UNIVERSITY OF BIRMINGHAM

# USERS' TRUST IN OPEN LEARNER MODELS


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A thesis submitted to
The University of Birmingham
for the degree of
DOCTOR OF PHILOSOPHY


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Computer Engineering
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February 2014

# ABSTRACT

This thesis is to investigate learner trust in an open learner model. Issues of trust become more important in an open learner model (OLM) because the model is available for learners to inspect and this may increase their perceptions of how a system evaluates their knowledge and updates the model. It is important to provide learners with a trustworthy environment because it can engage them to continue to use the system.

In this thesis we investigate learner trust in two main perspectives: from the perspective of the system as a whole and from the perspective of OLM features. From the perspective of the system as a whole, we investigate the extent to which learners trust and accept the OLM system on their first use, the extent to which learners continue using the OLM optionally after their initial use, and the extent to which learner trust and accept the OLM after long term of use. From the perspective of OLM features in the OLM environment, we investigate learner trust based on most common features: (i) complexity of model presentation; (ii) level of learner control over the model; (iii) the facility to view peer models and release one's own model to peers.

Learners appear to have a different level of trust in the OLM. Learners trust the system more in the short period of time. Learners also trust the different

view of model presentation and the different level of learner control in OLM. In terms of peer models, the named peer model is trusted more than the anonymous model. Based on the findings, a set of requirements is established to help the designer in OLM to design a more trustable OLM.

# ACKNOWLEDGEMENTS

Special thanks to Dr. Susan Bull for her never ending help and patience.

Thank you to my beloved family especially to my husband: Azlihan b. Abd. Aziz, children: Nurin Umairah, Nurhan Danish Haikal & Ahmad Nukman Ukail, and parents: Hj. Ahmad b. Hj. Salleh & Hjh. Supina bt. Musa and Hj. Abd. Aziz b. Hj. Tosiran & Hjh. Sarmah bt. Hj. Satir for never ending support and love.

Thank you to Diana Perez-Marin, Andrew Mabbott, Vania Dimitrova for allowing screenshots of their OLM to be included in this thesis. Thank you to Alice Kerly, Rashidi Johan and Matthew Johnson for suggestions, ideas and assistance in this project. Thank you to Hj. Roslan bin Mohamed Ali for checking the spelling and grammar of this thesis.

Thank you ALLAH, the Most Gracious, Most Merciful.

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# Chapter 1

# INTRODUCTION

Intelligent Tutoring Systems (ITS) are computer-based instructional systems that provide adaptive (individualised) teaching, guidance or tutoring. An ITS assesses each learner's actions in the interactive environments and develops a model of user knowledge, user expertise and skills. The ITS then tailors instructional strategies that best suit the learner, based on their inferred learner model. The learner model in most adaptive teaching systems exists as a machine view and is hidden from the student. However, in open learner models (OLMs), the learner model is available for learners to view. Open learner models externalise a computer-based learning environment inferences about the users' knowledge according to their recent interaction with the environment. Opening the model to the learners may increase their perception of how the system evaluates their knowledge and updates the models. This raises questions of trust related to whether the learners believe the evaluations are correct or whether they trust the system as a whole. Therefore, issues of trust in OLM are the main purpose in this research. In this chapter we introduce the fields that motivate us into this research, describe the research questions and provide the structure of the thesis.

## 1.1 Open Learner Model

Open learner model is the extension of learner modelling that enables learners to access their inferred knowledge or understanding. It is an interactive learning where learners can view their knowledge model, difficulties and misconceptions. Open learner model has often been argued to support reflection and an active learning environment (Bull et al., 2003). This is in line with Kay's argument that student self-knowledge is crucial especially for life-long and self-directed learning. She further suggests that giving learners accountability for their learning may lead to more effective learning (Kay, 1997). Opening the model to the learners can direct them to explore their knowledge and keep track of their progress in a specific domain. OLMs can also promote independent learning by offering the learners information about their knowledge state that they would not usually see (e.g. a breakdown of understanding of concepts at a fine-grained level; descriptions of misconceptions held).

Learner models can be externalised using simple or more detailed representations of understanding. Simple representations often display learner knowledge using skill meters that show achievements as a set of progress bars for a set of domain concepts (Mitrovic & Martin, 2007; Weber & Brusilovsky, 2001). Simple model views are more limited in information, though they may take different forms, they are often similar in content to skill meters. Detailed presentations of learner models use different methods of showing the model contents, for example: hierarchical tree structures (Kay, 1997); textual descriptions of knowledge and misconceptions (Bull & Pain, 1995); conceptual graphs (Dimitrova et al., 2001); Bayesian networks (Zapata-Rivera, 2004).

