of understanding would improve learning</td>
<td></td>
</tr>
<tr>
<td></td>
<td>OLMs would help learner to learn with other learners</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Content displays on OLMs would help to identify misconception</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Content displays on OLMs would assist to solve the problem</td>
<td></td>
</tr>
</tbody>
</table>
A seven-point Likert scale is employed for each statement in each construct ranging from one describing strongly disagree to seven to indicate strongly agree. The seven-point Likert scale is selected due to its advantages in providing more accurate and
consistent results for multivariate analysis than a five-point Likert-type scale or a three-point Likert-type scale (Hair et al., 2010).

The survey instrument refinement comprises of the pre-test and the pilot-test of the instrument. The purpose of conducting the pre-test is to validate the content validity of the survey instrument (Hair et al., 2010). The content validity refers to the extent to which measurement items capture the different dimensions or aspects of a construct (Netemeyer et al., 2003; Hair et al., 2010). The content validity is evaluated through the examination of the logical sequencing, wording comprehensibility, interpretation constancy, and the overall impression of the clarity of the survey (Hair et al., 2010). In the pre-test of the survey instrument, the survey is reviewed by six experts who specialize in TBCL and technology adoption to ensure the semantics correspondence between measurement items in the item pools and the underlying variables intended to be measured. Several of the original items are revised based on the constructive comments from the expert review. The improved survey instrument is adopted for the pilot study.

The survey consists of three main sections to gather learners’ information. The first section gathers the information of the demographic characteristics of the participants in the adoption of OLMs in Malaysian higher education. The second section is relates to the assessment of the learning style of individual learners based on the VARK learning style inventory (Fleming, 2008). The third section includes a series of questions designed to access learners’ attitudes and perceptions towards the acceptance of OLMs on the adoption of OLMs from the perspectives of individual
characteristics, system characteristics, interface characteristics, trust, and information sharing intention perspectives based on the items proposed in Table 4.3.

In the pilot test stage, the improved version of the survey instrument is distributed to the 101 undergraduate IT students who have been exposed to a learning management system in a university in Malaysia. Capturing the online learning experience from these participants provides reliable data regarding their attitudes towards the adoption of OLMs. This study utilises a web-mediated survey tool called Qualtric to collect the data from participants who are introduced to OLMs through the scenario-based OLM prototype, using Adobe Captivate 7 (Sek et al. 2014a).

To test the reliability of the questionnaire, Cronbach’s alpha is commonly used for testing the internal consistency of the measurement model. It is used to measure the interrelatedness of a set of items in a survey questionnaire (Netemeyer et al., 2003; Hair et al., 2010). For the data obtained from the pilot study, a reliability test is performed using SPSS 22.0 for Window based on the 101 responses. The Cronbach’s alpha (α) as shown in Table 4.3 indicates that the average of the Cronbach’s alpha value is ranged between 0.827 to 0.921. This shows that the survey instrument has a high level of reliability (Hair et al. 2010).

An exploratory factor analysis is conducted to further examine the factor structure of the 61-items in the proposed measurement model. This factor analysis is used to determine the discriminate validity of the measurement model. Discriminant validity refers to which a construct is truly distinct from other constructs both in terms of how
much it correlates with other constructs and how distinctly measured variables represent only this single construct (Hair et al. 2010). Sixty-one items are analysed using factor analysis in SPSS 22.0. Principal component analysis is used as the extraction method and varimax as the rotation method. The result of the exploratory factors analysis is shown in Table 4.3.

The summarisation of the range of factor loading for the 61-item as shown in Table 4.3 indicates that all the items are significantly loaded on the single factor. The significant high factor loadings of all the items on the single factor indicate that there are no cross-loadings for each item within the constructs. This result supports the discriminant validity of the measurement model (Hair et al., 2010).

**Table 4.3 Constructs Reliability and Factor Loadings Based on the Pilot Study**

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Reliability(α)</th>
<th>Range of factor loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motivation – (6 Items)</td>
<td>0.959</td>
<td>(0.741 – 0.831)</td>
</tr>
<tr>
<td>Computer Self-Efficacy – (4 Items)</td>
<td>0.930</td>
<td>(0.750 – 0.802)</td>
</tr>
<tr>
<td>Online Learning Experience – (4 Items)</td>
<td>0.898</td>
<td>(0.745 – 0.770)</td>
</tr>
<tr>
<td>System Interactivity – (6 Items)</td>
<td>0.957</td>
<td>(0.750 – 0.826)</td>
</tr>
<tr>
<td>System Adaptability – (5 Items)</td>
<td>0.972</td>
<td>(0.778 – 0.854)</td>
</tr>
<tr>
<td>Screen Design – (4 Items)</td>
<td>0.960</td>
<td>(0.841 – 0.864)</td>
</tr>
<tr>
<td>Navigation – (4 Items)</td>
<td>0.954</td>
<td>(0.792 – 0.837)</td>
</tr>
<tr>
<td>Trust – (5 Items)</td>
<td>0.977</td>
<td>(0.872 – 0.899)</td>
</tr>
<tr>
<td>Perceived Usefulness – (6 Items)</td>
<td>0.972</td>
<td>(0.812 – 0.898)</td>
</tr>
<tr>
<td>Perceived Ease of Use – (5 Items)</td>
<td>0.975</td>
<td>(0.854 – 0.881)</td>
</tr>
<tr>
<td>Attitude – (4 Items)</td>
<td>0.901</td>
<td>(0.815 – 0.841)</td>
</tr>
<tr>
<td>Intention to Use – (4 Items)</td>
<td>0.967</td>
<td>(0.860 – 0.872)</td>
</tr>
<tr>
<td>Information Sharing Intention – (4 Items)</td>
<td>0.964</td>
<td>(0.846 – 0.862)</td>
</tr>
</tbody>
</table>

Based on this exploratory factors analysis, thirteen factors are generated. These are motivation, computer self-efficacy, online learning experience, system interactivity, system adaptability, screen design, navigation, trust, information sharing intention,
perceived usefulness, behavioural intention, perceived ease-of-use and attitude. The result from the pilot test reveals that the survey instrument has a high level of reliability and validity for assessing learners’ attitudes and perceptions towards the adoption of OLMs. These pre-tests and pilot tests suggest a fair degree of initial content validity and reliability to the survey instrument (Straub et al., 2004).

An OLM scenario-based prototype is presented to the participant before they answer the survey. This type of scenario-based prototype is appropriate to be adopted in this study because there are few OLMs available for adoption in Malaysian higher education. In this study, the description of OLMs’ pedagogical features such as presentation formats, type of interactions, and interface layouts are made available for each participant for facilitating the assessment of learners’ acceptance of OLMs. The development of the OLM scenario-based prototype is discussed in the following.

### 4.5.2 OLMs Scenario-based Prototyping Development

The development of OLMs scenario-based prototyping is based on the ARCS motivational model. The ARCS motivational model consists of four components including attention (A), relevance (R), confidence (C), and satisfaction (S) which are the conditions that need to be met for learners to have a motivation to engage with collaborative technologies (Keller, 1987; Marshall and Wilson, 2011). Incorporating the ARCS motivational model in collaborative technologies not only encourages learners to engage with collaborative technologies in their learning processes. It can also help in enhancing and sustaining learners’ learning motivations to continuously utilize these technologies (Di Serio et al., 2013).
An ARCS-based motivational model focuses mainly on motivating learners with respect to their attention, relevance, confidence, and satisfaction (Keller, 1987). Attention refers to capturing the interest of learners and stimulating their curiosity to learn. Relevance refers to meeting learners’ needs and goals to stimulate positive attitudes. Confidence refers to helping learners believe that they can succeed. Satisfaction refers to reinforcing accomplishments with internal and external rewards (Keller, 1987; Marshall and Wilson, 2011).

Attention is a strategy for arousing and sustaining learners’ interest in engaging with the collaborative technology (Lee and Kim, 2012). Effective stimuli are able to arouse the learner’s attention and curiosity (Keller, 1987). An appropriate instructional design can help in gaining and sustaining learners’ attention towards the adoption of collaborative technologies (Marshall and Wilson, 2011).

Relevance is about how well the design of instructional activities accommodates learners’ learning interests, goals and needs (Keller, 1987). Relevance helps learners associate their prior learning experience with the given instructional materials provided by the collaborative technology in collaborative learning environment. It also enables learners to understand the applicability of learned knowledge or skills in their future tasks (Huett et al., 2008). An appropriate design of instructional activities that match learners’ instructional preferences and learning goals can promote their motivations in engaging with collaborative technologies (Huett et al., 2008).
The confidence of learners would be further enhanced when they are able to achieve their goals if enough effort has been made (Di Serio et al., 2013). When learners believe they have the ability to control the outcomes of their behaviour through engagement with collaborative technology, they are more motivated to adopt the collaborative technology in collaborative learning.

Satisfaction refers to positive feelings about learners’ past or current learning experiences with collaborative technologies (Lee and Kim, 2012). Providing valuable feedbacks on learners’ accomplishments would produce positive feelings in their engaging experiences with collaborative technologies (Di Serio et al., 2013). Allowing learners to use collaborative technologies to apply their newly acquired knowledge can increase their satisfaction and thus further enhance learners’ levels of motivation to engage with collaborative technologies (Lee and Kim, 2012; Di Serio et al., 2013; Hung et al., 2013).

Motivation is a critical factor in determining the success of the implementation of a collaborative technology in collaborative learning (Hodges, 2004; ChanLin, 2009; Lee and Kim, 2012). An appropriate combination of motivational strategies and supporting tools can enhance learners’ motivations (Hodges, 2004). To encourage learners’ engagement with OLMs, the development of the OLMs prototyping is based on a combination of the motivational model with supporting motivational tools to provide a rich OLMs learning environment for motivating learners in their learning. The proposed an OLM-based learning environment is shown in Figure 4.3.
The integration of the ARCS motivational model in designing the OLM-based learning environment is able to attract and sustain learners’ motivations to further engage with OLMs (Sek et al., 2014b). Table 4.4 illustrates how the ARCS motivational model, the ARCS supported strategies and motivational tools are adopted as a framework for designing an OLM-based learning environment. Six motivational tools have been proposed in this study. These tools are model representation, model comparison, model improvement, model presentation, model progress alert, and model introduction. All these tools are able to support the ARCS motivational model as shown in Table 4.4.
Table 4.4 The Description of the Corresponding ARCS Components, Motivation Strategies and Motivational Tools

<table>
<thead>
<tr>
<th>ARCS Components</th>
<th>Motivational Strategies</th>
<th>Motivational Tools</th>
</tr>
</thead>
</table>
| Attention       | Capturing the learners’ attention during the process of teaching and learning. Various activities which can stimulate curiosity to learn should be considered to sustain learners’ attention | Model Representation  
Model Comparison  
Model Presentation  
Model Progress Alert  
Model Introduction |
| Relevance       | Creating awareness of the importance of learning. Diverse activities need to be introduced to meet the learners’ needs, interests and goals. Establish connections between instructional content with learners’ goals | Model Improvement  
Model Presentation |
| Confidence      | Assisting the learners to build the belief that their goal can be achievable if enough effort has been made | Model Representation  
Model Comparison  
Model Improvement  
Model Presentation  
Model Introduction |
| Satisfaction    | Providing valuable feedbacks on learners’ accomplishments. Allowing learners to have an opportunity to apply their newly acquired knowledge | Model Representation  
Model Comparison  
Model Improvement  
Model Introduction |

The model representation tool is used for displaying learners’ learning information. This tool allows learners to reflect on what they have completed and what knowledge is lacking. They are able to obtain some feedbacks from their interactions with their visually presented learning information. The learning information such as knowledge level and misconceptions of learners during their teaching and learning processes are shown to create awareness and attract learners’ attention. This model representation tool is able to promote learners’ motivations by allowing them to view their learning information on topics learned and misconceptions. In addition, a visual presentation of learners’ learning information not only can catch learners’ attention to view their models, but also can help them to be self-aware of their learning progresses, resulting in increased confidence in their learning, and satisfaction with the learning experience.
The model comparison tool aims at providing learners with an opportunity to compare their learner models with their peers and instructors. This tool can provide learners with information about how peers have progressed in their learning. By allowing this action, learners are able to compare their learning progresses with their peers. If their learning is lagging compared with their counterparts, learners can try to improve it by putting more efforts. This encourages learners to work harder to be at the same pace as their peers. This tool is able to catch learners’ attention when they have a chance to view their peers’ models. After reviewing peers’ learning information, learners would have some confidence on what have been achieved by their peers. In addition, learners’ satisfaction can be improved if peers can show and share information on how they have accomplished their tasks.

The model improvement tool is used to provide learners with extra learning materials to further improve learners’ understanding of the topics that they are lagging behind. For example, if learners can complete the learning materials provided by instructors in the system with a good result, their learning progresses will be updated according to their current levels of understanding. Learners will be provided with the relevant learning materials by instructors according to their knowledge backgrounds. They have to put their initiatives to study these learning materials. This is important as it gives learners awareness that they have a full control of the outcome of their study. Consequently, this would improve learners’ confidence in their learning. In addition, learners’ satisfaction will also be enhanced if they are able to complete the learning materials provided according to the study plan.
The model presentation tool allows learners to select the representation format of their learning information. Learners are able to select their preferred formats. For example, a learner can choose formats ranging from skill meters, texts to concept maps to represent their learning progresses. This option is able to improve learners’ motivation as different learners have their own ways to interpret learning information (Sek et al., 2015b). Visual learners like their learning materials to be presented in a visual form (Fleming, 2001). Whereas for aural learners, they like their learning materials to be printed in text formats (Fleming, 2001). If the learning material can be presented to learners according to their learning preferences, their motivation can be enhanced (Hung et al., 2013).

The model progress alert tool is designed to provide notification to learners about their learning progresses. Learners are able to receive this notification if their learning is lagging behind peers or do not follow the study plan. This notification alerts learners by using different colors and wording to attract learners’ attention. For example, red color together with wording such as ‘urgent’ is triggered if learners’ learning progress is lagging behind, the learners have to attend to this warning immediately. The learners’ motivation would improve as the notification provided by this tool supports learners to continue engaging in this learning environment.

The model introduction tool is used to provide learning guidelines to learners with respect to the learning objective, goals, contents and the corresponding learning outcomes of the course. The availability of course information in OLM-based learning environment can stimulate learners’ engagement with the model
introduction tool. The learning guidance provided in this tool would be able to help in gaining and maintaining learners’ attention by showing some indications on how the topics are built and the interconnection of each topic to one another. Supporting learners in making such connections increases their confidence. Learners’ satisfactions can also be enhanced if they are able to complete the tasks by following the guidelines provided in the learning guidance.

The OLM scenario-based prototyping tool mainly serves for introducing the features, functionality and characteristics of the OLM-based learning environment. This prototyping tool is necessary for this study because the development of OLMs in Malaysian higher education institutions for collaborative learning is still at its infancy stage. The availability of OLMs as a collaborative technology is limited to very few universities in Malaysia. With the introduction of the OLM-based learning environment to the participants through the use of scenario-based prototyping tool, the participants are able to obtain an overview of an OLM-based learning environment for facilitating collaborative learning.

### 4.6 The implementation of the Research Methodology

The purpose of this study is to assess learners’ attitudes and perception towards the acceptance of OLMs. To facilitate this, a conceptual framework is proposed as shown in Figure 3.4. This conceptual framework needs to be tested and validated. The validation and test process is carried out based on the use of a quantitative research methodology. With the adoption of such a methodology, a survey is used.
In the distribution of the survey, the selection of the appropriate sample size is critical for generating consistent and reliable results in the subsequent data analysis (Hair et al., 2010). Two approaches are adopted in this stage for ensuring the adequate sample size. The first approach concerns with the calculation of the required sample size for the SEM technique used in the data analysis. The second approach is based on the power analysis to calculate the appropriate sample size. The preliminary requirement for conducting SEM is that the absolute minimum sample size must be at least greater than the number of correlations in the input data matrix, with a ratio of 5 to 10 respondents per items (Hair et al., 2010). Since there are 61 estimated items in the conceptual model as shown in Table 4.2, the sample size to ensure an appropriate use of SEM is 305 to 610.

The second approach is related to the power analysis. Power analysis is a useful approach for measuring (a) how large the sample size is for enabling accurate and reliable statistical results and (b) how likely the statistical results can detect an effect of the given samples to the population (Rudestam and Newton, 2007; Hair et al., 2010). If the sample size is too low, the statistical results would lack the precision for providing reliable answers to the research question under investigation. If the sample size is too high, time and resources would be wasted with a minimal gain (Netemeyer et al., 2003; Rudestam and Newton, 2007).

There are three parameters in the power analysis to be considered including (a) the effect size, (b) the statistical power, and (c) the significance level (Keppel 1991; Rudestam and Newton, 2007). The effect size is a measure of the strength of the
relationship between the sample and the population (Cohen, 1988). The statistical power is the probability of detecting a statistically significant effect (Hair et al., 2010). The significance level is a measure of a false rejection of the null hypothesis (Cohen, 1988). The effect size of 0.20, the significance level $\alpha$ of 0.05 and the power of 0.80 is considered adequate in predicting an appropriate sample size in the power analysis in a survey based research project (Hair et al., 2010).

Given the total approximate number of 450,000 students enrolled in Malaysian universities at the time of data collection and the recommended value for the above parameters, the appropriate sample size calculated in the power analysis is 384. Appendix E presents the calculation of the sample size using the power analysis. To summarize the results from the use of the two approaches in calculating the sample size for this study, the recommended sample size is 384. This suggests that the findings of this study can be generalized to learners in Malaysian higher institutions if more than 384 valid surveys are collected from the respondents for data analysis.

To select an appropriate sampling frame for the survey data collection, the population of interest and the sampling method need to be considered carefully (Saunders et al., 2009). This study aims to investigate learners’ attitude and perception towards the acceptance of OLMs in Malaysia higher education institutions. The population of interest is therefore set as a census of undergraduates in Malaysian higher education institutions.
Two sampling methods including convenience sampling and snowball sampling are employed in this study. The convenience sampling is a non-probability sampling technique where subjects are selected because of their convenient accessibility and proximity to the researcher (Battaglia, 2008). It is used in exploratory research where the researcher is interested in getting an inexpensive approximation (Battaglia, 2008). The snowball sampling is a non-probability sampling technique where existing study subjects recruit future subjects from among their acquaintances. To create a snowball sample, there are two steps involved: (a) trying to identify one or more units in the desired population and (b) using these units to find further units and so on until the sample size is met.

In this study, the units that have been identified are from a few universities in Malaysia. These units have been chosen based on the use of a convenience sampling method. After the identification of the desired population, snowball sampling is applied for gaining access to a wide range of undergraduates in Malaysia.

The survey is conducted in Malaysian higher education institutions between April 2014 and December 2014. The names and email addresses of the learners in Malaysian higher education institutions are obtained from the respective universities administers in Malaysia. An initial e-mail is sent out to 750 learners to explain the purpose of the research and the invitation to participate. Forty-two e-mails are undeliverable. The email directs the learners to the website where the survey is located. Three follow-up reminders are sent to the learners that have not responded to
the survey after six weeks. 565 responses are received in all rounds, contributing to 79.80 per cent response rate.

4.7 Data Analysis Techniques

Quantitative data analysis is performed in five steps. In step one, preliminary data analysis including missing data assessment, outlier assessment, and normality assumption assessment is conducted to prepare the survey data for further analysis. In step two, a demographics analysis is conducted for addressing research question one. The descriptive statistics is used to analyse the demographics characteristics of the participant, the education background of the participant, the familiarity of the OLM-based learning environment, and the reason for using OLMs in collaborative learning. The purpose of using descriptive statistics is to present quantitative descriptions in a manageable form. The chi-square goodness-of-fit test is performed to see whether a frequency distribution fits a specific pattern.

In step three, the multivariate data analysis which includes exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and SEM is adopted for testing and validating the proposed conceptual framework. The SEM approach is used for answering the second research question on the validity of the determinants that influence learners’ acceptance of OLMs.

In step four, one-way analysis of variances is performed for addressing research question three. Such an analysis is related to the examination of the relationship
between learners’ learning styles and their acceptance of OLMs for collaborative learning (Pallant, 2010). In step five, an independent t-test is used to investigate the impact of gender differences on learners’ acceptance of OLM-based collaborative learning. This test is suitable to be used for answering research question four because of its ability to determine the differences between male and female learners in the acceptance of OLMs. Figure 4.4 shows a summary of the research methods adopted for answering all the research questions in this study.

**Figure 4.4**  A Summary of the Research Methods for Data Analysis
4.7.1 Preliminary Data Analysis

The preliminary data analysis needs to be conducted before performing the data analysis. The researcher has to make sure that the assumptions guiding the multivariate analysis are fulfilled in the relevant research domain (Cruz, 2010). The preliminary data analysis is an important stage that needs to be performed as this process can ensure the collected data from the survey is clean and prepared for further statistical analyses. There are three processes in the preliminary data analysis including missing data evaluation, outlier assessment, skewness and kurtosis assessment for evaluating the normality of the dataset.

Missing Data Evaluation

Missing data is the item values that are not responded to by the participant in the survey (Hair et al., 2010). It can cause bias results in the data analysis as well as the reduction of sample size available for analysis (Kline, 2005; Hair et al., 2010). To effectively handle the issue of missing data, appropriate remedies are adopted for dealing with the data collected from the web-based survey. To properly handle the missing data from the web-based survey, an initiative is taken to prevent missing values from the data entry as shown in Figure 4.5. A reminder message prompts up for the survey participants to respond to if there are any missing questions. As a result, there is no discarded data in the web-based survey.
Figure 4.5  Message for Avoiding Missing Response

Outlier Assessment

Outliers are extreme data values with a unique combination of characteristics that are different from other data values (Hair et al., 2010). Outliers are judged as an unusually high or low value on a variable or a unique combination of values across several variables that make the observation stand out from others. The existence of outliers may have a significant effect on the consequent model fit, parameter estimates, and standard errors in the dataset (Hair et al. 2010; Byrne, 2010). Two types of outliers exist, namely univariate and multivariate.

The univariate outliers are outliers on a single variable (Kline, 2005; Hair et al., 2010). They can be detected by using boxplot examination in SPSS. The outliers
appear at the extremes of the boxplot that represent the thirteen variables in this study. The outliers of the dataset are labelled with case numbers. Based on this criterion, a total of 29 cases are identified as outliers. The detailed results are shown in Appendix C.

The multivariate outliers are outliers on a combination of variables (Hair et al., 2010). To effectively identify the multivariate outliers in the dataset, the Mahalanobis distance is computed (Ullman and Bentler, 2003; Kline, 2005). The Mahalanobis distance measures the uniqueness of a single observation based on differences between the observation’s values and the mean values for all other cases across all independent variables (Hair et al. 2010). The data need to be deleted if the probability calculated based on the Mahalanobis distance and chi-square value is smaller than 0.001 (Kline, 2005; Hair et al., 2010). In this study, the probability based on the Mahalanobis distance and the chi-square value is calculated using SPSS 22.0. As a result, 32 responses are removed from the analysis. The detailed results are shown in Appendix D.

**Normality Test**

An assessment of the normality of data is a prerequisite for SEM analysis because normal data is an underlying assumption in SEM parametric testing. There are two methods of assessing normality, namely skewness and kurtosis. Skewness is a measure of asymmetric that describes the shape of the distribution. A distribution with a positive skewness value would have a longer tail towards the right side of the
normal curve. On the other hand, a distribution with a negative value would have longer tail towards the left side of the normal curve (Kline, 2005; Hair et al., 2010). Kurtosis is a measure of the flatness of the distribution in the dataset (George and Mallery, 2005). A kurtosis value near zero indicates a shape close to a normal distribution. A positive value indicates a distribution more peaked than a normal distribution, whereas a negative value shows a shape flatter than a normal distribution.

Generally, a value between ± 3 for measuring the skewness and a value between ± 10 for measuring the kurtosis in a dataset are considered acceptable (Kline, 2005). These ranges of values are required for the data to be considered as normally distributed (Kline, 2005). As presented in Table 4.4, overall the skewness statistics for all thirteen variables are ranging from -0.255 to -0.710 and the kurtosis statistics are ranging -0.147 to + 0.772 indicating that the normality assumption of the dataset is not violated (Hair et al., 2010; Kline, 2005).

Overall, the original number of the survey responses of 565 is reduced to 504 after deleting 61 unusable cases. More specifically, 11 cases are removed in the missing data assessment, 29 cases are deleted in the univariate outlier assessment, and 21 cases are eliminated in the multivariate outlier assessment, leading to the 504 valid cases in the dataset for the consequent statistical analysis.
Table 4.5  Measures of Kurtosis and Skewness for Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Kurtosis</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motivation</td>
<td>0.432</td>
<td>-0.367</td>
</tr>
<tr>
<td>Computer Self-Efficacy</td>
<td>0.772</td>
<td>-0.710</td>
</tr>
<tr>
<td>Online Learning Experience</td>
<td>0.539</td>
<td>-0.737</td>
</tr>
<tr>
<td>System Adaptability</td>
<td>0.513</td>
<td>-0.442</td>
</tr>
<tr>
<td>System Interactivity</td>
<td>0.734</td>
<td>-0.636</td>
</tr>
<tr>
<td>Screen Design</td>
<td>0.340</td>
<td>-0.404</td>
</tr>
<tr>
<td>Navigation</td>
<td>0.561</td>
<td>-0.608</td>
</tr>
<tr>
<td>Trust</td>
<td>0.354</td>
<td>-0.536</td>
</tr>
<tr>
<td>Perceived Usefulness</td>
<td>0.226</td>
<td>-0.322</td>
</tr>
<tr>
<td>Perceived Ease of Use</td>
<td>0.047</td>
<td>-0.336</td>
</tr>
<tr>
<td>Information Sharing Intention</td>
<td>0.385</td>
<td>-0.398</td>
</tr>
<tr>
<td>Attitude</td>
<td>-0.147</td>
<td>-0.255</td>
</tr>
<tr>
<td>Intention to use</td>
<td>-0.048</td>
<td>-0.340</td>
</tr>
</tbody>
</table>

4.7.2 Descriptive Data Analysis

Descriptive statistics are used to describe the basic characteristics and features of the data in a study. Descriptive statistics simply describes what is or what the data shows. Numerous advantages are present from using descriptive statistics including summarizing a data set in visual form without employing a probabilistic formulation as well as helping simply large amounts of data in an easy to understand formats such as tables, graphs, and charts.

There are two types of statistics that are used to describe raw data including measures of central tendency and measures of dispersion. The measures of central tendency indicate the middle and commonly occurring points in a data set. Three main measures of central tendency including mean, median, and mode are commonly used in descriptive statistics. The measures of dispersion indicate how spreads out the data are around the mean. The most commonly used measures of dispersion are variance, standard deviation, range, percentiles.
Descriptive statistics are an appropriate method for investigating the current pattern and trends for the adoption of OLMs in Malaysian higher education. The information about participants’ demographics characteristics such as education background, gender, the engagement experience with web-based learning courses, the familiarity with the OLM-based learning environment, and the reason for using the OLM in collaborative learning are presented using descriptive statistics. The detail discussions of the descriptive statistics for investigating the current pattern and trends for the adoption of OLMs in Malaysian higher education are presented in Chapter 5.

4.7.3 SEM Based Multivariate Analysis

SEM is widely accepted as one of the most powerful multivariate statistical approaches available in quantitative data analysis (Anderson and Gerbing, 1988; Hair et al., 2010). The adoption of SEM in this study is mainly due to its ability to include unobserved variables in representing abstract concepts while considering for the measurement error and its capability for simultaneously assessing the multiple correlations and covariance among variables in the model validity test (Anderson and Gerbing, 1988; Kline, 2005).

As illustrated in Figure 4.6, there are eight main steps in conducting the SEM multivariate analysis (Anderson and Gerbing, 1988; Hair et al., 2010). The first step is the formulation of a theory (Anderson and Gerbing, 1988). In this stage, the development and identification of the measurement model is done based on specific theories. A series of priori hypothesized relationships among unobserved theoretical constructs are proposed based on a comprehensive review of the related literature. In
addition, a set of observed indicator variables is also identified to measure those unobservable theoretical constructs. The second step is the development of the measurement model. In this step, the unobservable theoretical constructs involved in a theory are represented by observable indicator variables (Hair et al., 2010).

The third step is the selection of sample and obtaining measures for analysing the proposed conceptual model (Anderson and Gerbing, 1988; Hair et al., 2010). The fourth step is the preliminary data analysis in which the data collected from the survey is assessed for missing data, unengaged responses, skewness and kurtosis, and outliers. After the preliminary data analysis process, the data is clean and ready for the further EFA analysis.

The fifth step is the EFA process. EFA is generally used to discover the factor structure of a measure and to examine its internal reliability. EFA can be used to reduce the number of items in a scale so that the remaining items maximize the explained variance in the scale and maximize the scale’s reliability. The EFA process in this study involves four stages including construct reliability assessment, data adequacy assessment, convergent validity assessment, and discriminant validity assessment (Anderson and Gerbing, 1988; Hair et al., 2010).
Figure 4.6  Procedures for SEM Data Analysis

- Theory Formulation
- Develop and Specify Measurement Model
- Select Sample and Collect Measures
- Preliminary Data Analysis
  - Investigation of missing Data, unengaged responses, skewness and kurtosis, and outliers
  - Adequacy, construct reliability, convergent validity, discriminant validity, reliability check
- Exploratory Factor Analysis
- Confirmatory Factor Analysis
  - Goodness-of-fit, validity and reliability check
- Structural Model Analysis
- Structural Equation Modelling Results
Construct Reliability

Construct reliability refers to the interrelatedness of items in a survey questionnaire. To test the construct reliability, Cronbach’s alpha is commonly used. For the data obtained from the survey, a reliability test is performed using SPSS 22.0 for Window based on the 504 responses. The Cronbach’s alpha (α) as shown in Table 4.6 indicates that the average of the Cronbach’s alpha value is ranged from 0.851 to 0.954. This means that the constructs are of a high level of reliability (Kline, 2005; Anderson and Gerbing, 1988; Hair et al. 2010). Based on these findings, the internal consistency of the survey instrument is acceptable.

Adequacy

Adequacy refers to the sufficiency and quality of the data. The adequacy of the sample data can be assessed using Kaiser-Meyer-Olkin (KMO) test. For achieving the sampling adequacy, the value for KMO test should be more than 0.50 (Hair et al. 2010). The data obtained from the survey has been evaluated for the sampling adequacy indicating that the KMO value is 0.974. This shows that the dataset is adequate for factor analysis.

Table 4.6  Summary of the Constructs Reliability

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Cronbach’s Alpha (α)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motivation</td>
<td>0.921</td>
</tr>
<tr>
<td>Computer Self-Efficacy</td>
<td>0.885</td>
</tr>
<tr>
<td>Online Learning Experience</td>
<td>0.851</td>
</tr>
<tr>
<td>System Adaptability</td>
<td>0.893</td>
</tr>
<tr>
<td>System Interactivity</td>
<td>0.916</td>
</tr>
<tr>
<td>Screen Design</td>
<td>0.905</td>
</tr>
<tr>
<td>Navigation</td>
<td>0.877</td>
</tr>
<tr>
<td>Trust</td>
<td>0.919</td>
</tr>
<tr>
<td>Perceived Usefulness</td>
<td>0.952</td>
</tr>
<tr>
<td>Perceived Ease of Use</td>
<td>0.954</td>
</tr>
<tr>
<td>Information Sharing Intention</td>
<td>0.910</td>
</tr>
<tr>
<td>Attitude towards</td>
<td>0.939</td>
</tr>
<tr>
<td>Intention to use</td>
<td>0.926</td>
</tr>
</tbody>
</table>
Convergent Validity

Convergent validity refers to the degree to which two measures designed to measure the same construct are related. It has been used to assess the correlation of variables within a single construct. The measurement of convergent validity of a construct can be assessed based on the factor loading value from the EFA analysis. The value of factor loading more than 0.6 is considered as significant loading (Hair et al., 2010). Figure 4.7 provides evidences for the convergent validity of the dataset. The factor loading values ranging from 0.644 to 0.921 indicate that all the variables are well loaded on the respective constructs, supporting the convergent validity criteria of the measurement instruments in this study.

Discriminant Validity

Discriminant validity refers to the extent to which factors are distinct and uncorrelated (Hair et al., 2010). Variables should relate more strongly to their own factor than to another factor. The examination of the pattern matrix from the EFA analysis is able to determine the discriminant validity (Hair et al., 2010). A cross-loading value more than 0.2 between two variables is an indication of the discriminant validity. Figure 4.7 shows that results of the EFA analysis of the dataset. The cross-loading value for each variable is more than 0.2. This shows that all variables are highly correlated in the same construct, supporting the discriminant validity of the measurement instruments in this study.
## Figure 4.7 Exploratory Factor Analyses of Measurement

<table>
<thead>
<tr>
<th>Factor</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>MO_4</td>
<td>.961</td>
<td>.108</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.110</td>
</tr>
<tr>
<td>MO_2</td>
<td>.925</td>
<td>.108</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>.137</td>
</tr>
<tr>
<td>MO_3</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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Extraction Method: Principal Axes Factoring.
Rotation Method: Promax with Kaiser Normalization.
Rotation converged in 9 iterations.
The sixth step is to evaluate the measurement model’s validity. The validity and reliability of the measurement model is performed. The interactive model modification process is continued through refinement and retesting until the validity and reliability of the measurement model satisfy. This process results in dropping the items that do not meet the validity and reliability test.

At the end of the model modification process, the overall measurement model is evaluated based on the goodness of fit statistics for testing the fit between the dataset and the model. The most commonly adopted statistics are the ratio of $\chi^2$ to degrees of freedom ($\chi^2$/df), the root mean square error of approximation (RMSEA), goodness of fit index (GFI), adjusted GFI (AGFI), normed fit index (NFI), comparative fit index (CFI), tucker-lewis index (TLI), and standardised root mean squared residual (RMSR) (Hair et al., 2010). Table 4.7 shows the purpose of each goodness-of-fit statistics and the guidelines for the acceptance threshold values for these statistics.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Purposes</th>
<th>Thresholds</th>
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</thead>
<tbody>
<tr>
<td>$\chi^2$/df</td>
<td>The ration of chi-Squared and its degree of freedom</td>
<td>$\leq 3.00$</td>
</tr>
<tr>
<td>RMSEA</td>
<td>Analysis of residuals</td>
<td>$\leq 0.08$</td>
</tr>
<tr>
<td>GFI</td>
<td>Indicate the degree to which the overall model predicts the observed correlation matrix</td>
<td>$\geq 0.90$</td>
</tr>
<tr>
<td>AGFI</td>
<td>Measure adjusted for degree of freedom</td>
<td>$\geq 0.80$</td>
</tr>
<tr>
<td>NFI</td>
<td>Measures how much better the assumed model fits</td>
<td>$\geq 0.90$</td>
</tr>
<tr>
<td>CFI</td>
<td>Measure of how much better the model fits compare to an independent model</td>
<td>$\geq 0.90$</td>
</tr>
<tr>
<td>TLI</td>
<td>Compare the proposed model with the null model</td>
<td>$\geq 0.90$</td>
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<tr>
<td>RMSR</td>
<td>Average covariance residuals</td>
<td>$\leq 0.10$</td>
</tr>
</tbody>
</table>

The seventh step is the assessment of the validity of the structural model. The assessment of the structural model validity is done to understand how well the
hypothesized relationships among the unobservable theoretical constructs are valid (Kline, 2005; Anderson and Gerbing, 1988; Hair et al., 2010). If the structural model is valid, conclusions are drawn on the validity of the hypotheses. If the structural model is not valid, steps have to be taken to improve the validity of the structural model. The final step in the SEM analysis involves in summarising the findings based on the measurement and structural model analysis (Hair et al., 2010).

4.7.4 Correlation Analysis

A correlation analysis is to measure the strength of a linear relationship between two continuous variables (Bluman, 2012). The correlation coefficient (r) is used to measure the strength of the relationship between independent variable (x) and the dependent variable (y) (Bluman, 2012). The r indicates the extent to which the pairs of numbers for these two variables lie on a straight line. The formula to calculate the r is presented in Equation 4.1.

\[ r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n(\sum x^2) - (\sum x)^2][n(\sum y^2) - (\sum y)^2]}} \]  

(4.1)

Where \( n \) is the number of data pairs.

The range of \( r \) is from -1 to +1. If there is a strong positive linear relationship between the variables, the value of \( r \) is close to +1. A positive linear relationship means that as the value of one variable increases, the value of the other variable increases. If there is a strong negative linear relationship between independent
variable and dependent variable, the value of \( r \) is close to -1. This indicates that an increase in one variable tends to be associated with a decrease in the other variable. When there is a weak relationship or no linear relationship between the two variables, the value of \( r \) is close to 0 (Bluman, 2012).

### 4.7.5 Chi-Square Test for Independence

A chi-square test for independence is used to determine if there is a significant relationship between two categorical variables (Bluman, 2012). The chi-square test for independence is suitable to be applied in data put into classes. It has been used for testing the following hypothesis:

**Null hypothesis:** \( H_0: \text{Variable A and Variable B are independent} \)

**Alternative hypothesis:** \( H_a: \text{Variable A and Variable B are not independent} \)

In the chi-square test for independence, expected frequencies are calculated on the assumption that the two variables are independent. If the variables are independent, the differences between the observed frequencies and the expected frequencies are small. When the observed frequencies are closely match the expected frequencies, the differences between \( O \) and \( E \) are small and the chi-square test statistic is close to 0. As such, the null hypothesis is unlikely to be rejected.

The formula for calculating the chi-square test for independence is shown as follows:

\[
\chi^2 = \sum \frac{(O-E)^2}{E}
\]  (4.2)
Where $O$ = the observed frequency and $E$ = the expected frequency

The rejection or acceptance of null hypotheses is accessed based on the calculated $\chi^2$ value. If the calculated $\chi^2$ value is more than the chi-square critical value or the $p$-value is less than the significance level ($\alpha$), the null hypothesis is rejected.