There are different levels of control over learner access to their models. For instance, users may simply inspect the model contents (Mitrovic, 2003); directly provide information to the model (Kay, 1997); be required to demonstrate their knowledge or skills in order to change the model (Mabbott & Bull, 2006); and jointly negotiate the model with the system (Bull & Pain, 1995). Learners may also be able to release their model to peers and instructors (Bull et al., 2007).

## 1.2 Trust in Open Learner Model

In OLM, learners may have more or less control over their learner model contents. Some OLMs are inspectable, without allowing more direct user contributions to the model information (Mitrovic, 2003, Bull & Britland, 2007); some allow or encourage users to contribute additional information to be used together with system inferences (Kay, 1997); some allow direct editing (overwriting) of model attributes (Mabbott & Bull, 2006); some allow user challenges to the model in an attempt to persuade it to change representations if they can demonstrate their knowledge (e.g. by attempting a short diagnostic test) (Mabbott & Bull, 2006); and some are maintained through student-system negotiation of the represented beliefs (Dimitrova, 2003; Kerly, Ellis, & Bull, 2008). Kay (2001) identified several risks when control is given to learners, which includes when learners enter incorrect information to their model, or underestimate or overestimate their knowledge in self-assessments. Tanimoto (2005) also suggests the risk of tampering with the model by the student, which could affect the validity of the learner model; and the potential of biased design where designers avoid modelling the components that are problematic for transparency, and thus weaken the model's pedagogical value. Therefore, while control may help increase learner trust since they have the opportunity to influence the model contents if they disagree with them, such control may also reduce system effectiveness. Furthermore, previous research suggests that students may be uncomfortable with direct editing of their model, but prefer an OLM that offers less direct control as in persuaded and negotiated OLMs (Mabbott & Bull, 2006). This would suggest that students can have trust in an OLM or, at least, they may have greater confidence in the system to judge their knowledge, than in their own self-assessment skills.

Designing trustable open learner models may be a critical factor in the success of the next generation of open learner models (Dimitrova et al., 2007). In addition to having confidence in adaptation, this also relates to the right of access to personal data and learner control over this data (Kay, 2001). Some students are keen to release their learner model to peers, suggesting a level of trust not only in their learner model, but also in the manner in which other users might use their model data – for example, to help students identify their comparative progress, to promote competition amongst peers to increase motivation and goal setting, and to facilitate collaborative learning (Bull et al., 2007). Therefore, to investigate trust in an open learner model, the definition of trust in a learner model has been establish as "*the individual user's belief in, and acceptance of the system's inferences; their feelings of attachment to their model; and their confidence to act appropriately according to the model inferences*" (Ahmad & Bull, 2008).

# 1.3 Objectives of the Research

The objectives of this research are:

- To investigate issues of trust in open learner models
- To identify the features that engender learner trust in open learner models
- To provide a set of requirements for designing an open learner model that can incorporate a variety of issues that may enhance trust for a range of users.

Based on the research objectives, this research will contribute a set of requirements for designing open learner models that are trustable to the learners. The requirements can be one of the useful resources for OLM developers in designing trustable OLM system. The requirements also can be used together with the existing OLM framework (SMILI☺)(Bull & Kay, 2007) in order to increase user trust in the system.

## 1.5 Structure of the Thesis

This thesis is organised into 8 chapters. Chapter 1 introduces the fields that motivate this research, the research questions and the importance of the study. Chapter 2 explores the literature related to user trust and its characteristics in various fields especially in online and adaptive systems. We discussed how trust is also relevant in open learner modelling. Chapter 3 describes open learner models, their features and issues of trust that are associated in the environment. Chapter 4 presents the initial study of trust in OLM systems. From here we focus on three features to be included in the investigation of user trust in OLM which are (i) the presentation of the learner model; (ii) the learner control over the learner model; and (iii) the use of peers models in the environment. Chapter 5 describes the system that we used in this research. Chapter 6 focuses on the evaluation of the definition of trust in learner models and user trust in the system as a whole. We investigate the extent to which learners trust (and accept) the OLM in the short-term and long-term use of the system and present the relationship between learners trust and several criteria that may influence trust in OLM. Chapter 7 describes the evaluations of trust in three features of OLM that were identified from Chapter 4. Finally, in Chapter 8 we illustrate the key findings of this research, the contribution and points to directions for future research opportunities.