### 4.7.6 One-Way Analysis of Variance

One-way analysis of variance (ANOVA) is a statistical data analysis technique used for determining whether there are any significant differences between the means of three or more independent groups. In the one-way ANOVA data analysis, all the means are compared simultaneously. $F$ test is used for testing a hypothesis concerning the means of three or more populations which is shown in the following.

**Null hypothesis:** 
$H_0: \mu_1 = \mu_2 = \ldots = \mu_k$

**Alternative hypothesis:** 
$H_a$: At least one mean is different from the others.

In the one-way ANOVA computational process, the sum of squares between groups, the sum of square within groups, and the mean squares are produced. Table 4.8 shows the results of a one-way ANOVA test.

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of squares</th>
<th>D.F.</th>
<th>Mean Square</th>
<th>$F$</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between groups</td>
<td>SSB</td>
<td>k-1</td>
<td>MSB</td>
<td>MSB/MSW</td>
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<tr>
<td>Within Groups</td>
<td>SSW</td>
<td>N-k</td>
<td>MSW</td>
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<td>Total</td>
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</table>
The $SSB$ is denoted as the sum of square between groups. The $SSW$ is the sum of squared within groups. The mean square between ($MSB$) is obtained by dividing the $SSB$ with $k-1$. The mean square within ($MSW$) is calculated by dividing the $SSW$ with $N-k$. The $F$ value is computed based on the division of $MSB$ with $MSW$. The $N$ is denoted as the sum of sample sizes for groups. The $k$ is the number of groups.

In the process of conducting a one-way ANOVA, two different estimates of the population variance are made including between-group variances and within-group variances as shown in Table 4.7. The test statistics for a one-way ANOVA is the ratio of two variances as shown in Equation 4.3

$$ F = \frac{MSB}{MSW} \quad (4.3) $$

If there is no difference between the means, the $MSB$ is approximately equal to the $MSW$. The $F$ test value is approximately equal to 1. This means the null hypothesis is fail to be rejected. However, when the means differ significantly, the $MSB$ will be much larger than the $MSW$. The value of $F$ significantly greater than 1 suggests that null hypothesis should be rejected (Bluman, 2012).

**4.7.7 Independent Samples t-test Analysis**

The independent $t$-test is a statistics analysis method for evaluating the difference between the means of two independent groups (Pallant, 2010). The $t$ test evaluates whether the mean value of the acceptance level for one group differs significantly
from the mean value of the test variable for the second group. In independent samples $t$-test, two hypotheses are constructed to test the difference between two means. The first hypothesis which is the null hypothesis has an assumption that the two means of the two independent groups are the same. The second hypothesis which is the alternative hypothesis has an assumption that the two means of the two independent groups are not the same. The mathematical representation of the hypotheses for the independent samples $t$-test is shown as follows:

**Null hypotheses:**

$$H_0: \mu_1 = \mu_2 \quad \text{or} \quad H_0: \mu_1 - \mu_2 = 0$$

**Alternative hypotheses:**

$$H_a: \mu_1 \neq \mu_2 \quad \text{or} \quad H_a: \mu_1 - \mu_2 \neq 0$$

Where $\mu_1$ stands for the mean for the first group and $\mu_2$ stands for the mean for the second group.

The formula to calculate the $t$-test value is presented in Equation 4.4. If the $t$-test test is greater than the critical value, then null hypotheses are rejected.

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad (4.4)$$

where $(\bar{x}_1 - \bar{x}_2)$ is the observed difference between sample means. The expected value $(\mu_1 - \mu_2)$ is equal to zero when no difference between population means is hypothesized. The denominator $\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$ is the standard error of the difference between two means.
4.8 Concluding Remarks

This chapter presents the research methodology adopted for adequately addressing the research question. A quantitative research methodology is adopted for adequately answering the research questions. A conceptual framework proposed in Chapter 3 is used for better understanding the adoption of OLMs in Malaysian higher education. Various analysis methods are adopted for examining (a) the emerging pattern of the adoption of OLMs in Malaysian higher education, (b) the critical factors for the adoption of OLMs, (c) the relationship between learners’ learning styles and their perceptions towards the adoption of OLMs for collaborative learning and (d) the gender differences in attitudes towards the adoption of OLMs. Comprehensive discussions of the analysis of survey data are presented in the subsequent chapters.
Chapter 5

Emerging Patterns of the Adoption of Open Learner Models

5.1 Introduction

A pattern is an empirically proven solution to a recurring problem that occurs in a particular context (Borchers, 2008; Kamthan, 2010). It provides a description of a problem and the solution to adequately addressing this problem in a specific situation (Alexandar, 1977). The identification of patterns in a specific problem can provide feasible solutions to the future events based on the exploration of the current recurring problem (Borchers, 2008; Kamthan, 2010). For example, exploring learners’ adoption patterns of collaborative technologies with respect to their levels of computer literacy can provide information about the usage patterns of learners with different levels of computer literacy (Rhema and Miliszewska, 2014). This information is important for improving the adoption of collaborative technologies in collaborative learning. With the availability of such information, assistance can be provided to help learners who have difficulty in adopting collaborative technologies in collaborative learning.
With the rapid development of ICT, the adoption of collaborative technologies is becoming popular for improving collaboration in teaching and learning in universities (Huang, 2015). The popularity of collaborative technologies is due to the benefits that collaborative technologies have provided in an effective learning environment. Such benefits include improved participation of learners in learning and enhanced sharing of learning information (Hu and Hui, 2012). To fully realize the benefits of collaborative technologies, OLMs are widely adopted in teaching and learning processes as a collaborative technology for promoting the engagement of learners in collaborative learning.

The adoption of OLMs allows learners to share their learning information and compare with each other’s progress in collaborative learning. It provides learners with an opportunity to develop their self-reflection and self-assessment skills. There are many studies that have been carried out to understand how OLMs can be utilized effectively and efficiently from different perspectives. Chen et al. (2007), for example, introduce animal companions to encourage learners’ engagement with OLMs in collaborative learning. Kerly et al. (2008) propose a conversation agent to promote learners’ participation in OLM-based learning environment. There is, however, little research into the use of OLMs from the perspective of learners, particularly in relation to the pattern and trend of their use.

The development of OLMs in Malaysian higher education is still in its infancy stage. The government of Malaysia has increased initiatives to improve the adoption of OLMs in collaborative learning. Obtaining information about the trend and pattern of
the adoption of OLMs in the initial stage of the implementation is critical to the Malaysian government for improving the adoption of OLMs. The exploration of the pattern and trend of the adoption of OLMs is therefore important and necessary to have a better understanding of the use of OLMs from the learners’ perspective.

The purpose of this chapter is to investigate the extent to which OLMs are utilized in Malaysian higher education, leading to the identification of the emerging pattern and trend in the adoption of OLMs. To effectively achieve the above objective, various types of information from learners including (a) learners’ attitudes towards the adoption of OLMs with respect to different level of web-based learning experience, computer and web literacy-based technology skill, and (b) the purpose of the adoption of OLMs in collaborative learning are collected through online survey. This chapter presents the finding from the survey for revealing the emerging pattern and trend of the adoption of OLMs in Malaysian higher education.

To fulfil the objective of this chapter, the content of this chapter is organized into four sections. Section 5.2 explores the current pattern of the adoption of OLMs to facilitate collaborative learning in Malaysian higher education. Section 5.3 presents a discussion of the findings from Section 5.2, leading to the identification of the emerging patterns and trends for the adoption of OLMs in Malaysian higher education. Section 5.4 ends the chapter with concluding remarks.
5.2 Emerging Patterns of the Adoption of OLMs

There are several ways to describe a pattern in the adoption of educational technologies in collaborative learning (Bhuasiri et al., 2012; Rhema and Miliszewska, 2014). Bhuasiri et al. (2012), for example, investigate patterns in the adoption of a collaborative technology from the perspective of gender, web-based learning experience, web and computer literacy. Rhema and Miliszewska (2014) follow the same way to analyse the patterns of the adoption of collaborative technologies with respect to learners’ demographic characteristics, experience in using educational technologies, and web and computer skills.

To pinpoint the emerging patterns for the adoption of OLMs in Malaysian higher education, this section analyses the adoption of OLMs in Malaysian higher education from three perspectives including (a) the overall profile of learners in the adoption of OLMs in Malaysian higher education, (b) the purpose of the adoption of OLMs, (c) the learner’s attitudes towards the adoption of OLMs with respect to genders, web-based learning experiences and computer and web literacy.

Understanding the overall profile of learners is of tremendous importance for identifying the emerging pattern and trend of using OLMs in collaborative learning (Rhema and Miliszewska, 2014). This profile is represented by the age, the gender, the year of study at university, the course of study, the web-based learning experience of learners, and the learner’s learning experience in using OLMs (Ngai et al., 2007; Bhuasiri et al., 2012). The reason for considering these dimensions is because they directly affect how a learner adopts OLMs in collaborative learning.
For example, the learning experience of learners in engaging with web-based learning environment tends to help the learners to use collaborative technologies more effectively (Rhema and Miliszewska, 2014; Balakrishnan, 2015).

There is a continuing argument about the use of collaborative technologies between males and females (Ding et al., 2011; Huang et al., 2013; Kimbrough et al., 2013). The development of the profile of learner helps higher education institutions to understand the requirements and expectation of learners in their adoption of OLMs better. Such an understanding can lead to specific strategies and policies being developed for improving the adoption of OLMs in collaborative learning.

Table 5.1 presents the overall profile of learners for the adoption of OLMs in Malaysian higher education based on the valid response from this survey. It reveals that most of the 504 respondents are male (53.0 per cent) and are at the age of 21-23 years (64.9 per cent). About 50 per cent of the respondents are in year 1 and year 3 of study at university.

<table>
<thead>
<tr>
<th>Profile</th>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than 20</td>
<td>31</td>
<td>6.2</td>
</tr>
<tr>
<td>21 – 23</td>
<td>327</td>
<td>64.9</td>
</tr>
<tr>
<td>24 – 26</td>
<td>133</td>
<td>26.4</td>
</tr>
<tr>
<td>27 – 29</td>
<td>6</td>
<td>1.2</td>
</tr>
<tr>
<td>More than 30</td>
<td>7</td>
<td>1.4</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>237</td>
<td>47.0</td>
</tr>
<tr>
<td>Male</td>
<td>267</td>
<td>53.0</td>
</tr>
<tr>
<td><strong>Year of study at university</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1\textsuperscript{st} year</td>
<td>147</td>
<td>29.2</td>
</tr>
<tr>
<td>2\textsuperscript{nd} year</td>
<td>99</td>
<td>19.6</td>
</tr>
<tr>
<td>3\textsuperscript{rd} year</td>
<td>157</td>
<td>31.2</td>
</tr>
<tr>
<td>4\textsuperscript{th} year</td>
<td>101</td>
<td>20.0</td>
</tr>
</tbody>
</table>
Figure 5.1 indicates that the participant of this study is from various backgrounds including engineering (29.4 per cent), computer science/information technology (27.6 per cent), social science (24.0 per cent), and business/management (19.0 per cent). This demonstrates that the adoption of OLMs is exemplified by a fair distribution of learner across various dimensions.

![Figure 5.1 The Distribution of Field of Study of the Participant](image)

The experience in engaging with collaborative technologies would influence the adoption of other new collaborative technologies in collaborative learning (Al-rahmi et al., 2015). Figure 5.2 shows that 87.3 per cent of the respondents are experienced in using collaborative technologies in their studies. Only 12.7 per cent of the respondents have no experience in adopting collaborative technologies. This indicates that the adoption of collaborative technologies in collaborative learning has become popular in Malaysian higher education.
Figure 5.2  The Learner’s Web-based Learning Experience

Figure 5.3 exemplifies that the adoption of OLMs in collaborative learning is still very low as only 17.0 per cent of the respondents have experience in using OLMs. About 83.0 per cent of the respondents have no experience in dealing with OLMs in collaborative learning. This demonstrates that OLMs are underutilized in facilitating collaborative learning in Malaysian higher education.
The enjoyment of learners in using computers in learning processes can facilitate the adoption of collaborative technologies in collaborative learning (Mun and Hwang, 2003). As Table 5.2 indicates, learners who enjoy using computers in learning tend to have a more positive attitude towards the adoption of OLMs. A total 64.8 per cent of the respondents who feel happy in adopting computers for learning are willing to adopt OLMs for collaborative learning.

### Table 5.2 The Distribution of Learners’ Enjoyment of Using Computer and Their Attitudes towards the Adoption of OLMs

<table>
<thead>
<tr>
<th>Enjoy of using computer</th>
<th>Attitudes</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Negative</td>
<td>Neutral</td>
</tr>
<tr>
<td></td>
<td>Count</td>
<td>Count</td>
</tr>
<tr>
<td>Yes</td>
<td>58</td>
<td>104</td>
</tr>
<tr>
<td>No</td>
<td>2</td>
<td>13</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>117</td>
</tr>
</tbody>
</table>

Learners often have multiple purposes in adopting OLMs for collaborative learning. Understanding the pattern of multiple purposes for adopting OLMs in learner is of great importance. To reflect this adequately, the survey instrument is designed to allow respondents to select multiple responses regarding their purposes for adopting OLMs. There are 2164 responses given by 504 respondents, indicating that many respondents have multiple purposes for adopting OLMs.

Table 5.3 presents a summarized view of the learners’ multiple purposes pattern in adopting OLMs. It is evident that the most common reasons for adopting OLMs are to do reflection on learning, to use as a navigation aid on learning, to view learning
progresses, and to do planning on learning. Their proportions among all responses are 21.8 per cent, 21.1 per cent, 19.6 per cent, and 15.8 per cent respectively.

Table 5.3 The Overview of the Purpose of Adopting OLMs

<table>
<thead>
<tr>
<th>Purposes</th>
<th>Single purpose</th>
<th>Multi-purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Frequency</td>
<td>Percentage</td>
</tr>
<tr>
<td>To do reflection on learning</td>
<td>472</td>
<td>93.7</td>
</tr>
<tr>
<td>To use as a navigation aid on learning</td>
<td>456</td>
<td>90.5</td>
</tr>
<tr>
<td>To view learning progress</td>
<td>423</td>
<td>83.9</td>
</tr>
<tr>
<td>To do planning on learning</td>
<td>341</td>
<td>67.7</td>
</tr>
<tr>
<td>To improve the accuracy</td>
<td>243</td>
<td>48.2</td>
</tr>
<tr>
<td>To compare instructors’ expectation</td>
<td>123</td>
<td>24.4</td>
</tr>
<tr>
<td>To view peers’ learner models</td>
<td>105</td>
<td>20.8</td>
</tr>
</tbody>
</table>

Learners’ web-based learning experiences play an important role in determining learners’ adoption of other new collaborative technologies in collaborative learning (Kim and Moore, 2005). Table 5.4 presents learners’ attitudes towards the adoption of OLMs with respect to learners’ engagement experience in web-based learning. It shows that 66.4 per cent of the respondents who have web-based learning experience tend to have a positive attitude towards the adoption of OLMs.

Table 5.4 The Distribution of Learners’ Web-based learning Experience and Their Attitudes towards the Adoption of OLMs

<table>
<thead>
<tr>
<th>Web-based Learning Experience</th>
<th>Attitudes</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Negative</td>
<td>Neutral</td>
</tr>
<tr>
<td>Yes</td>
<td>55</td>
<td>93</td>
</tr>
<tr>
<td>No</td>
<td>5</td>
<td>24</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>117</td>
</tr>
</tbody>
</table>
The results of the \( t \)-test \((t=3.351, \ df =502, \ p=0.001)\) as shown in Table 5.5 indicates that there is a significant difference in the learners’ attitudes towards the adoption of OLMs in collaborative learning based on learners’ web-based learning experience.

**Table 5.5  The Summary of the Independent \( t \)-test**

<table>
<thead>
<tr>
<th>Learners’ attitudes</th>
<th>Experience</th>
<th>Inexperience</th>
<th>Mean difference</th>
<th>( t )</th>
<th>( p )-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5.286</td>
<td>4.867</td>
<td>0.419</td>
<td>3.351</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Learners’ web knowledge such as how to upload and download information from the web can facilitate learners’ engagement with collaborative technologies (Nambisan and Wang, 2000). Table 5.6 indicates that learners’ attitudes towards the adoption of OLMs based on learners’ web knowledge. It shows that 71.4 per cent of the respondents who have higher level of web knowledge tend to have a positive attitude towards the adoption of OLMs. Furthermore, the result from the correlation analysis shows a significant positive relationship between learners’ web knowledge and their attitudes. The Pearson correlation value of 0.491 with \( p < 0.05 \) indicates that learners who are better acquainted with web knowledge have more positive attitudes towards the adoption of OLMs in collaborative learning.

**Table 5.6  The Distribution of Learners’ Web Knowledge and Their Attitudes towards the Adoption of OLMs to Web Knowledge**

<table>
<thead>
<tr>
<th>Web Knowledge</th>
<th>Attitudes</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Negative</td>
<td>Neutral</td>
</tr>
<tr>
<td></td>
<td>Count</td>
<td>Count</td>
</tr>
<tr>
<td>Poor</td>
<td>33</td>
<td>10</td>
</tr>
<tr>
<td>Average</td>
<td>8</td>
<td>30</td>
</tr>
<tr>
<td>Good</td>
<td>19</td>
<td>77</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>117</td>
</tr>
</tbody>
</table>
Learners’ web usage such as the engagement rate with web-based learning management systems would have an impact on learners’ adoption of collaborative technologies (Alharbi and Drew, 2014). Table 5.7 shows the learners’ attitudes towards the adoption of OLMs based on web usage. A total 70.0 per cent of the respondents who actively participate in web-based learning management system tend to have a positive attitude towards the adoption of OLMs. The correlation analysis reveals that there is a significant positive relationship between learners’ web usage and learners’ attitudes towards the adoption of OLMs. The Pearson correlation value of 0.493 with $p < 0.05$ shows that learners who have higher level of web usage tend to have more positive attitudes towards the adoption of OLMs.

### Table 5.7 The Distribution of Learners’ Web Usage and Their Attitudes towards the Adoption of OLMs

<table>
<thead>
<tr>
<th>Web Usage</th>
<th>Attitudes</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Negative</td>
<td>Neutral</td>
</tr>
<tr>
<td></td>
<td>Count</td>
<td>Count</td>
</tr>
<tr>
<td>Poor</td>
<td>34</td>
<td>4</td>
</tr>
<tr>
<td>Average</td>
<td>4</td>
<td>19</td>
</tr>
<tr>
<td>Good</td>
<td>22</td>
<td>94</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>117</td>
</tr>
</tbody>
</table>

Learners’ computer skills would have an impact on learners’ adoption of collaborative technology (Buabeng-Andoh, 2012). Table 5.8 reveals learners’ attitudes towards the adoption of OLMs based on learners’ computer skills. There is 69.8 per cent of the respondents with good computer skills who tend to have a positive attitude towards the adoption of OLMs. The correlation analysis shows that there is a significant positive relationship between learners’ attitudes and computer skills towards the adoption of OLMs. The Pearson correlation value of 0.482 with $p$
< 0.05 indicates that learners who have a better computer skill tend to have more positive attitudes towards the adoption of OLMs in collaborative learning.

### Table 5.8 The Distribution of Learners’ Computer Skills and Their Attitudes towards the Adoption of OLMs

<table>
<thead>
<tr>
<th>Personal Computer Skills</th>
<th>Attitudes</th>
<th></th>
<th></th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Negative</td>
<td>Neutral</td>
<td>Positive</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Count</td>
<td>Count</td>
<td>Count</td>
<td></td>
</tr>
<tr>
<td>Poor</td>
<td>21</td>
<td>5</td>
<td>27</td>
<td>53</td>
</tr>
<tr>
<td>Average</td>
<td>11</td>
<td>33</td>
<td>53</td>
<td>97</td>
</tr>
<tr>
<td>Good</td>
<td>28</td>
<td>79</td>
<td>247</td>
<td>354</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>117</td>
<td>327</td>
<td>504</td>
</tr>
</tbody>
</table>

Learners’ web skills such as web programming skills would influence learners’ adoption of collaborative technologies in collaborative learning (Ward et al., 2009). Table 5.9 indicates the learners’ attitudes towards the adoption of OLMs based on learners’ web skills. A total 68.5 per cent of the respondents who have a good programming skill react positively in the adoption of OLMs. The correlation analysis shows that there is a significant positive relationship between learners’ attitudes and learners’ web skills towards the adoption of OLMs in collaborative learning. The Pearson correlation value of 0.643 with $p < 0.05$ reveals that learners who have good web skills tend to have more positive attitudes towards the adoption of OLMs.

### Table 5.9 The Distribution of Learners’ Web Skills and Their Attitudes towards the Adoption of OLMs

<table>
<thead>
<tr>
<th>Web Skills</th>
<th>Attitudes</th>
<th></th>
<th></th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Negative</td>
<td>Neutral</td>
<td>Positive</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Count</td>
<td>Count</td>
<td>Count</td>
<td></td>
</tr>
<tr>
<td>Poor</td>
<td>24</td>
<td>9</td>
<td>25</td>
<td>58</td>
</tr>
<tr>
<td>Average</td>
<td>10</td>
<td>32</td>
<td>80</td>
<td>122</td>
</tr>
<tr>
<td>Good</td>
<td>26</td>
<td>79</td>
<td>222</td>
<td>324</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>117</td>
<td>327</td>
<td>504</td>
</tr>
</tbody>
</table>
5.3 Research Findings and Implications

The analysis of the OLM adoption patterns in Malaysian higher education institutions above shed light on several major findings. The following section discusses the interpretation based on these findings.

The adoption of OLMs in Malaysian higher education is not encouraging. This could be due to the fact that the development of OLMs to facilitate collaborative learning in Malaysian higher education is still at its infancy stage. Not many of the higher education institutions are aware of the effectiveness of adopting OLMs in fostering collaborative learning. The relatively low rate of the adoption of OLMs in Malaysian higher education further justifies the need for this study giving that there is a continuously financial support and encouragement from the Malaysian government in introducing collaborative technologies to facilitate collaborative learning.

The survey shows that learners who enjoy using computers for learning tend to have a positive attitude towards the adoption of OLMs. Learners who have less interest in adopting computer in learning tend to have a negative attitude towards the adoption of OLMs. This might be because learners who do not master computer would not interest in using collaborative technology in collaborative learning. Furthermore, learners who have web-based learning experience are more willing to adopt OLMs in collaborative learning as compared to learners who without web-based learning experience. This could be due to the fact that the web-based learning experience of learners in engaging with collaborative technologies has facilitated the adoption of OLMs in collaborative learning.
The survey results suggest that the main purpose for the learners to adopt OLMs is for reflection, navigation aid on learning, viewing learning progress, and planning on learning. This implies that learners’ priority to adopt OLMs in collaborative learning is to keep track on their own learning progress. Learners do not have the interest to adopt OLMs for comparing their learning progress with instructors’ expectation. They also have less motivation to adopt OLMs for inspecting peers’ learning progresses. This shows that learners are more concerned about their individual learning instead of other learners.

The survey indicates that learners who have a good computer and web competency tend to have a positive attitude towards the adoption of OLMs in collaborative learning. The might be because the knowledge of learners in engaging with computer and web can facilitate the adoption of OLMs in collaborative learning.

## 5.4 Concluding Remarks

The purpose of this chapter is to investigate the emerging patterns for the adoption of OLMs in Malaysian higher education, thus providing answers to the first research question: *What are the current patterns and trends of the adoption of OLMs in Malaysian higher education?* This is done by examining the demographic characteristics of the surveyed undergraduates in Malaysia, and exploring OLMs adoption patterns in Malaysian higher education.
The findings reveal that the adoption of OLMs in Malaysian higher education is generally low. Learners have multiple purposes in adopting OLMs for collaborative learning. Most learners display less interest in showing their learner model to their peers and instructors. There exist differences in learners’ attitudes towards the adoption of OLMs based on web-based learning experience. Additionally, learners with good computer and web skills tend to have more positive attitudes towards the adoption of OLMs in collaborative learning.
Chapter 6

Critical Factors for the Adoption of Open Learner Models

6.1 Introduction

Critical factors are those areas that must be addressed properly for the successful implementation of collaborative technologies in collaborative learning (Bhuasiri et al., 2012). They have to be properly managed during the planning of the implementation of collaborative technologies in collaborative learning (Cheawjindakarn et al., 2013). The identification of the critical factors for the adoption of collaborative technologies is crucial for improving learners’ adoption of these collaborative technologies (Bhuasiri et al., 2012).

Various studies have been conducted in investigating the critical factors for improving the adoption of collaborative technologies from different perspectives including human factors, system design factors, environmental factors, as well as technological factors (Sek et al., 2015a; Abdullah and Ward, 2016). These studies, however, do not have a common agreement on the critical factors that influence the adoption of collaborative technologies. This is because different collaborative technologies have their own unique characteristics to facilitate collaborative learning.
Such a unique characteristic of the collaborative technologies therefore could affect the critical factors for the adoption of collaborative technologies (Cheawjindakarn et al., 2012; Sek et al., 2015a).

The development of OLMs in Malaysian higher education is still in its infancy stage (Sek et al., 2015a). Not many Malaysian higher education institutions are aware of OLMs in facilitating collaborative learning. As a result, the utilization of OLMs in facilitating collaborative learning in Malaysian higher education is not encouraging. Furthermore, factors that influence the adoption of OLMs in Malaysian higher education are still unclear. A better understanding of the critical factors for the adoption of OLMs is, therefore, desirable for the improvement of the adoption of OLMs in collaborative learning in Malaysian higher education.

The purpose of this chapter is to investigate the critical factors for the adoption of OLMs in collaborative learning in Malaysian higher education. This chapter is organized into five sections. Section 6.2 presents the measurement model validation, followed by the hypothesis testing using structural model analysis in section 6.3. Section 6.4 presents the discussion on the critical factors that influence the adoption of OLMs in Malaysian higher education. Finally, section 6.5 provides some concluding remarks.
6.2 Measurement Model Validation

The measurement model validation is an essential process for examining the validity of the measurement model before conducting further analysis (Anderson and Gerbing, 1988; Hair et al., 2010). The purpose of the measurement model validation is to validate whether the proposed items are a good representation of the constructs in the conceptual framework (Hair et al., 2010). This process is performed by (a) examining the fitness between the measurement model and the survey data, and (b) empirically evaluating the validity and reliability of the respective variables in the measurement model (Anderson and Gerbing, 1988; Hair et al., 2010).

The validation of the conceptual framework proposed in Chapter 3 can be done through SEM analysis. SEM is one of the most powerful statistical methods for analysing multivariate data. The applicability of SEM in this study is due to its ability to include latent variables for representing unobserved concepts while accounting for the measurement error and its capability to simultaneously assess multiple correlations and covariance among variables in the model validity test (Brown, 2006; Byrne, 2010).

In the SEM analysis, CFA is performed on the initial measurement model by using AMOS 22.0 based on the survey data. It is a statistical technique used to test how well the number of factors and the loadings of measured variables on them conforms to what is expected by the pre-established theory (Hair et al., 2010). There are three steps involved in the CFA process. The first step is the model specification. An adequate sample size of 504 valid surveys and the data set with the multivariate
normality distribution and linearity fulfil the prerequisite for the use of the maximum likelihood method in the estimation (Hair et al., 2010).

The second step is the assessment of fitness indices of the congeneric and the overall measurement models to determine the overall goodness-of-fit of the models. This is an iterative model modification process for developing the best set of items to represent a construct through refinement and retesting. It involves the purification of the congeneric and measurement models by eliminating measured variables and latent constructs that do not fit well with the data. The dropping of the items in the congeneric and measurement models is based on the assessment of the modification indices and standard residuals. This interactive process is continued until both the congeneric and measurement models fit well with the data. The last step is the assessment of the reliability and validity of the overall measurement model. In this process, the overall measurement model is assessed for the convergent validity and discriminant validity (Hair et al., 2010).

### 6.2.1 Congeneric Models Fitness Assessment

The assessment of the congeneric models fitness is performed to obtain an initial goodness-of-fit of individual factors before the assessment of goodness-of-fit of the full measurement model. The full measurement model is decomposed into several one factor congeneric models. All one factor congeneric models are assessed for their validity separately using data collected from the survey. This process is taken to improve the validity of the individual construct. The modification indices and the standard residuals are analysed. Modifications are made to obtain satisfactory
goodness-of-fit indices of the respective congeneric model. As presented in Table 6.1, the goodness-of-fit of all the congeneric models is within the acceptance level. These goodness-of-fit measures show that the fitness between the model and the data is satisfactory. The CFA analysis of all the congeneric models can be obtained from Appendix F. This indicates that these individual congeneric models can be combined for further assessment of the goodness-of-fit of the full measurement model.

Table 6.1 Goodness-of-fit Results of the Congeneric Models

<table>
<thead>
<tr>
<th>Constructs</th>
<th>χ²/df ≤5.00a</th>
<th>RMSEA ≤ 0.08a</th>
<th>GFI ≥0.90a</th>
<th>AGFI ≥ 0.80a</th>
<th>NFI ≥0.90a</th>
<th>CFI ≥0.90a</th>
<th>TLI ≥0.90a</th>
<th>RMSR ≤ 0.10a</th>
</tr>
</thead>
<tbody>
<tr>
<td>MO</td>
<td>2.145</td>
<td>0.015</td>
<td>0.990</td>
<td>0.970</td>
<td>0.993</td>
<td>0.992</td>
<td>0.992</td>
<td>0.014</td>
</tr>
<tr>
<td>CSE</td>
<td>4.286</td>
<td>0.019</td>
<td>0.999</td>
<td>0.956</td>
<td>0.992</td>
<td>0.994</td>
<td>0.982</td>
<td>0.016</td>
</tr>
<tr>
<td>OLE</td>
<td>1.404</td>
<td>0.008</td>
<td>0.999</td>
<td>0.986</td>
<td>0.998</td>
<td>1.000</td>
<td>1.000</td>
<td>0.072</td>
</tr>
<tr>
<td>SA</td>
<td>0.175</td>
<td>0.000</td>
<td>1.000</td>
<td>0.998</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>0.003</td>
</tr>
<tr>
<td>SI</td>
<td>4.961</td>
<td>0.024</td>
<td>0.971</td>
<td>0.932</td>
<td>0.977</td>
<td>0.982</td>
<td>0.969</td>
<td>0.025</td>
</tr>
<tr>
<td>SD</td>
<td>0.314</td>
<td>0.001</td>
<td>0.999</td>
<td>0.997</td>
<td>1.000</td>
<td>1.000</td>
<td>1.003</td>
<td>0.003</td>
</tr>
<tr>
<td>NA</td>
<td>0.200</td>
<td>0.001</td>
<td>1.000</td>
<td>0.998</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>0.025</td>
</tr>
<tr>
<td>TR</td>
<td>3.416</td>
<td>0.016</td>
<td>0.987</td>
<td>0.960</td>
<td>0.990</td>
<td>0.993</td>
<td>0.986</td>
<td>0.015</td>
</tr>
<tr>
<td>PU</td>
<td>3.334</td>
<td>0.015</td>
<td>0.981</td>
<td>0.957</td>
<td>0.990</td>
<td>0.993</td>
<td>0.988</td>
<td>0.012</td>
</tr>
<tr>
<td>PEOU</td>
<td>2.682</td>
<td>0.010</td>
<td>0.992</td>
<td>0.969</td>
<td>0.996</td>
<td>0.997</td>
<td>0.994</td>
<td>0.007</td>
</tr>
<tr>
<td>ISI</td>
<td>0.047</td>
<td>0.001</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>0.001</td>
</tr>
<tr>
<td>ATT</td>
<td>1.168</td>
<td>0.005</td>
<td>0.998</td>
<td>0.989</td>
<td>0.999</td>
<td>1.000</td>
<td>0.999</td>
<td>0.004</td>
</tr>
<tr>
<td>ITS</td>
<td>0.756</td>
<td>0.000</td>
<td>0.999</td>
<td>0.992</td>
<td>0.999</td>
<td>1.000</td>
<td>1.000</td>
<td>0.004</td>
</tr>
</tbody>
</table>

* Recommended value

6.2.2 Full Measurement Model Fitness Assessment

The assessment of the goodness-of-fit of the full measurement is a process for obtaining the goodness-of-fit indices of the combination of all the congeneric models as discussed in section 6.2.1. All the thirteen constructs are combined for the CFA analysis. For the full measurement model assessment, all the constructs are freely correlated with one another. The results of the initial full measurement model are given in Appendix G. As presented in Table 6.2, the overall fitness of the initial full
measurement model is a reasonable fit. All the fitness values are within the acceptance level (Hair et al., 2010). These goodness-of-fit measures indicate that the fitness between the model and data is satisfactory.

A further analysis of the standard residuals and the modification indices reveals that the initial full measurement model could be improved. Two items including one item in OLE and another item in behavioural intention have been deleted. These two items are deleted due to larger standardised residuals. Table 6.2 shows a comparison of the goodness-of-fit statistics of the initial measurement model presented in Appendix G and the final full measurement model presented in Appendix H. It is clear that the goodness-of-fit indices of the final full measurement model have been further improved. The final full measurement model of this study appears to have a good fit with the data (Byrne, 2010; Hair et al., 2010). This final full measurement model can proceed for reliability and validity assessment.

Table 6.2  A Comparison of Goodness-of-Fit Statistics of Initial and Final Full Measurement Models

<table>
<thead>
<tr>
<th>Model</th>
<th>$\chi^2$/df</th>
<th>RMSEA  $\leq$ 0.08</th>
<th>GFI  $\geq$ 0.90</th>
<th>AGFI $\geq$ 0.80</th>
<th>NFI $\geq$ 0.90</th>
<th>CFI $\geq$ 0.90</th>
<th>TLI $\geq$ 0.90</th>
<th>RMSR $\leq$ 0.10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Full Measurement Model</td>
<td>1.532</td>
<td>0.029</td>
<td>0.859</td>
<td>0.842</td>
<td>0.907</td>
<td>0.966</td>
<td>0.963</td>
<td>0.026</td>
</tr>
<tr>
<td>Final Full Measurement Model</td>
<td>1.521</td>
<td>0.033</td>
<td>0.911</td>
<td>0.847</td>
<td>0.915</td>
<td>0.981</td>
<td>0.986</td>
<td>0.012</td>
</tr>
</tbody>
</table>

*Recommended value
6.2.3 Reliability and Validity of the Final Full Measurement Model

The reliability and validity assessment for the final full measurement model is conducted to validate the measurement model. Two main assessments including the convergent validity and the discriminant validity are conducted in this process.

Convergent Validity

Convergent validity assesses the extent to which the items measuring a construct converge together for measuring a single construct (Kline, 2005; Hair et al., 2010). There are three main procedures to assess the convergent validity of a set of measurement items in relation to their corresponding variables. These procedures are the indicator reliability, the composite reliability, and the average variance extracted (Fornell and Larcker, 1981; Hair et al., 2010).

The indicator reliability can be computed by squaring the standardized factor loading obtained in the analysis. The standardised factor loading value should be at least at 0.50, and ideally at 0.70 or higher with all standardised factor loadings statistically significant (Fornell and Larcker, 1981; Hair et al., 2010). As indicated in Table 6.3, the indicator reliability for all indicators is above 0.50. This indicates that all the items are well loaded on the respective variables supporting the convergent validity of the measurement model.

The composite reliability is conducted to check whether there is an evidence of similarity between the measures of theoretically related constructs (DeVellis, 2003;
Kimmo et al. 2006). A variable is considered to be of internal consistency if the composite reliability value meets or surpasses the recommended level of 0.70 (Segars, 1997; Hair et al., 2010). The formula to calculate the composite reliability is shown in Equation 6.1.

$$\theta_c = \frac{(\sum \sigma_i)^2}{(\sum \sigma_i)^2 + \sum \text{var} (\epsilon_i)}$$  \hspace{1cm} (6.1)

Where $\theta_c$ denotes the composite reliability of the item. $\sigma_i$ represents the factor loading for the indicator $i$. The error variances $\text{var}(\epsilon_i)$ can be obtained by using $1 - \sigma_i^2$. As presented in Table 6.3, the composite reliability value for all the constructs is above 0.70. This shows that all the items within the respective constructs being tested in this study meet the statistical requirement for further analysis.

The average variance extracted (AVE) is a measure of the amount of variance captured by the variable in relation to the amount of variance attributable to the measurement error (Hair et al., 2010). It is suggested that AVE should be greater than 0.50 to show the convergent validity (Hair et al., 2010). The formula to obtain the value of AVE is presented as follows:

$$AVE = \frac{\sum \sigma_i^2}{\sum \sigma_i^2 + \sum \text{var} (\epsilon_i)}$$  \hspace{1cm} (6.2)
As indicated in Table 6.3, the test results of the AVE values of all constructs are well beyond the recommended value of 0.50. This indicates that the measurement model presents an adequate convergent validity of the measurement model for further analysis.