# Chapter 2

# USER TRUST

Trust is a subject that covers many aspects of daily life especially the inter-personal relationship. It is a common term used in everyday language, but each person has a slightly different view of its meaning. Trust has been widely studied and a keen interest in many fields including socio-psychology, education, e-commerce, automated systems and online transactions. In this chapter, we consider trust in various fields by looking into different elements and characteristics of trust. Then, we will focus on the study of trust in online and adaptive systems which covers adaptive news systems, recommender systems and adaptive educational systems. We end the chapter with a discussion of how trust is relevant in open learner modelling.

## 2.1 Understanding Trust

Trust is a multidimensional concept that can be studied from a viewpoint of many disciplines including social psychology (Deutsch 1960; Rotter 1980; Koller, 1988), sociology (Lewis and Weigert, 1985), e-commerce and online systems (Gefen, 2000; Kim, Ferrin, & Rao, 2008; Corritore, Kracher, & Wiedenbeck, 2003) and human-computer interaction (Madsen & Gregor, 2000).

Multidimensional concept means that trust is built from a relationship between different trust-building mechanism, and these mechanisms will influence the specific trust constructs (McKnight, Choudhury, & Kacmar, 2002). Therefore, each discipline offers different perspectives into the condition, its definition, the process through which it develops and the ways of utilizing it. This is because the term trust itself is quite vague (McKnight & Chervany, 2000) and so far, scholars have yet to find a universal definition of trust acceptable in all fields (Rousseau, Sitkin, Burt, & Camerer, 1998; Mcknight & Chervany, 2002). Trust becomes a weak concept because it is always seen as context-matters. However, there are several necessary conditions that lead to the existence of trust, as describes in the following section.

### 2.1.1 Pre-condition of Trust

Trust in certain situation only becomes relevant when the condition of risks exists. Several authors found that risk is required for the state of trust (Mayer, Davis, & Schoorman, 1995; Rousseau, Sitkin, Burt, & Camerer, 1998). Risk can be seen as the expected harm due to errors in the system or an attack on the system, and it can be measured as a result of this event (Jøsang & Presti, 2004). Trust has also been defined in terms of acceptance of risks (Sheppard & Sherman, 1998). For example, in order to obtain useful information in an online health system (Luo & Najdawi, 2004), users have to disclose highly sensitive personal information of their medical conditions. Users are also taking a big risk if they trust online medical information especially if the information provided is incorrect. Users have to deal with a lot of risks to their health, and their lives may be threatened.

Trust is identified based on the components of risks which are uncertainty and vulnerability (Lee & See, 2004). Uncertainty arises from the inability to verify the integrity, efficiency, and other actions (Blomqvist, 1997; Mayer et al., 1995), while vulnerability refers to the exposure of a person to physical or emotional harm. Trust with the components of uncertainty and vulnerability can be seen in e-commerce because trust often relates to user uncertainty concerning vendor activities, and overcoming the perceptions of the risk of sharing personal information (McKnight & Chervany, 2002). According to Friedman, Kahn, & Howe (2000), customers are vulnerable to certain violations of trust in online commercial transactions, such as the loss of money and privacy. Therefore, since customers lack direct contacts with the company and have to hand over sensitive information in order to complete the transaction, purchasing online is considered risky. Table 2.1 summarises the domain of trust definition.

Table 2.1: Domain of trust definition

| | **Domain** |
|---|---|
| Blomqvist (1997) | Uncertainty |
| Fogg & Tseng (1999) | Credibility |
| Friedman et al. (2000) | Vulnerability |
| Gambetta (1998) | Interdependence |
| Lee & See, (2004) | Uncertainty, vulnerability |
| McKnight & Chervany (2002) | Uncertainty |
| Mayer et al. (1995) | Vulnerability |
| Rousseau et al. (1998) | Interdependence |

Other than risk and its components, interdependence is also required for the state of trust (Rousseau et al., 1998; Gambetta, 1988). Interdependence refers to the situation where one party (*X*) needs something from another party (*Y*) to satisfy its desire, and that party (*Y*) has the potential to meet the needs. In other words, the relationship between the two parties (party who trust (*trustor*) and the trusted party (*trustee*)) is very important in trusting relationship. The two parties may be humans (Rempel, Holmes, & Zanna, 1985), organisations (Blomqvist, 1997), computer systems (Dhaliwal & Benbasat, 1996), objects like products (Wang & Emurian, 2005) and others. The trustor may conceptualise trustor's beliefs and attitudes (Rempel et al., 1985; Blomqvist, 1997), faith (Rempel et al., 1985), confidence (Tintarev & Masthoff, 2007), intention behaviours and the disposition to trust others (McKnight, Cummings, & Chervany, 1998). On the other hands, trustee may conceptualise characteristics held by trustee. Mayer et al. (1995) suggest that trustee characteristics include ability, integrity, and benevolence. Trustees may also possess characteristics like predictability, honesty and competency (McKnight et al., 1998) and credibility (Fogg & Tseng, 1999).