Table 6.3  Convergent Validity and Reliability for the Measurement Model

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Items</th>
<th>Standardised Factor Loadings (&gt; 0.707)</th>
<th>Indicative Reliability ($R^2$ (&gt;0.50))</th>
<th>Composite Reliability (&gt; 0.70)</th>
<th>Average Variance Extracted (&gt;0.50)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MO</td>
<td>MO_1</td>
<td>0.767</td>
<td>0.588</td>
<td>0.922</td>
<td>0.662</td>
</tr>
<tr>
<td></td>
<td>MO_2</td>
<td>0.803</td>
<td>0.645</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>MO_3</td>
<td>0.827</td>
<td>0.684</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>MO_4</td>
<td>0.816</td>
<td>0.666</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>MO_5</td>
<td>0.819</td>
<td>0.671</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>MO_6</td>
<td>0.849</td>
<td>0.721</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CSE</td>
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<td>0.709</td>
<td>0.887</td>
<td>0.662</td>
</tr>
<tr>
<td></td>
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<td>0.759</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>CSE_3</td>
<td>0.784</td>
<td>0.615</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CSE_4</td>
<td>0.753</td>
<td>0.567</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>0.846</td>
<td>0.647</td>
</tr>
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</tr>
<tr>
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<td>OLE_3</td>
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<td>0.622</td>
</tr>
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<td></td>
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<tr>
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<td>SA_3</td>
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<td>0.560</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>SA_4</td>
<td>0.759</td>
<td>0.576</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SA_5</td>
<td>0.773</td>
<td>0.598</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI</td>
<td>SI_1</td>
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<td>0.569</td>
<td>0.916</td>
<td>0.646</td>
</tr>
<tr>
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<td>0.615</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SI_3</td>
<td>0.797</td>
<td>0.635</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SI_4</td>
<td>0.793</td>
<td>0.629</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SI_5</td>
<td>0.847</td>
<td>0.717</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SI_6</td>
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<tr>
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<td>0.613</td>
<td>0.908</td>
<td>0.711</td>
</tr>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SD_3</td>
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<td>0.748</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SD_4</td>
<td>0.783</td>
<td>0.613</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NA</td>
<td>NA_1</td>
<td>0.816</td>
<td>0.666</td>
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</tr>
<tr>
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<td>NA_2</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>NA_3</td>
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<td>0.650</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>NA_4</td>
<td>0.824</td>
<td>0.679</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TR</td>
<td>TR_1</td>
<td>0.803</td>
<td>0.645</td>
<td>0.920</td>
<td>0.667</td>
</tr>
<tr>
<td></td>
<td>TR_2</td>
<td>0.835</td>
<td>0.697</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>TR_3</td>
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<tr>
<td></td>
<td>TR_4</td>
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<td>0.806</td>
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</tr>
<tr>
<td>PU</td>
<td>PU_1</td>
<td>0.845</td>
<td>0.714</td>
<td>0.953</td>
<td>0.770</td>
</tr>
</tbody>
</table>
Discriminant Validity

The discriminant validity measures the degree to which the indicators of theoretically distinct concepts are unique from each other (Byrne, 2010; Hair et al., 2010). The measure of theoretically different constructs should have low correlations with each other. A low cross-construct correlation is an indication of the discriminant validity. The discriminant validity of the construct is assessed by comparing the square roots of the AVE from each latent construct with the correlation between the construct and all other constructs in the model. The square root of AVE should be greater than any of the correlation for that construct to show the discriminant validity (Segar and Grover, 1998; Hair et al., 2010).

As indicated in Table 6.4, the square roots of the AVE for a given construct indicated as a diagonal element in Table 6.4 are greater than the off-diagonal elements in the
corresponding rows and columns. This indicates that the measurement model presents an adequate discriminant validity for further analysis. The results of the above CFA analysis indicate that the full measurement model is well fit with the data. The full measurement model can proceed for further hypothesis testing.

### 6.3 Structural Model Analysis

A structural model shows the theoretical constructs and their relationships in the pre-specified conceptual framework (Hair et al., 2010). Structural model analysis is a process to assess the explanatory power of the independent variables in the model. The structural model analysis can be done by examining the significance of the path coefficient in the structural model. The validity of the structural model and its relationships are, then, tested (Byrne, 2010; Hair et al., 2010). Based on the significance of the relationships in the structural model, the corresponding hypotheses are accepted or rejected (Hair et al., 2010).

In the structural model analysis process, a path analysis for the structural model with latent variables is performed to evaluate the hypothesised causal relationship. Before the structural model analysis is performed, the overall fitness of the structural model with the observed data is examined in order to access the fitness of the model. As indicated in Table 6.5, the goodness-of-fit indices of the structural model are within the acceptance threshold. This indicates that the structural model has a sufficient validity. The structural model can proceed for the path analysis.
### Table 6.4  Inter Constructs Correlation

<table>
<thead>
<tr>
<th>Constructs</th>
<th>AVE</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>MO</td>
<td>0.662</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.814</td>
</tr>
<tr>
<td>CSE</td>
<td>0.662</td>
<td>0.571</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OLE</td>
<td>0.647</td>
<td>0.453</td>
<td>0.638</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td>0.804</td>
</tr>
<tr>
<td>SA</td>
<td>0.622</td>
<td>0.606</td>
<td>0.587</td>
<td>0.552</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.789</td>
</tr>
<tr>
<td>SI</td>
<td>0.646</td>
<td>0.583</td>
<td>0.632</td>
<td>0.602</td>
<td>0.692</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.804</td>
</tr>
<tr>
<td>SD</td>
<td>0.711</td>
<td>0.633</td>
<td>0.635</td>
<td>0.554</td>
<td>0.742</td>
<td>0.715</td>
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<td></td>
<td>0.843</td>
</tr>
<tr>
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<td>0.646</td>
<td>0.628</td>
<td>0.613</td>
<td>0.720</td>
<td>0.795</td>
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<td></td>
<td></td>
<td></td>
<td>0.803</td>
</tr>
<tr>
<td>TR</td>
<td>0.667</td>
<td>0.517</td>
<td>0.514</td>
<td>0.428</td>
<td>0.623</td>
<td>0.628</td>
<td>0.640</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>0.835</td>
</tr>
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<td>0.618</td>
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<td>0.685</td>
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<td>0.718</td>
<td>0.718</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.878</td>
</tr>
<tr>
<td>PEOU</td>
<td>0.805</td>
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<td>0.523</td>
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<td>0.673</td>
<td>0.799</td>
<td>0.714</td>
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<td></td>
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</tr>
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<td>0.598</td>
<td>0.550</td>
<td>0.640</td>
<td>0.567</td>
<td>0.730</td>
<td>0.673</td>
<td>0.850</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ATT</td>
<td>0.796</td>
<td>0.545</td>
<td>0.481</td>
<td>0.424</td>
<td>0.571</td>
<td>0.568</td>
<td>0.600</td>
<td>0.542</td>
<td>0.524</td>
<td>0.672</td>
<td>0.677</td>
<td>0.650</td>
<td></td>
<td>0.892</td>
</tr>
<tr>
<td>BI</td>
<td>0.808</td>
<td>0.598</td>
<td>0.526</td>
<td>0.447</td>
<td>0.622</td>
<td>0.587</td>
<td>0.655</td>
<td>0.605</td>
<td>0.599</td>
<td>0.743</td>
<td>0.707</td>
<td>0.581</td>
<td>0.638</td>
<td>0.899</td>
</tr>
</tbody>
</table>

*Note. Diagonals represent the square root of average variance extracted, and the other matrix entries are the factor correlation.*
Table 6.5  
**Goodness-of-fit Results of the SEM**

<table>
<thead>
<tr>
<th>Model</th>
<th>$\chi^2$/df</th>
<th>RMSEA</th>
<th>GFI</th>
<th>AGFI</th>
<th>NFI</th>
<th>CFI</th>
<th>TLI</th>
<th>RMSR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structural Model</td>
<td>1.550</td>
<td>0.033</td>
<td>0.860</td>
<td>0.845</td>
<td>0.912</td>
<td>0.967</td>
<td>0.964</td>
<td>0.05</td>
</tr>
</tbody>
</table>

* Recommended value

Table 6.6 shows the results of the path analysis of the structural model with respect to individual characteristics, system characteristics, interface characteristics, and information sharing characteristics. The path analysis of the influence of individual characteristics on the adoption of OLMs in collaborative learning shows support for H1a (MO→PU), H2a (MO→PEOU), and H2b (CSE→PEOU) with path estimates of 0.100, 0.109, and 0.167 and $P$ value less than 0.001. With respect to the influence of the system characteristics on the adoption of OLMs, the path analysis shows support for H3a (SA→PU) and H4a (SA→PEOU) with path estimates of 0.274 and 0.112 and $P$ value less than 0.001.

The path analysis of the influence of interface characteristics on the adoption of OLMs shows support for H5a (SD→PU), H6a (SD→PEOU), and H6b (NA→PEOU) with path estimates of 0.107, 0.447, and 0.127 and $P$ value less than 0.001. In term of the influence of information sharing characteristics on the adoption of OLMs, the path analysis shows support for H8 (PEOU→ISI), H9 (PU→ISI), and H11 (TR→ISI) with path estimates of 0.564, 0.204, and 0.092 and $P$ value less than 0.001. The structural model shows support for H7 (PEOU→PU), H10 (PU→BI), H12 (ISI→ATT), and H13 (ATT→BI) with path estimates of 0.507, 0.605, 0.679 and 0.248 and $P$ value less than 0.001. The results of path analysis are also depicted in
Figure 6.1 with significant paths denoted with bold lines and insignificant paths with dashed lines.

Table 6.6 Structural Model Path Standardized Coefficients

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Relationships</th>
<th>Estimates</th>
<th>p-value</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a: PU ← MO</td>
<td>0.100**</td>
<td>0.005</td>
<td>Supported</td>
<td></td>
</tr>
<tr>
<td>H1b: PU ← CSE</td>
<td>-0.028</td>
<td>0.478</td>
<td>Not Supported</td>
<td></td>
</tr>
<tr>
<td>H1c: PU ← OLE</td>
<td>0.04</td>
<td>0.287</td>
<td>Not Supported</td>
<td></td>
</tr>
<tr>
<td>H2a: PEOU ← MO</td>
<td>0.109*</td>
<td>0.011</td>
<td>Supported</td>
<td></td>
</tr>
<tr>
<td>H2b: PEOU ← CSE</td>
<td>0.167***</td>
<td>0.000</td>
<td>Supported</td>
<td></td>
</tr>
<tr>
<td>H2c: PEOU ← OLE</td>
<td>-0.041</td>
<td>0.361</td>
<td>Not Supported</td>
<td></td>
</tr>
</tbody>
</table>

System Characteristics

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Relationships</th>
<th>Estimates</th>
<th>p-value</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>H3a: PU ← SA</td>
<td>0.274***</td>
<td>0.000</td>
<td>Supported</td>
<td></td>
</tr>
<tr>
<td>H3b: PU ← SI</td>
<td>0.018</td>
<td>0.702</td>
<td>Not Supported</td>
<td></td>
</tr>
<tr>
<td>H4a: PEOU ← SA</td>
<td>0.112*</td>
<td>0.036</td>
<td>Supported</td>
<td></td>
</tr>
<tr>
<td>H4b: PEOU ← SI</td>
<td>0.031</td>
<td>0.588</td>
<td>Not Supported</td>
<td></td>
</tr>
</tbody>
</table>

Interface Characteristics

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Relationships</th>
<th>Estimates</th>
<th>p-value</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>H5a: PU ← SD</td>
<td>0.107*</td>
<td>0.043</td>
<td>Supported</td>
<td></td>
</tr>
<tr>
<td>H5b: PU ← NA</td>
<td>-0.003</td>
<td>0.951</td>
<td>Not Supported</td>
<td></td>
</tr>
<tr>
<td>H6a: PEOU ← SD</td>
<td>0.447***</td>
<td>0.000</td>
<td>Supported</td>
<td></td>
</tr>
<tr>
<td>H6b: PEOU ← NA</td>
<td>0.127*</td>
<td>0.057</td>
<td>Supported</td>
<td></td>
</tr>
</tbody>
</table>

Information Sharing Characteristics

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Relationships</th>
<th>Estimates</th>
<th>p-value</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>H8: ISI ← PEOU</td>
<td>0.564***</td>
<td>0.000</td>
<td>Supported</td>
<td></td>
</tr>
<tr>
<td>H9: ISI ← PU</td>
<td>0.204**</td>
<td>0.003</td>
<td>Supported</td>
<td></td>
</tr>
<tr>
<td>H11: ISI ← TR</td>
<td>0.092*</td>
<td>0.023</td>
<td>Supported</td>
<td></td>
</tr>
</tbody>
</table>

6.4 Critical Factors for the Adoption of OLMs

This study presents an investigation of the critical factors that influence the adoption of OLMs in collaborative learning. The results of this study indicate that MO, SA, SD, CSE, and NA are significant for the adoption of OLMs in collaborative learning.
The OLE and SI show no influence on the adoption of OLMs. The PU, PEOU, and trust demonstrate a positive influence on the adoption of OLMs by affecting the ISI.
Figure 6.1  The Final Structural Model
Individual Characteristics

Individual characteristics including MO, CSE and OLE are discovered to have different effects on learners’ adoption of OLMs in collaborative learning. In this study, MO has positively influenced PU in the adoption of OLMs. This finding is consistent with all the previous collaborative technology adoption studies (Park et al., 2007; Chen and Tseng, 2012). Learners’ motivations to engage with OLMs in collaborative learning would increase if they can use OLMs to achieve good academic performances. This suggests that learners’ awareness of the benefits of adopting OLMs would motivate them to adopt OLMs in collaborative learning.

The MO of learners does have a significant direct influence on PEOU. This finding is congruent with the finding of Park, Lee, and Cheong (2007) and Chen and Tseng (2012). If learners feel that the engagement with OLMs is easy to use, their motivations to adopt OLMs in collaborative learning would increase. This indicates that simple and easy-to-use OLMs interfaces are able to improve learners’ engagement with OLMs in collaborative learning.

The CSE has a significant direct influence on the PEOU in the adoption of OLMs. This result is in line with existing research in the adoption of collaborative technologies in collaborative learning (Padilla-Meléndez, Garrido-Moreno, and Del Aguila-Obra, 2008; Terzis and Economides, 2011). Learners who are confident in using OLMs for accomplishing their tasks would find easy to use OLMs.
Learners with high CSE in engaging with OLMs would positively influence learners’ adoption of OLMs (Yuen and Ma, 2008; Abdullah et al., 2016). This suggests that the improvement of learners’ confident level in engaging with OLMs would help them to find it easy to adopt OLMs in collaborative learning.

The CSE has an insignificant influence on the PU in the adoption of OLMs. There is no positive significant relationship between CSE and PU. This finding is consistent with existing studies in the adoption of collaborative technologies (Igbaria and Iivari, 1995; Lee et al., 2013; Ma et al., 2013). Learners who are confident in using OLMs to perform learning task do not find the usefulness of adopting OLMs. This phenomenon happens because learners do not have a real engagement with OLMs in collaborative learning. They are unable to feel the usefulness of adopting OLMs. If learners are given the opportunity to directly engage with OLMs, they tend to experience in the usefulness of adopting OLMs in collaborative learning.

The OLE has no significant direct influence on both the PU and PEOU towards the adoption of the OLMs. This finding is consistent with previous studies in the adoption of collaborative technologies in collaborative learning (Pituch and Lee, 2006; Lau and Woods, 2009). Learners’ PEOU and PU in the adoption of OLMs do not depend on the previous OLE. One possible explanation for such a finding could be due to the fact that the participant in this study has experiences in using other collaboration technologies. They may feel that different collaboration technologies have different features and functionalities. Previous OLE is unable to help them in predicting the PU and PEOU of OLMs. It may only help them for operating basic...
functionalities of OLMs. To obtain the advantages of OLMs and the easiness to use the OLMs, the participants need to have a real engagement with OLMs in collaborative learning. Another possible explanation for this phenomenon could be due to the fact that participants of this study are all highly computer literate. They have considerable experience in engaging with technologies in collaborative learning. Learners’ OLE should not be treated as an issue in the OLM-based collaborative learning environment.

System Characteristics

System characteristics including SA and SI are observed to have different effects on learners’ adoption of OLMs in collaborative learning. In this study, SA has a significant positive influence on PU in the adoption of OLMs. This result is consistent with the existing studies in the adoption of collaborative technologies in collaborative learning (Tobing et al., 2008). The delivery of learning materials based on learners’ current level of understanding would increase learners’ PU in the adoption of OLMs. This suggests that providing customisation of learning materials with respect to learners’ level of understanding would increase the adoption of OLMs in collaborative learning.

The SA has a significant positive impact on the PEOU in the adoption of OLMs in collaborative learning. This finding is coherent with previous studies in a web-based collaborative learning environment (Tobing et al., 2008). Learners are demotivated to engage in web-based collaborative learning if personalisation of learning materials to
Critical Factors for the Adoption of Open Learner Models

the learners is not provided (Cantoni et al., 2004; Essalmi et al., 2010). Learners would feel easy to use OLMs in collaborative learning if the adaptation of learning materials based on learners’ level of understanding is provided. This suggests that OLMs which provides customisation of learning materials to the learner is able to improve the PEOU in the adoption of OLMs.

The SI has no significant positive influenced on both the PU and PEOU. These results are consistent with the previous study in the adoption of collaborative technologies in collaborative learning (Pituch and Lee, 2006; Lau and Woods, 2009). The SI does not have any relationship with both the PU and the PEOU. This indicates that learners do not focus on the interaction functionality of OLMs. This phenomenon could be due to the fact that learners do not have intentions to reveal their learning progress status to their instructors or peers. They do not want to have any interaction with their friends about their current level of understanding. Learners may feel uncomfortable to share their personal learning information with their friends especially for those learners who are lagging. This suggests that learners should have an option to activate the sharing feature in OLMs if they want to have an interaction with their peers or instructors.

Interface Characteristics

Interface characteristics including SD and NA are observed to have different effects on the adoption of OLMs in collaborative learning. The SD has a significant direct
positive influence on PU. This finding echoes the result of Hasan and Ahmed (2007) and Cho et al. (2009) and Joo et al. (2014) in which the design of user interface is recognised as a critical factor for improving the adoption of collaboration technologies in collaborative learning. Learners would relate SD with the functionality of the collaborative technology (Hasan and Ahmed 2007). A good SD of the collaborative technology would allow learners to adopt it to complete their tasks without difficulties (Joo et al., 2014). Collaborative technologies that offer more functionalities are often perceived more useful (Hasan and Ahmed 2007; Cho, Cheng, and Lai. 2009; Liu et al., 2010). The integration of useful functionalities in OLMs would directly impact the PU of the adoption of OLMs in collaborative learning. This suggests that a good arrangement of OLMs’ interface is able to improve the adoption of OLMs in collaborative learning.

The NA has a significant direct influence on PEOU. This finding is in line with the result of Jeong (2011) and Thong, Hong, and Tam, (2002) in which NA is identified as a critical factor that influences learners’ PEOU of the collaborative technologies. A good NA of collaborative technologies can help learners to search and obtain necessary knowledge effectively. A poor NA can lead to disorientation and increase cognitive load that impedes effective learning (Katuk and Zakaria, 2015). This suggests that NA aids can be provided to learners to prevent disorientation by indicating the browsing status when engaging with OLMs. The removal of unnecessary screens for keeping the NA simple can help to reduce the cognitive load of learners when engaging with OLMs.
The NA has no significant direct influence on PU. This result is in line with the previous study in the adoption of collaborative technologies in collaborative learning (Jeong, 2011). The NA does not directly impact PU. It has an indirect impact on the PU through the PEOU in the adoption of OLMs. This means that learners would feel that OLMs are usefulness if they can navigate the interface of OLMs without difficulties. Learners’ tend to rate OLMs as less usefulness if they find the interface of OLMs is difficult to navigate. This suggests that effort should be made to help in designing an easy to navigate OLMs interface.