Therefore, trust can be characterised by the existence of risk conditions that involves uncertainty and vulnerability, and the existence of dependency relationship between trustor and trustee. Similarly, Wang & Emurian (2005) have proposed four characteristics that are accepted by most researchers studying trust in both offline and online trust:

- There must be a *trustor* (trusting party) and a *trustee* (party to be trusted) in any trust relationship - these two parties might be persons, organisations, or products. The trust will be developed based on the ability of the trustee to act and be confident with the trustor, and the degree of trust between the trustor and the trustee
- Trust involves *vulnerability* – Trust exists in uncertain and risky environments. Trustor relies on the trustee not to exploit vulnerability and will take the risk of losing something and put themselves in vulnerable situation.
- Trust will *affect actions* (mostly risk taking behaviours) – the forms of actions produced will differ based on the situation. For example A lends his money to B because he trusts B will pay back the money.
- Trust is a *subjective matter* – the roles of trust are viewed differently by different people/discipline in different situations. This is due to individual differences and situational factors.

It is known that trust is the interest of researchers from various disciplines as mentioned earlier. In general, studies of trust can be categorised into the interactions that involve human-to-human, human-to-machine and human-to-human mediated by machines. The description of each category can be found in the following section.

#### 2.1.1.1 Human-to-human

Trust in human-to-human interactions is the focus of researchers in the field of socio-psychology. From a sociological perspective, trust may be considered as a cooperative relationship which based on cognitive, emotional and behavioural aspects (Lewis & Weigert, 1985). Trust is also interpreted as observed agent behaviour in potentially risky situations (Worchel, 1979) or as agent characteristic perceived by others as trustworthy (Cook & Wall, 1980; Dasgupta, 1990). However, trust in psychology is more focused on personal traits that deal with belief, expectation and feelings. The expectation on another party to behave appropriately (with positive consequences) will affect the degree of trust. The higher the expectation individuals have in another party, the higher their degree of trust in that party (Koller, 1988). Trust between humans is the dynamic expectation that will change dynamically as the results of experience in the relationship (Rempel et al., 1985). Trust is an important concept in psychology because it is crucial for personality development (Erikson, 1993) and social life (Rotter, 1980).

#### 2.1.1.2 Human-to-machine

Trust between human-to-machine focuses on interactions between human operators with automated systems. Lee & See (2004) define automation as technology that actively selects data, transforms information, makes decisions, and controls processes. Trust in automated systems can be defined as '*the attitude that an agent will help achieve an individual's goals in a situation* *characterised by uncertainty and vulnerability'* (Lee & See, 2004). Basically, studies on trust between human-to-machine have been drawn from earlier work on trust between humans (Rempel et al., 1985). Muir (1987) in his study suggested, trust that exists between humans may also be used to trust the automated systems. To prove Muir's statement empirically, Jian, Bisantz, & Drury (2000) have done a series of experiments on three conditions of trust: general trust, trust between people, and trust between human and automated systems. The results obtained reveal that words related to trust are very similar among the three conditions of trust (see Table 2.2).

Table 2.2: Most related words of trust in three conditions of trust (Jian et al., 2000)

| | **Words** | | | | | | |
|---|---|---|---|---|---|---|---|
| **Conditions** | Trustworthy | Honesty | Loyalty | Reliability | Honour | Integrity | Familiarity |
| General trust | / | / | / | / | / | | |
| Trust between people | / | / | / | / | | / | |
| Trust between human and automated systems | / | | / | / | / | | / |

Trust in a human-machine relationship is essential if operators decide whether to use automatic or manual control (e.g. Lee & Moray, 1992,1994; Muir & Moray, 1996). Previous findings related to trust in process–control systems showed that operators' performance was affected significantly by their degrees of trust towards the machines (Sheridan, 1988; Lee & Moray, 1992; Muir & Moray, 1996; Jian et al., 2000). Operators' trust focuses on the automatic control device and is defined as the expectation that the automatic device will function properly (Muir 1987, 1994; Jian et al., 2000). However, if the operator considers to continue using manual controls when choosing automated controls, it proves that self-confidence is a component of trust between humans and machines (Lee & Moray 1992, 1994; Riley, 1996).