**TAM Variables**

The PEOU has a significant direct positive influence on PU in the adoption of OLMs. This finding is congruent with previous studies in the adoption of collaboration technologies in collaborative learning (Liu et al., 2010; Abdullah et al., 2016). The significant positive relationship between PU and PEOU indicates that when learners can adopt OLMs easily, they would find that OLMs are useful in facilitating collaborative learning. The PEOU also exerts an indirect effect on the BI through PU, which shows that learners tend to adopt OLMs if they perceive them to be easy to use and useful. This suggests that the usefulness and easy to use of OLMs can improve the adoption of OLMs in collaborative learning.
Information Sharing Intention Variable

The PU is critical in determining the willingness of learners to share their learning information through the adoption of OLMs in collaborative learning. This result is consistent with the finding in Papadopoulos et al. (2013), suggesting that learners’ intentions to share information would increase if they are able to obtain a good grade with the adoption of collaborative technologies in collaborative learning. Learners’ intentions to share their information would increase if they are able to improve their academic performance with the adoption of OLMs. This suggests that to encourage learners to share their learning information in OLM-based learning environment, learners’ PU of the adoption of OLMs need to be improved.

The significant impact of the PEOU on the ISI of the adoption of OLMs in collaborative learning is in line with previous studies (Cheung & Vogel, 2013; Hung and Cheng, 2013). The willingness of learners in adopting collaborative technologies for information sharing would increase if they are able to use the collaborative technology without difficulties (Hung and Cheng, 2013). This means that the design of OLMs has to be simple and easy-to-use to encourage learners’ engagement with OLMs in collaborative learning.

TR has an impact on learners’ ISI in OLM-based collaborative learning. This finding is consistent with the previous studies including Chai and Kim’s (2010) and Ye et al.’s (2006). When learners’ trust in the adoption of OLMs has increased, their willingness to share learning information with other learners would improve. This
indicates that learners’ ISI would improve if they are able to obtain reliable and trustworthy learning resources shared by each other in OLM-based collaborative learning environment.

**Attitude Variable**

The ISI has a direct positive influence on learners’ ATT towards the adoption of OLMs in collaborative learning. Such finding is consistent with existing study by Cheung and Vogel (2013) where learners’ ISI has a direct impact on learners’ ATT towards the adoption of collaborative technologies in collaborative learning. This indicates that learners’ ATT towards the adoption of OLMs would increase if learners’ intentions to share their learning information with other learners are high. This suggests that developing a secure and reliable OLM-based learning environment can improve the adoption of OLMs in collaborative learning.

**Intention to Use**

The ATT has a significant direct influence on the BI of the adoption of OLMs in collaborative learning. This result is coherent with the existing research in the adoption of collaborative technologies in collaborative learning (Padilla-Meléndez, Garrido-Moreno, and Del Aguila-Obra, 2008; Lee and Ryu, 2013). Learners’ positive attitudes would directly influence learners’ intentions to adopt OLMs in collaborative learning. This suggests that the development of user-friendly and easy to use OLMs is essential for improving learners’ intentions to adopt OLMs in
collaborative learning. Once learners can attain significant benefits in engaging with OLMs, their intentions to adopt OLMs in collaborative learning would increase.

The PU has a significant direct influence on the BI in the adoption of OLMs. This finding is coherent with previous studies in which learners’ BI of the adoption of collaboration technology is directly influenced by the PU of the collaboration technologies (Sanchez-Franco, 2010; Padilla-Meléndez, Garrido-Moreno, and Del Aguila-Obra, 2008; Merhi, 2015; Lee and Ryu, 2013). Learners’ intentions to adopt OLMs in collaborative learning would increase if they perceived that OLMs help them to improve their academic performances. This suggests that the introduction of the usefulness of OLMs in facilitating collaborative learning is essential to improve the adoption of OLMs in collaborative learning.

6.5 Concluding Remarks

This chapter presents an investigation of the critical factors for the adoption of OLMs in Malaysian higher education. The conceptual framework proposed in Chapter 3 is first tested and validated with the use of SEM on the survey data collected from 565 undergraduate students in Malaysia. The convergent validity, discriminant validity and reliability are examined. The goodness-of-fit of the final measurement model is evaluated after validity and reliability assessments. The findings demonstrate a good fit between the final measurement model and the survey data.
The hypotheses testing for the proposed conceptual framework is conducted through structural model analysis. The validity of the structural model and its relationships are tested. Based on the significance of the relationships in the structural model, the corresponding hypotheses are accepted or rejected leading to derive conclusions. The findings reveal that MO, SA, SD, CSE, and NA are the critical factors for the adoption of OLMs. The OLE and SI are not critical factors for the adoption of OLMs. The PU, PEOU, and trust have an indirect positive impact on the adoption of OLMs by affecting the ISI.
Chapter 7

Learning Styles and Gender Differences

7.1 Introduction

Individual differences are the characteristics that make each learner unique in adopting collaborative technologies for collaborative learning (Lee et al., 2009; Hood and Yoo, 2013; Huang et al., 2013). The successful implementation of collaborative technologies in collaborative learning depends very much on the individual differences rather than the collaborative technology itself (Ruttun and Macredie, 2012). This is because different learners have different perceptions and attitudes towards the adoption of collaborative technologies. Two individual differences including learning styles and gender differences are important dimensions that have an impact on learners’ adoption of collaborative technologies in collaborative learning (Ames, 2003; Lee et al., 2009; Huang et al., 2013).

Learners with different learning styles have their own preferred ways in acquiring, processing, and storing learning information from different sensory dimensions through the interaction with collaborative technologies (Lee et al., 2009). There is a natural tendency for individual learners to constantly prefer one kind of sensory
inputs such as visual, verbal, or tactile over another when engaging with collaborative technologies in collaborative learning environments (Lee et al., 2009).

Knowing learners’ sensory learning styles not only helps in designing collaborative technologies that can suit various types of sensory learners. It also helps to improve learners’ motivations to engage with collaborative technologies (Huang, Hood, and Yoo, 2013). This is because different sensory learners have a tendency to engage with collaborative technologies which can suit their preferences in obtaining learning information (Hood, and Yoo, 2013).

Different sensory learners have their own unique interaction preferences with the features available in collaborative technologies for collaborative learning (Hood, and Yoo, 2013). By knowing the preferences of learners in interacting with the features available in collaborative technologies, appropriate instructional design strategies can be applied in designing collaborative technologies for improving the acceptance of these collaborative technologies in collaborative learning (Lee et al., 2009; Hood, and Yoo, 2013). As such, the investigation of the relationship between learners’ sensory learning styles and their attitudes towards the adoption of OLMs would provide a better understanding of the attitude of different types of sensory learners in the adoption of OLMs.

Gender differences have been identified as one of the important factors that influence the adoption of collaborative technologies in collaborative learning (Terzis and
The willingness of males and females in engaging with collaborative technologies is influenced by the features and functionalities of collaborative technologies (Hu and Hui, 2011; Huang et al., 2013; Sek et al., 2015a). Various collaborative technologies have their own characteristics. As a result, the effect of the gender on the adoption of different collaborative technologies would be different (Brown et al., 2010; Huang et al., 2013; Sun and Jeyaraj, 2013; Sek et al., 2015a). An investigation on the relationship between gender differences and attitudes towards the adoption of OLMs can help determine how to provide assistance to learners in a more targeted manner.

To have a better understanding of the relationship between individual differences and attitudes towards the adoption of OLMs in collaborative learning, an investigation on the relationship between learners’ learning styles and their attitudes towards the adoption of OLMs as well as gender differences and attitudes towards the adoption of OLMs are highly desirable. Such an investigation is needed for (a) helping the OLM instructional designers in applying suitable design strategies to design a better OLM-based collaborative learning environment that can suit different types of sensory learners, and (b) assisting the educational instructors to adopt appropriate instructional strategies for optimal integration of OLMs in collaborative learning.

This chapter aims to investigate the relationship between individual differences and attitudes towards the adoption of OLMs in collaborative learning. To effectively achieve this objective, this chapter is organized into five sections. Section 7.2 discusses individual differences in the adoption of collaborative technologies in
Learning Styles and Gender Differences

collaborative learning. Section 7.3 shows data analysis and results of the relationship between individual differences and attitudes towards the adoption of OLMs in collaborative learning. Section 7.4 presents the findings and the discussion from section 7.3 leading to the identification of the relationship between learners’ learning styles and their attitudes towards the acceptance of OLMs. Furthermore, this section also discusses the gender differences towards the adoption of OLMs. Section 7.5 ends the Chapter with concluding remarks.

7.2 Individual Differences in the Adoption of Collaborative Technologies

Learners have substantial differences in their ability and sensitivity to process stimuli (Hood and Yoo, 2013). Consequently, different individuals would respond differently to the functionalities provided by collaborative technologies (Lee et al., 2009). Learners with different learning styles would exercise different preferences in their selection of collaborative technologies in collaborative learning (Lee et al., 2009). These preferences are related to matching their preferred sensory dimensions with the affordances of the respective collaborative technologies in collaborative learning. For example, a learner who has a strong aural preference prefer to engage with a collaborative technology that provides high audio capability whereas a learner who prefers to read and write printed words is likely to choose a collaborative technology that provides textual communication.
There has been a substantial body of research indicating that learners would have a positive attitude towards the adoption of collaborative technologies if these collaborative technologies can be adapted to match their preferred learning styles (Ding et al., 2011; Huang et al., 2013; Kimbrough et al., 2013). As such, knowing the attitudes of different types of sensory learners in the adoption of OLMs is necessary. This is because appropriate design strategies to accommodate various types of sensory learners can be applied in designing OLMs for improving the adoption of OLMs in collaborative learning.

Learners’ gender differences play an important role in influencing their adoption of collaborative technologies in collaborative learning (Ding et al., 2011; Huang et al., 2013; Kimbrough et al., 2013). Females typically have more discomfort in adopting a new collaborative technology in collaborative learning, whereas males have more willingness to try out a new collaborative technology (Li et al., 2008; Simsek, 2011). Such differences are partly because females are more computer anxiety as compared to males in the adoption of collaborative technologies (Kimbrough et al., 2013). Furthermore, females are more expressive and social-oriented. This means females focus more on the ease of use of the collaborative technologies. Males, on the other hand, are more task-oriented (Shi et al., 2009).

Various studies indicate that understanding gender differences in the adoption of collaborative technologies in collaborative learning can help academicians to apply appropriate instructional strategies in teaching and learning. Such a move is able to increase learners’ adoption of collaborative technologies in collaborative learning.
To improve the successful implementation of OLMs in collaborative learning, it is crucial to investigate what the attitude of males and females is towards the adoption of OLMs in collaborative learning.

7.3 Data Analyses and Results

There are four learning styles including (a) visual, (b) aural, (c) read/write, and (d) kinesthetics that have been identified based on the VARK learning styles inventory. Table 7.1 shows the distribution of these four learning styles and the corresponding descriptive statistics of learners’ attitudes towards the acceptance of OLMs. From a total of 504 respondents, about 31.3 per cent of the learners are on the aural learner. The visual, read/write, and Kinesthetics learning style preferences appear to share similar percentages of 24.0 per cent, 17.5 per cent, and 27.2 per cent respectively.

There are four statements in measuring learners’ attitudes towards the adoption of OLMs for collaborative learning. For each statement, a seven-point Likert scale is employed ranging from one describing strongly disagree until seven indicating strongly agree. A high mean score reflects learners have a positive attitude towards the adoption of OLMs. On the other hand, a low mean score indicates learners have a negative attitude towards the adoption of OLMs. As indicated in Table 7.1, Kinesthetics learners have a highest mean score of 5.28 on the acceptance of OLM for collaborative learning. The second highest mean score is the visual learner which carries a value of 5.27. The read/write type of learners obtained the lowest mean score of 5.18 in accepting OLM for collaborative learning.
Table 7.1  Descriptive Statistics of the Acceptance of OLMs with respect to Learning Styles

<table>
<thead>
<tr>
<th>Learning Styles</th>
<th>Frequency</th>
<th>Percentages</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual</td>
<td>121</td>
<td>24.0</td>
<td>5.27</td>
<td>0.953</td>
</tr>
<tr>
<td>Aural</td>
<td>158</td>
<td>31.3</td>
<td>5.20</td>
<td>0.954</td>
</tr>
<tr>
<td>Read/Write</td>
<td>88</td>
<td>17.5</td>
<td>5.18</td>
<td>0.972</td>
</tr>
<tr>
<td>Kinesthetics</td>
<td>137</td>
<td>27.2</td>
<td>5.28</td>
<td>0.910</td>
</tr>
</tbody>
</table>

7.3.1 Exploring Learning Style Differences

Relationship between Learners’ Learning Style and Attitudes

Learners’ attitudes are evaluated based on seven-point Likert continuous scale. To allow the chi-square test for independence to be used to examine the relationship between learners’ learning styles and their attitudes towards the adoption of OLMs in collaborative learning, the learners’ attitudes measured in continuous scale needs to be changed to categorical scale. This can be done by grouping the total continuous scores into a few groups. Scores from 3.5 to 13.5, 13.5 to 18.5, and 18.5 to 28.5 are classified as having negative, neutral, and positive attitudes towards the adoption of OLMs in collaborative learning respectively.

Table 7.2 shows the result of the chi-square test for investigating the relationship between learners’ learning styles and their attitudes towards the adoption of OLMs. It indicates that the relationship between learners’ learning styles and their attitudes towards the adoption of OLMs is not significant, $\chi^2(6, n = 504) = 3.302, p = 0.770$. This suggests that learners’ attitudes towards the adoption of OLMs are not affected by the learners’ learning styles. Visual, aural, read/write, and Kinesthetics learners
exhibit almost the same positive attitudes towards the adoption of OLMs. Their proportions among are 63.6 per cent, 64.6 per cent, 65.9 per cent, and 65.7 per cent respectively. This shows that there are no huge variations in the learners’ attitudes towards the adoption of OLMs among different types of learners.

**Table 7.2 The Distribution of Learners’ Learning Styles and Their Attitudes towards the Adoption of OLMs**

<table>
<thead>
<tr>
<th>Learning Styles</th>
<th>Attitudes</th>
<th>Count</th>
<th>Percentage</th>
<th>Count</th>
<th>Percentage</th>
<th>Count</th>
<th>Percentage</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Negative</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Visual</td>
<td></td>
<td>16</td>
<td>13.2</td>
<td>28</td>
<td>23.1</td>
<td>77</td>
<td>63.6</td>
<td>121</td>
</tr>
<tr>
<td>Aural</td>
<td></td>
<td>15</td>
<td>9.5</td>
<td>41</td>
<td>25.9</td>
<td>102</td>
<td>64.6</td>
<td>158</td>
</tr>
<tr>
<td>Read/Write</td>
<td></td>
<td>9</td>
<td>10.2</td>
<td>21</td>
<td>23.9</td>
<td>58</td>
<td>65.9</td>
<td>88</td>
</tr>
<tr>
<td>Kinesthetics</td>
<td></td>
<td>20</td>
<td>14.6</td>
<td>27</td>
<td>19.7</td>
<td>90</td>
<td>65.7</td>
<td>137</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>60</td>
<td>11.9</td>
<td>117</td>
<td>23.2</td>
<td>327</td>
<td>64.9</td>
<td>504</td>
</tr>
</tbody>
</table>

Table 7.3 shows the result of the one-way ANOVA of the learners’ learning styles and their attitudes towards the adoption of OLMs. It shows that there are no statistically significant differences in attitudes among different types of learners towards the adoption of OLMs, $F (3, 500) = 0.345, p = 0.793$. This implies that the OLMs collaboration technology provides similar benefits to all types of learners, irrespective of their preferred learning styles. As indicated in Table 7.1, the mean values for visual, aural, read/write and kinesthetics learners are 5.27, 5.20, 5.18, and 5.28 respectively. This shows that there are no huge differences between learners’ attitudes towards the adoption of OLMs with respect to different types of learners.
Table 7.3  The Summary of Learners’ Learning Styles and Their Attitudes towards the Adoption of OLMs

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of squares</th>
<th>D.F.</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between groups</td>
<td>0.924</td>
<td>3</td>
<td>0.308</td>
<td>0.345</td>
<td>0.793</td>
</tr>
<tr>
<td>Within Groups</td>
<td>446.487</td>
<td>500</td>
<td>0.893</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>447.411</td>
<td>503</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

7.3.2  Exploring Gender Differences

Relationship between Learners’ genders and Attitudes

Table 7.4 shows the result of the chi-square test on the relationship between genders and attitudes towards the adoption of OLMs in collaborative learning. It reveals that there is no significant relationship between genders and attitudes towards the adoption of OLMs, $\chi^2(2, n = 504) = 0.389$, $p = 0.823$. This suggests that learners’ attitudes towards the adoption of OLMs in collaborative learning are not affected by the gender differences. As indicated in Table 7.4, majority of females and males have a positive attitude towards the adoption of OLMs. The percentage is quite similar for both females and males which represent 65.8 per cent and 64.0 per cent respectively. This indicates that not much difference exist between males and females in attitudes towards the adoption of OLMs in collaborative learning.
Table 7.4  The Distribution of Genders and Learners’ Attitudes towards the Acceptance of OLMs

<table>
<thead>
<tr>
<th>Genders</th>
<th>Negative</th>
<th>Neutral</th>
<th>Positive</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Count</td>
<td>Percentage</td>
<td>Count</td>
<td>Percentage</td>
</tr>
<tr>
<td>Male</td>
<td>34</td>
<td>12.7</td>
<td>62</td>
<td>23.2</td>
</tr>
<tr>
<td>Female</td>
<td>26</td>
<td>11.0</td>
<td>55</td>
<td>23.2</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>11.9</td>
<td>117</td>
<td>23.2</td>
</tr>
</tbody>
</table>

Table 7.5 presents the results of the $t$-test in investigating the gender differences in attitudes towards the adoption of OLMs in collaborative learning. It reveals that there are no significant differences in attitudes towards the adoption of OLMs between males (Mean = 5.255, Standard Deviation = 0.969) and females (Mean = 5.212, Standard Deviation = 0.913), $t$ (502) = 0.507, p-value = 0.612. As indicated in Table 7.5, the magnitude of the difference in the means between females and males (mean difference = 0.043, 95% CI: -0.208 to 0.12) is very small. The result shows that the attitudes of females and males towards the adoption of OLMs in collaborative learning do not vary too much.

Table 7.5  The Gender Differences in Attitudes towards the Acceptance of OLMs

<table>
<thead>
<tr>
<th>Genders</th>
<th>Mean</th>
<th>Mean difference</th>
<th>t</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>5.255</td>
<td>0.043</td>
<td>0.507</td>
<td>0.612</td>
</tr>
<tr>
<td>Male</td>
<td>5.212</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
7.4 Findings and Discussion

7.4.1 Learning Styles

There is no relationship between learners’ learning styles and their attitudes towards the adoption of OLMs in collaborative learning. All types of learners have the same positive attitudes towards the adoption of OLMs. Auditory learners usually are not motivated to engage with collaborative technologies in collaborative learning (Li, 2015). They prefer to work independently (Pamela, 2011; Battalio, 2009). However, the finding as shown in Table 7.2 indicates that 64.6 per cent of the aural learners intends to adopt OLMs in collaborative learning. As indicated in Table 7.1, the mean score is 5.20. This shows that aural learners have a high motivation to participate in OLM-based collaborative learning. This finding is consistent with that of Battalio (2009) who asserts that auditory learners appear to be more positive in dealing with collaborative technologies for collaborative learning.

Auditory learners value collaborative technologies in collaborative learning if they are able to work independently with these collaborative technologies (Ke and Carr-Chellman, 2006). The adoption of OLMs for collaborative learning allows learners to collaborate with their peers independently and freely without having any difficulties have positively influence the auditory learners towards the adoption of OLMs. Furthermore, the proposed learning activities such as discussion, conversations, audio and video recordings in OLM-based collaborative learning can encourage auditory learners to adopt OLMs in collaborative learning. Various electronic media
including Podcast, YouTube, and audio recording can be introduced for improving the aural learners’ engagements with OLMs in collaborative learning.

Kinesthetics learners prefer to engage in collaborative technologies which can provide a lot of interaction activities with their peers for obtaining learning information. (Battalio, 2007; Li, 2015). In this study, about 65.7 per cent of the total kinesthetics learners as shown in Table 7.2 have expressed a preference for adopting OLMs in collaborative learning. The same indication also appear in Table 7.1 which shows the highest mean score of 5.28 among other types of learners in their willingness to adopt OLMs in collaborative learning. Consistent with Li (2015), this finding lends some support to existing research indicating that kinesthetics learners demonstrate a preference for engaging with collaborative technologies in collaborative learning. This shows that the availability of OLMs in facilitating interaction activities has attracted kinesthetics learners to participate in OLMs-based collaborative learning environment.

Kinesthetics learners are motivated to engage with learning activities such as physical activity, demonstrations, and discussion provided in OLM-based learning environment. This show that various electronic media such as forum, wiki, weblog, and chat can be integrated to facilitate these learning activities improve kinesthetics learners’ adoption of OLMs in collaborative learning.
Visual learners prefer their learning information is presented to them using images, graphs, pictures, colours, and maps. They prefer to have visual learning strategies integrated into collaborative learning environments (Pamela, 2011). In Table 7.2, about 63.6 per cent of the total visual learners have a preference to adopt OLMs in collaborative learning. Visual learners’ willingness to adopt OLMs in collaborative learning is also reflected in the mean score of 5.27 as indicated in Table 7.1. This finding is supported by the research conducted by Franzoni and Assar (2009) showing that visual learners are keen to engage with collaborative technologies in collaborative learning. The functionalities available in OLM-based learning environments which allow sharing and interaction activities among peers have stimulated learners’ interest to engage in this collaborative technology. Learning activities such as simulation and presentation available in OLMs learning environment which allows interactive activities with peers have stimulated visual learners’ interest to engage with OLM-based learning environment. Electronic media such as forum, wiki, animation, videos, and wiki can be introduced to promote the adoption of OLMs in collaborative learning for visual learners.

Read/write learners prefer to engage with collaborative technologies in collaborative learning when learning information is printed in words on the collaborative technologies’ interfaces which require a lot of reading (Battalio, 2009). Table 7.2 shows 65.9 per cent of the total read/write learners are willing to adopt OLMs in collaborative learning. The evidence also shows in Table 7.1 which indicates that the read/write learning style preference possess a mean score of 5.18 in adopting OLMs in facilitating collaborative learning. This is consistent with Battalio (2007) who
claims that read/write learners are willing to engage with collaborative technologies when the learning material are presented in written forms on the collaborative technologies’ interface. The interface of OLMs which consists of a lot of written reading materials has created a suitable learning environment for read/write learners to interact with their peers in collaborative learning. Learning activities such as written feedback, essays writing, and note taking can be introduced to encourage read/write learners to engage with OLMs. Electronic media including wiki, e-book, weblog, email, and forum can be integrated to improve the engagement of read/write learners with OLMs in collaborative learning.

7.4.2 Gender differences

The independent t-test results as shown in Table 7.5 indicates that there is no significant difference in the mean acceptance scores of OLM-based collaborative learning for males and females. This finding contradicts with studies conducted by Huang et al. (2013) and Kimbrough et al. (2013). Both females and males show the same interest in adopting OLMs in collaborative learning. The availability of the learners’ model comparison tool in OLM-based collaborative learning environment attracts males to engage with OLMs. This is because males are able to have an opportunity to view their peers’ learning progress and status through the learners’ model comparison tool in OLMs. This tool not only provides the learning information of other learners, but it also creates a competitive learning environment for each learner to compete with each other. In this competitive learning environment, males tend to complete their assignments and tasks more quickly.
Males’ adoption of OLMs in collaborative learning can be further improved if they can adopt OLMs to their task more efficiently and effectively.

Females have the same interest as compared to males in the adoption of OLMs in collaborative learning. This is because in OLM-based collaborative learning environment, females can utilize OLMs for interacting and communicating with other learners. Females are more expressive and prefer to engage with social-oriented activities. They tend to emphasize more on maintaining a relationship with other learners instead of competing with other learners. This indicates that to further enhance females’ engagement with OLMs during their teaching and learning processes, chat conversation technologies or online communication technologies can be integrated into the OLM-based learning environment. With this integration, females not only can communicate and interact with other learners smoothly and privately. It also helps in establishing good relationships among learners as well as enabling the formation of social ties among learners in collaborative learning.

7.5 Concluding Remarks

The aim of this Chapter is to investigate the individual differences including learners’ learning styles and gender differences towards the adoption of OLMs for collaborative learning, thus providing answer for the following research questions: a) What is the relationship between learning styles of learners and their attitudes towards the acceptance of OLMs in collaborative learning?, b) Are there any
differences in attitudes between learners with different learning styles towards the acceptance of OLMs in collaborative learning?, c) What is the relationship between genders and attitudes towards the acceptance of OLMs in collaborative learning? , and d) Are there any differences in attitudes between male and female learners towards the acceptance of OLMs in collaborative learning? This is done by using various statistical data analysis methods including chi-square test for independence, one-way ANOVA and independent t-test on the surveyed data collected from students in Malaysian universities.

The findings show that there are no significant differences between learning styles of learners and their attitudes towards the adoption of OLMs in collaborative learning. Furthermore, findings reveal that there is no difference between females and males in the adoption of OLMs in collaborative learning. The results of this study provide academicians and OLMs instructional designers with a profound insight into the individual differences in the adoption of OLMs in collaborative learning.
Chapter 8

Conclusion

8.1 Introduction

The objective of this study is to investigate learners’ attitudes and perceptions towards the adoption of OLMs for collaborative learning in Malaysian higher education. Specifically, the study aims to (a) investigate the current adoption of OLMs in Malaysian higher education, (b) identify the critical factors for the adoption of OLMs in Malaysian higher education, (c) explore the relationship between learning styles of learners and their attitudes towards the acceptance of OLMs for collaborative learning, and (d) examine the gender difference in attitudes towards the acceptance of OLMs in Malaysian higher education.

To achieve these research objectives, the main research question for this study is formulated as follows:

*How can the adoption of OLMs be improved in Malaysian higher education?*

To answer this main research question, several subsidiary questions are developed as follows:

1) *What are the current patterns and trends of the adoption of OLMs in Malaysian higher education?*
b) What are the critical factors that influence the adoption of OLMs in Malaysian higher education?

c) What is the relationship between learning styles of learners and their attitudes towards the acceptance of OLMs in collaborative learning?

d) Are there any differences in attitudes between learners with different learning styles towards the acceptance of OLMs in collaborative learning?

e) What is the relationship between genders and attitudes towards the acceptance of OLMs in collaborative learning?

f) Are there any differences in attitudes between male and female learners towards the acceptance of OLMs in collaborative learning?

To adequately answer the research questions as above, a quantitative research methodology is adopted. Using an online survey, a proposed conceptual framework is tested and validated for the adoption of OLMs in Malaysian higher education. Individual differences in the adoption of OLMs in collaborative learning are explored with various statistical data analysis methods.

The objective of this chapter is to discuss the research findings and contributions and their implications and to point out the limitations of this study and some suggestions for future research. The rest of the Chapter is organized into four sections. Section 8.2 presents the summary of the key findings of this study. Section 8.3 covers the contribution and the implication of this study, followed by the discussion of the limitations of this study and some suggestions for further research in Section 8.4.
8.2 Summary of the Research Findings

The current OLMs adoption rate in Malaysian higher education is low. Table 5.1 shows that 81 per cent of the total respondents do not have experience in engaging with OLMs. This phenomenon could be partly due to the fact that the development of OLMs in collaborative learning in Malaysian higher education is still at the infancy stage. Many of the Malaysian higher education institutions are not aware of the potential benefits of adopting OLMs for collaborative learning.

There are various purposes that have been identified in the adoption of OLMs as indicated in Table 5.3. Learners adopt OLMs in collaborative learning for viewing their own learning progresses as well as for doing reflection on learning. They are interested to engage with OLMs for doing planning on learning. Furthermore, learners who have an intention to adopt OLMs are willing to use it as a navigation aid on learning to achieve learning goals.

Learners’ web-based learning experiences have a profound impact on their adoption of OLMs in collaborative learning. Learners who have a web-based learning experience are willing to adopt OLMs. Furthermore, learners’ computer and web literacies do play a significant role in the adoption of OLMs in collaborative learning. Learners who have a good computer and web literacies tend to have a positive attitude towards the adoption of OLMs. This reveals that learners’ exposure to various educational technologies in their teaching and learning processes would positively influence their attitudes towards the adoption of OLMs.
This research develops a new conceptual framework for investigating the critical factors that influence the adoption of OLMs in collaborative learning. The framework consists of five main dimensions for evaluating the adoption of OLMs, namely, individual characteristics, system characteristics, interface characteristics, design characteristics, and information sharing characteristics. Each dimension is represented by a set of critical factors for better assessing the adoption of OLMs.

The significance positive impact of motivation on perceived usefulness and the ease of use of OLMs suggest that learners’ motivation to engage with the OLM is directly affected by the ease of use of OLMs as well as the usefulness of OLMs. Learners are keen to engage with OLMs if they are able to improve their academic performances with the help of OLMs in collaborative learning. Furthermore, learners’ motivation to engage with OLMs would further improve if OLMs are easy to be used in the collaborative learning environment. The computer self-efficacy has a significant positive effect on the perceived ease of use of OLMs. This suggests that learners’ computer self-efficacy could reduce their barriers in adopting OLMs. If learners have higher computer self-efficacy, they would not feel any difficulties in adopting OLMs in collaborative learning.

The system adaptability has a direct positive influence on the perceived usefulness of OLMs suggest that the personalization of learning materials based on learners’ level of knowledge can help to improve the adoption of OLMs. Furthermore, the significant positive effect of system adaptability to the perceived ease of use of
OLMs indicates that the customization of learning materials with respect to learners’ level of understanding can facilitate the adoption of OLMs in collaborative learning.

The significant positive influence of screen design to the perceived usefulness of OLMs reveals that learners’ perceived usefulness of OLMs would improve if the screen design of OLMs is well designed. Furthermore, learners’ perceived ease of use of OLMs would increase if a well-designed interface of OLMs is provided to facilitate learners’ engagement with OLMs in collaborative learning. In addition, an easy to navigation interface in OLMs would have a positive influence on learners’ perceived ease of use of OLMs in collaborative learning. This suggests that learners’ adoption of OLMs would increase if an easy to use navigation aid is provided in facilitating collaborative learning.

The perceived ease of use has a significant direct positive impact on the perceived usefulness of OLMs indicates that the easy to use OLMs would influence learners’ perceived usefulness of OLMs in collaborative learning. This suggests that if learners are able to adopt OLMs without difficulties, their perceived usefulness of adopting OLMs in facilitating collaborative learning would increase.

The perceived usefulness and the perceived ease of use have a direct positive effect on the information sharing intention of learners in an OLM-based collaborative learning environment. This suggests that learners’ intentions to share their learning information would improve if learners perceive that OLMs are easy to be used and more useful. Furthermore, emphasis should be given on the security aspects of
OLMs as trust has a significant impact on the learners’ information sharing intentions in adopting OLMs for collaborative learning. Learners’ information sharing intentions would increase if the security aspects of OLMs are not the main issue. When learners’ information sharing intentions increase, their attitudes towards the adoption of OLMs would improve which in turn influence learners’ intentions to adopt OLMs for collaborative learning.

There are no significant differences in attitudes between different learning styles of learners. Table 7.3 reveals that there are no huge variations in learners’ attitudes towards the adoption of OLMs with respect to different learning styles of learners. Four different types of learners including visual learners, aural learners, read/write learners, and kinesthetics learners have the same positive attitudes towards the adoption of OLMs. This implies that OLMs provide similar benefits to all types of learners, irrespective of their learning styles.

Auditory learners like to obtain new ideas from their peers and instructors through discussion or lecturing. In this study, auditory learners are motivated to engage with OLMs in collaborative learning. This shows that the OLM-based collaborative learning environment is able to attract auditory learners when they can share and acquire their learning information through discussion group, brainstorming, questions and answer, and problem-solving without any difficulties.

Kinesthetics learners prefer the use of a hands-on approach in collaborating with peers for obtaining learning information in collaborative learning. In this study,
kinesthetics learners have expressed a preference for adopting OLMs for collaborative learning. They have an interest to engage with OLMs for collaborative learning when they are able to collaborate with their peers through simulation, brainstorming, discussion group, questions and answers.

Visual learners prefer to obtain their learning information presented to them in images, graphs, pictures, colours, and maps. They prefer visual learning strategies integrated into collaborative learning environment. In this study, visual learners show a preference to adopt OLMs for collaborative learning.

Read/write learners prefer to engage with collaborative technologies when learning information is printed in words on the collaborative technologies’ interface which requires a lot of reading. In this study, read/write learners are willing to adopt OLMs for collaborative learning. The interface of OLMs consists of a lot of written reading materials and visual components. The combination of these components has created a suitable learning environment for read/write learners to have an interest to interact with peers for utilizing OLMs in collaboration learning.

There are no differences in attitude between males and females towards the adoption of OLMs in collaborative learning. As indicated in Table 7.5, both males and females show the same interest in adopting OLMs for collaborative learning. Males are more task-oriented. They prefer to work in competitive learning environment. An OLM-based collaborative learning environment allows males to have an opportunity to view their peers’ learning progress through the adoption of OLMs. OLMs not only
provide the opportunity for learners to access learning information of other learners, but it also creates a competitive learning environment for each learner to compete. In this competitive learning environment, males tend to complete their assignments and tasks more efficiently and effectively.

Females are more expressive and prefer to engage in social-oriented activities. They tend to be focused more on maintaining a relationship with other learners instead of competing with each other learners. Females have a same positive attitude as compared to males in the adoption of OLMs for collaborative learning. This suggests that females are able to interact and communicate smoothly and privately with other learners through the adoption of OLMs in collaborative learning.

8.3 Research Contributions and Implications

This study makes a major contribution to the field of OLMs research from both the theoretical and the practical perspectives. Theoretically this study contributes to the existing literature in the field of OLMs in higher education by (a) extending the TAM framework to the study of the adoption of OLMs, (b) developing a validated conceptual framework for investigating the critical factors of adopting OLMs in Malaysian higher education, (c) exploring the relationship between learning styles of learners and their attitudes towards the adoption of OLMs, and (d) investigating the differences in attitude between males and females towards the adoption of OLMs.
The TAM framework is extended to study the adoption of OLMs in collaborative learning in Malaysian higher education. This study further demonstrates the applicability of the TAM framework in examining the adoption of OLMs in collaborative learning with the empirical evidence.

Develop a validated conceptual framework for investigating the critical factors for the adoption of OLMs in Malaysian higher education. There is much research for investigating the adoption of collaborative technologies. The existing research, however, does not have a general agreement on the critical factors for the adoption of collaboration technologies for collaborative learning. Moreover, the research on the adoption of collaborative technologies in Malaysian higher education is focusing on different collaborative technologies. Such research may not be suitable to be applied in OLMs as different collaborative technologies have their own unique features and characteristics. This study fills this gap by providing the empirical evidence for the study of the adoption of OLMs in Malaysian higher education. Specifically, a conceptual framework for investigating the adoption of OLMs in Malaysian higher education is developed and empirically validated. Such a conceptual framework can also be used as an initial study in studying the adoption of OLMs in higher education of other developing and developed countries.

Investigate the association between learning styles of learners and their attitudes towards the adoption of OLMs. More specifically, this research presents an empirical evidence of the relationship between learning styles of learners and their attitudes towards the adoption of OLMs in collaborative learning. The results of this study
provide a better understanding of which types of learners tend to adopt OLMs for collaborative learning. Furthermore, this study also provides information about the functionalities and features of OLMs that are able to attract learners to further engage with OLMs in collaborative learning.

Investigate gender differences in attitudes towards the adoption of OLMs in collaborative learning. There is much research for investigating the gender differences in attitudes towards the adoption of collaborative technologies in collaborative learning. The existing research, however, does not provide conclusive results. The difference in attitude between males and females towards the adoption of OLMs is still unclear. This study provides an empirical evidence of the differences in attitudes between males and females towards the adoption of OLMs in collaborative learning. The gender analysis provides better explanations of the adoption of OLMs.

Practically, this study leads to several valuable findings to various stakeholders in the adoption of OLMs in collaborative learning including government department, higher education institutions, and OLMs instructional designers and developers. Specifically those findings can (a) help government departments formulate and develop specific policies and strategies in adopting OLMs for collaborative learning, (b) provide Malaysian higher education institutions with useful information, guidelines and collaborative technology for facilitating the development of practical strategies and policies for the successful implementation of OLMs for collaborative learning, (c) offer OLMs instructional developers and developers useful information
for the development of user friendly OLMs application in improving the acceptance of OLMs for collaborative learning.

The importance of this study to Malaysian government lies in its contribution towards the development and conceptualization policies and strategy in introducing OLMs for collaborative learning. Both private and government agencies have been continuously formulating strategies and policies for encouraging and enhancing the adoption of collaborative technologies in facilitating collaborative learning. As a result, any advance either in a better understanding of the adoption of OLMs for collaborative learning or through the introduction of various incentives in promoting the adoption of OLMs is valuable. By successfully identifying the critical factors for the adoption of OLMs, appropriate actions can be taken in advance to ensure successful implementation of the OLM in collaborative learning.

The significance of this study for Malaysian higher education institutions lies in its contribution in offering Malaysian higher education institutions useful information, guidelines and tools for assisting the development of feasible strategies and policies for the successful implementation of OLMs for collaborative learning. With a better understanding of the critical issues in the adoption of OLMs, Malaysian higher education institutions can more effectively manage their OLMs implementation in teaching and learning processes as well as further improve the adoption of OLMs in facilitating collaborative learning. By successfully selecting the most appropriate instructional teaching strategies to accommodate individual differences in implementing OLMs in collaborative learning, Malaysian higher education
institutions can make full use of the benefits of adopting OLMs for improving learners’ academic performance.

The importance of this study to OLMs application developers lies in encouraging the OLMs adoption in higher education institutions through offering OLMs developers useful information in applying appropriate design strategies for the development of OLMs applications. The OLM developers are able to apply suitable design strategies in designing user friendly interface to accommodate learners with different learning styles for attracting learners’ engagement with OLMs in their collaborative learning. Furthermore, this study further investigates the influence of gender differences on the acceptance of OLMs in collaborative learning. Such insights can assist OLMs designers and developers to apply appropriate instructional design strategies in developing OLMs applications in future.

8.4 Limitations and Future Research

There are some limitations in this study. First, this study only investigates the critical factors that influence the adoption of OLMs in Malaysian higher education. To gain more reliable and general view of this acceptance, the same study can be extended to more universities in other developing countries as well as developed countries.

Second, this study employs scenario-based web-mediated prototyping design for investigating the critical factors that influence the adoption of OLMs as well as examining the relationships between individual differences and their attitudes.
towards the adoption of OLMs in collaborative learning. Future study can be conducted to investigate these impacts towards the acceptance of OLMs by developing a real OLMs learning environment which learners are able to have a real experience in engaging with OLMs in collaborative learning.

Third, this proposed conceptual framework focuses on assessing the effect of multi-dimensional factors on the adoption of OLMs from the perspective of undergraduate learners only. There are other stakeholders in the adoption of OLMs such as post-graduate learners, instructors, system developers and instructional designers whose perceptions are also important for a complete OLMs assessment. Different stakeholders have different constraints, needs, and different motivations for adopting OLMs. Future research should consider these stakeholders to gain a better representation of the issues facing in the OLM implementation success. Finally, a longitudinal study can be conducted to examine how the dimensions being identified in the pre-adoption stage change over time in the post-adoption stage, when the learners have had experience in using OLMs in collaborative learning.
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Appendices

Appendix A

The Survey Questionnaire

RMIT UNIVERSITY

SCHOOL OF BUSINESS INFORMATION TECHNOLOGY AND LOGISTICS
RMIT UNIVERSITY

INVESTIGATING LEARNERS’ ATTITUDE AND PERCEPTION OF OPEN LEARNER MODELS IN COLLABORATIVE LEARNING ENVIRONMENT
General Instructions

1. Most questions can be answered by clicking the appropriate response on the scale. For some questions, you will be asked to write a short answer in the textbox.

2. Answer all questions as accurately as possible. Your answers will be treated confidentially.

A) DEMOGRAPHIC INFORMATION

*Please circle the appropriate numbers in the boxes below.*

1. Please specify your age.
   - [ ] Less than 20
   - [ ] 21 to 23
   - [ ] 24 to 26
   - [ ] 27 to 29
   - [ ] Above 30

2. Please specify your race (Applies to Malaysians).
   - [ ] Malay
   - [ ] Chinese
   - [ ] Indian
   - [ ] Others (Please specify: _____________________)

3. Please specify your gender.
   - [ ] Male
   - [ ] Female

4. Please specify the location of your secondary school.
   - [ ] Urban
   - [ ] Rural

5. Please specify the type of the university.
6. Please specify the year of your study at university.

- [ ] 1st year
- [ ] 2nd year
- [ ] 3rd year
- [ ] 4th year

7. Please specify your course programme.

- [ ] Engineering
- [ ] Computer science/IT
- [ ] Business/Management
- [ ] Social science

8. Have you heard about the open learner model before?

- [ ] Yes
- [ ] No

If YES, please specify the source(s)

- [ ] Lecturer/Instructor
- [ ] Friends
- [ ] Others (Please specify: _________________________)

9. Have you used any open learner models before?

- [ ] Yes
- [ ] No
If YES, please specify the subject(s)

☐ Engineering
☐ Computer science/ IT
☐ Business/Management
☐ Social science

10. Have you taken any computer-based or web-based learning courses before?

☐ Yes
☐ No

If YES, please specify the courses

☐ Engineering
☐ Computer science/ IT
☐ Business/Management
☐ Social science
☐ Others (Please specify: _____________________)

11. How much do you enjoy using a computer?

☐ Not applicable
☐ Not at all
☐ Not much
☐ Unsure
☐ Quite a lot
☐ Very much

12. Where do you have Internet access? (Tick all that apply)
13. The following statements are about your computer and internet technology skills. Please respond to all statements on a 1 to 7 scale where 1 represents very low and 7 represents very high.

<table>
<thead>
<tr>
<th>Skill</th>
<th>Very Low</th>
<th>Very High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Web Knowledge:</td>
<td>1 2 3 4 5 6 7</td>
<td></td>
</tr>
<tr>
<td>Web Usage:</td>
<td>1 2 3 4 5 6 7</td>
<td></td>
</tr>
<tr>
<td>PC Skills:</td>
<td>1 2 3 4 5 6 7</td>
<td></td>
</tr>
<tr>
<td>Web Skills:</td>
<td>1 2 3 4 5 6 7</td>
<td></td>
</tr>
</tbody>
</table>

14. Please indicate your preferred learning method.

- Picture, graphs, video, and graphics
- Discussion, explanation, listening
- Text-based input and output
- Hands on work, physical movement (touch, feel, hold, and move something)
15. What reason(s) you will use the open learner model? (Tick all that apply)

☐ To improve the accuracy of my learner model
☐ To do planning on learning
☐ To use as navigation aid on learning
☐ To do reflection on learning
☐ To view learning progress about myself
☐ To view peers’ learner models
☐ To compare instructors’ expectation

The following statements are about your attitude and perception toward the adoption of open learner model which has been introduced to you based on the scenario. Please indicate the degree to which you agree or disagree with each of the statement presented below by ticking on the most appropriate option on a 7-point scale anchored at 1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral, 5 = somewhat agree, 6 = moderately agree, and 7 = strongly agree.

16. Please indicate the extent to which you agree or disagree with the statement about your motivation to adopt the open learner model.

<table>
<thead>
<tr>
<th>I would enjoy learning by using OLMs</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>I find OLMs would be useful in studies</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>OLMs would help learners to do better in studies</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>OLMs would increase academic performance</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>It is easy to learn more using OLMs</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>OLMs can effectively enhance learning</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
</tbody>
</table>
17. Please indicate the extent to which you agree or disagree with the statement about your ability to perform learning task using the open learner model.

<table>
<thead>
<tr>
<th>Statement</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>I can easily access contents of OLMs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I can freely navigate contents of OLMs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I can use OLMs without the help from others</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I can use OLMs if there are user manuals available</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

18. Please indicate the extent to which you agree or disagree with the statement about your online learning experience for the adoption of an open learner model.

<table>
<thead>
<tr>
<th>Statement</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>I have previous experience in using online collaboration technologies</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I have online learning experience</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I know how to use online learning collaboration technologies</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I have experience in adopting collaborative technologies for collaborative learning</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

19. Please indicate the extent to which you agree or disagree with the statement about your perception on the interaction functions available in open learner model. (System Interactivity)

<table>
<thead>
<tr>
<th>Interaction Function</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLMs would enable interactive communication between instructors and learners</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OLMs can control the rhythm of learning</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OLM can control learning sequence.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OLM can select appropriate learning contents</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OLM can enable interactive communication between learners</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OLM can select learning materials based on current level of knowledge</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
20. Please indicate the extent to which you agree or disagree with the statement about your perception on the ability of open learner model to provide learning content that based on your knowledge level. (System Adaptability)

<table>
<thead>
<tr>
<th>Statement</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLMs provide learning content which is suited to current level of knowledge</td>
<td></td>
</tr>
<tr>
<td>Learning content presented with respect to current level of understanding would improve learning</td>
<td></td>
</tr>
<tr>
<td>OLMs would help learner to learn with other learners</td>
<td></td>
</tr>
<tr>
<td>Content displays on OLMs would help to identify misconception</td>
<td></td>
</tr>
<tr>
<td>Content displays on OLMs would assist to solve the problem effectively</td>
<td></td>
</tr>
</tbody>
</table>

21. Please indicate the extent to which you agree or disagree with the statement about your perception on the way of information presented on the open learner model. (Screen Design)

<table>
<thead>
<tr>
<th>Statement</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Layout design of OLMs is easy to read</td>
<td></td>
</tr>
<tr>
<td>OLMs would provide a means for taking test</td>
<td></td>
</tr>
<tr>
<td>Interface design of OLMs is consistent</td>
<td></td>
</tr>
<tr>
<td>OLMs would allow control over learning activity</td>
<td></td>
</tr>
</tbody>
</table>
22. Please indicate the extent to which you agree or disagree with the statement about your perception on the ease of discovering the relevant information and easy to move around in open learner model. (Navigation)

<table>
<thead>
<tr>
<th>Statement</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>It is easy to navigate in OLMs</td>
<td></td>
</tr>
<tr>
<td>I can easily navigate to where I want</td>
<td></td>
</tr>
<tr>
<td>Navigations in OLMs are clear.</td>
<td></td>
</tr>
<tr>
<td>Navigations would allow sharing of learning information easily</td>
<td></td>
</tr>
</tbody>
</table>

23. Please indicate the extent to which you agree or disagree with the statement about your trust towards the adoption of an open learner model. (Trust)

<table>
<thead>
<tr>
<th>Statement</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>I believe OLMs would accurately represent my current level of knowledge</td>
<td></td>
</tr>
<tr>
<td>I believe the content in OLMs is correct</td>
<td></td>
</tr>
<tr>
<td>I believe the information in OLMs is created based on correct and relevant information gathered about the student</td>
<td></td>
</tr>
<tr>
<td>I trust OLMs would correctly measure my learner model</td>
<td></td>
</tr>
<tr>
<td>I trust OLMs because I can compare to peers</td>
<td></td>
</tr>
</tbody>
</table>

24. Please indicate the extent to which you agree or disagree with the statement about your believes that using open learner model would improve your performance in studies.

<table>
<thead>
<tr>
<th>Statement</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLMs would give me more control on learning</td>
<td></td>
</tr>
<tr>
<td>OLMs would help learn the course content easily</td>
<td></td>
</tr>
<tr>
<td>OLMs would enhance learning effectiveness</td>
<td></td>
</tr>
<tr>
<td>OLMs would improve learning performance.</td>
<td></td>
</tr>
<tr>
<td>Using OLMs would help accomplish learning task quickly</td>
<td></td>
</tr>
<tr>
<td>I would find OLMs useful in</td>
<td></td>
</tr>
</tbody>
</table>
25. Please indicate the extent to which you agree or disagree with the statement about your believes that using open learner model would be free of effort.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning to use OLMs is easy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I find it easy to use OLMs</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>My interaction with OLMs is clear</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>I find OLMs flexible to interact with</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>It is easy to become skillful at using OLMs.</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

26. Please indicate the extent to which you agree or disagree with the statement about your attitude towards the adoption of an open learner model.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLMs is good for collaborative learning</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>I am desirable to use OLMs for collaborative learning</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I prefer to use OLMs for collaborative learning</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>I like to use OLMs for collaborative learning</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

27. Please indicate the extent to which you agree or disagree with the statement about your intention to use the open learner model.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>I intend to use OLMs whenever possible for collaborative learning</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>I intend to increase the use of OLMs for collaborative learning</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>I would adopt OLMs for collaborative learning</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I intend to adopt OLMs in collaborative learning</td>
<td></td>
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</tr>
</tbody>
</table>
28. Please indicate the extent to which you agree or disagree with the statement about your willingness to share your learning information using open learner model.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>I am willing to collaborate with peers using OLMs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I intend to continue sharing information using OLMs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am able to share learning information through OLMs</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I feel comfortable to share learning information through OLMs</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

THANK YOU VERY MUCH FOR YOUR TIME AND PARTICIPATION
Appendix B

The Invitation to Participate in Research

INVITATION TO PARTICIPATE IN A RESEARCH PROJECT
PROJECT INFORMATION STATEMENT

Project Title: Investigating Learners’ Attitude and Perception of Open Learner Models in Collaborative Learning Environment

Investigators:
Professor Hepu Deng
School of Business Information Technology and Logistics
Phone: +613 9925 5823 Email: hePU.deng@rmit.edu.au

Associate Professor Elspeth McKay
School of Business Information Technology and Logistics
Phone: +613 9925 5978 Email: elspeth.mckay@rmit.edu.au

Mr Sek Yong Wee
School of Business Information Technology and Logistics
Email: yongwee.sek@rmit.edu.au

Dear Sir/Madam,

You are invited to participate in a research project being conducted by RMIT University. This information sheet describes the project in straightforward language, or ‘plain English’. Please read this sheet carefully and be confident that you understand its contents before deciding whether to participate. If you have any questions about the project, please ask one of the investigators.

Who is involved in this research project? Why is it being conducted?
This research project is Sek Yong Wee’s PhD research study. He is a PhD student enrolled in the School of Business Information Technology and Logistics at RMIT
University, Melbourne. He is also a lecturer at Universiti Teknikal Malaysia Melaka (UTeM) and currently he is on PhD study leave. The research is supervised by Professor Hepu Deng and Associate Professor Elspeth McKay from the School of Business Information Technology and Logistics, College of Business, RMIT University.

This research investigates learners’ attitude and perception toward the use of open learner models in an adaptive e-learning environment. This research project has been approved by the RMIT Business College Human Ethics Advisory Network (BCHEAN). It adheres to the strict guidelines set by the Ethics Committee at RMIT University. This project is being undertaken as part of the requirements for the degree of Doctor of Philosophy in Information Systems at the School of Business Information Technology and Logistics, RMIT University.

**Why have you been approached?**
The reason you have been approached for this project is that you are studying in an online learning environment. Your input will help in the identification of the critical factors that influence the adoption of open learner models in technology-assisted learning in the Malaysian higher education environment.

(Nota: Reasons not applicable to the selected organization will be deleted from this PICF prior to sending.)

**What is the project about? What are the questions being addressed?**
Open learner models (OLM) are a computer-based representation of a learner’s current understanding level relating to the concept known, specific knowledge, and their misconceptions in a specific subject area. These open learner models not only allow a direct interaction and contribution from learners to the development and maintenance of their model content, but also be able to provide immediate feedback and responses about a learner’s current status of learning. The use of open learner models can increase a learner’s engagement in the learning process and provide them with better motivation.

Despite the usefulness of open learner models for improving the effectiveness of teaching and learning, the utilisation of these models are not encouraging. The objective of the project is to investigate learners’ attitude and perception towards the adoption of open learner models in an adaptive e-learning environment in the Malaysian higher education.

**If you agree to participate, what will I be required to?**
The completion time of the survey is expected to take approximately 25 minutes. Should you agree to participate, you need to click on the agree button indicating your agreement to participate at the bottom of the plain language statement page. This will take you to the survey page. Once you have responded to the survey, you need to click on the submit button. By clicking the submit button you are implying your consent to participate in this research.

**What are the possible risks or disadvantage?**
There are no perceived risks other than the inconvenience caused by participating in answering the online survey where the participant needs to have an access to the internet facility.

**What are the benefits associated with the participation?**
A possible benefit of participation in this research project is that the participant will be exposed to the feature available in open learner models. The participant would be able to have a better understanding on what information will be available in open learner models which can be used to improve their learning.

**What will happen to the information I provide?**
This project will use a secure RMIT University server to create, collect, store and analyse the data from the survey. The data collected will be securely stored for a period of five years in the School of Business IT and Logistics, RMIT University. The data on the RMIT University server will then be deleted and expunged. All information collected is strictly confidential and can only be accessed by the investigators. I can assure you that any data or information supplied will be treated in complete confidence, although the research findings may be written up in PhD thesis or in relevant academics journals. In any event, neither individuals nor their organizations will be identified without their express permission. Because of the nature of data collection, we are not obtaining written informed consent from you. Instead, we assume that you have given consent by your completion of the online questionnaire.

**What are my rights as a participant?**
As a participant, you have the right to:
- withdraw from participation at any time,
- have any unprocessed data withdrawn and destroyed, provided it can be reliably identified, and provided that so doing does not increase the risk for the participant, and have any questions answered at any time.

**What other issues should I be aware of before deciding whether to participate?**

**Security of the website**

Users should be aware that the World Wide Web is an insecure public network that gives rise to the potential risk that a user’s transactions are being viewed, intercepted or modified by third parties or that data which the user downloads may contain computer viruses or other defects.

**Security of the data**

This project will use an external site to create, collect and analyse data collected in a survey format. The site we are using is Qualtrics online survey. If you agree to participate in this survey, the responses you provide to the survey will be stored on a host server that is used by RMIT University server. No personal information will be collected in the survey so none will be stored as data. Once we have completed our data collection and analysis, we will import the data we collect to the RMIT server where it will be stored securely for five (5) years. The data on the RMIT University host server will then be deleted and expunged.
Whom should I contact if I have any questions?
If you have any queries regarding this research project, please contact either Mr Sek Yong Wee, Email: yongwee.sek@rmit.edu.au, Professor Hepu Deng, phone: +613 9925 5823, Email: hep.deng@rmit.edu.au, Associate Professor Elspeth McKay, phone: +613 9925 5978, Email: elspeth.mckay@rmit.edu.au

If you have any concerns about your participation in this project, which you do not wish to discuss with the researchers, then you can contact the Ethics Officer, Research Integrity, Governance and Systems, RMIT University, GPO Box 2476V VIC 3001. Tel: (03) 9925 2251 or email human.ethics@rmit.edu.au

Thank you very much for your contribution to this research.

Yours sincerely,

-------------------------- -------------------------- --------------------------
Sek Yong Wee       Professor Hepu Deng       Associate Professor Elspeth McKay
PhD Candidate     Primary Research Supervisor    Secondary Research Supervisor
Appendix C

Detecting Univariate Outliers
# Appendix D

Detecting Multivariate Outliers

<table>
<thead>
<tr>
<th>Case</th>
<th>Mahanalobis Distance</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>493</td>
<td>41.38660</td>
<td>0</td>
</tr>
<tr>
<td>359</td>
<td>40.51025</td>
<td>0</td>
</tr>
<tr>
<td>41</td>
<td>35.85626</td>
<td>0.00001</td>
</tr>
<tr>
<td>239</td>
<td>35.75337</td>
<td>0.00001</td>
</tr>
<tr>
<td>44</td>
<td>33.87071</td>
<td>0.00002</td>
</tr>
<tr>
<td>195</td>
<td>33.61234</td>
<td>0.00002</td>
</tr>
<tr>
<td>499</td>
<td>33.42304</td>
<td>0.00002</td>
</tr>
<tr>
<td>94</td>
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<td>0.00002</td>
</tr>
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<td>321</td>
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<td>482</td>
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<td>0.00003</td>
</tr>
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<td>37</td>
<td>32.82333</td>
<td>0.00003</td>
</tr>
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<td>123</td>
<td>31.94511</td>
<td>0.00004</td>
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<tr>
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Appendix E

Power Analysis

Sample size calculated at http://www.raosoft.com/samplesize.html
Appendix F

Congeneric Measurement Models

Motivation

Computer self-efficacy

Online learning experience
Behaviour Intention

Navigation

System Interactivity

System Design
System Adaptability

Trust

Perceived Usefulness

Perceived ease of use
Attitude

Information Sharing Intention
Appendix G

Initial Full Measurement Models
Appendix H

Final Full Measurement Models