#### 2.1.1.3 Human-to-computer

Trust between human-to-computer focuses on interactions between user and computer systems. According to Corritore et al., (2003), trust in e-commerce often cited the trust definition by Mayer et al. (1995) which describe trust as "*the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party*". Trust in e-commerce also referred to as confidence held by a person to what others will do (Gefen, 2000). Similarly in recommender systems, trust is referred to as increase of confidence (Tintarev & Masthoff, 2007). On the other hands, Cramer et al., (2008) refer to trust in recommendation as "*user's willingness to depend on a system and its recommendations in the specific context of the user and his or her task(s), even though the system might make mistakes*." In a more general context, Schmidt-Belz (2005) defines trust in adaptive systems as "*the believe that in interacting with another party or system, one is vulnerable but one's own interests are adequately respected and protected by the other party or system, and the other party or system is capable of performing*". This definition clearly shows the relationship of a party who trusts, a party who is being trusted, the vulnerability and the expectation of one party to another. In the context of decision aid systems Madsen & Gregor (2000) define trust as "*the extent to which a user is confident in, and willing to act on the basis of the recommendations, actions, and the decisions of an artificial intelligence decision aid*". This covers both users' confidence in the system and their willingness to act on the system's decisions and advice. Table 2.3 summarises the differences on the focus for each definition of trust quoted above.

Table 2.3: Differences in definition of trust

| | **Focus** |
|---|---|
| Mayer et al. (1995) | vulnerability |
| Cramer et al., (2008) | dependability |
| Schmidt-Belz (2005) | vulnerability |
| Madsen & Gregor (2000) | confidence |

### 2.1.2 Measurement of trust

Jian et al. (2000) have provided empirical evidence that the concept of trust and distrust can be measured using the same rating scale. The questionnaires with twelve items incorporate seven points rating scale in the range from 'not at all' to 'extremely'. Three-phased experimental studies have been done before the trust questionnaires were developed. The first phase of the study involved the collection of the various words related to concepts of trust and distrust. The second phase involved a questionnaire study to examine how close these words related to trust or distrust, and the third phase was a study to compare pairs of words. Participants were asked to rate the similarity of words that are paired. A multidimensional measurement scale for trust was then constructed based on data obtained from the second and third phase of studies.

Apart from Jian et al. (2000), the subjective measurement of trust using multiple rating scales has also been proposed by Muir & Moray (1996) and Madsen & Gregor (2000). Muir & Moray (1996) use rating scale to examine the level of operator's trust in a process control pump. The rating scale is between 'not at all' and 'extremely high'. Madsen & Gregor (2000) have built a trust measure called the Human-Computer Trust (HCT) scale. This scale has been drawn from earlier work including Rempel et al. (1985) and Muir & Moray (1996). The HCT scale consists of five main constructs which are perceived reliability, perceived technical competence, perceived understandability, faith and personal attachment. Each main construct has five items, bringing the total to 25 items. In this research, we adapt some questions from Jian et al. (2000) and Madsen & Gregor (2000).

## 2.2 Trust in Online and Adaptive Systems

The growth of internet technology has changed the way people interact. According to Marsh & Dibben (2003), trust between users and technology is vital in human-computer interactions because without it, efficiency and productivity will not be maximised. Furthermore, the increasing market demand, current trend of automation, and intelligent systems make trusting automation an important issue for systems researchers, developers and users (Lee & See, 2004). Yahoo! Inc., (2006) reported that the internet has become a trusted shopping information sources where most customers purchase online at the trusted and familiar sites. Customer trust in the web vendor also influences the intention to purchase products online (Gefen, 2000; Kim et al., 2008; McKnight, Choudhury, & Kacmar, 2002). Moreover, a lack of customer trust is a major obstacle in the success of e-commerce (Dayal et al., 2001). Therefore, consumer trust has indeed become a crucial factor influencing the success of e-commerce (Hoffman et al., 1999; Gefen, 2000).

Literature shows that trust in online systems may be influenced by several elements. Among these elements are the experience of using the internet (Corbitt et al., 2003; Metzger, 2006; Aiken & Bousch, 2006), perceived ease of use of a website (Sillence et al., 2004; Luo & Najdawi, 2004), quality of information (Sillence et al., 2004; Luo & Najdawi (2004), reputation of the organisation (Sillence et al., 2004, 2007; McKnight et al 2004 ), privacy and security (Hoffman et al., 1999; Luo & Najdawi, 2004; Aiken & Bousch, 2006), and experience and familiarity (Gefen, 2000; Yoon, 2002; Pavlou, 2003). On the other hand, Briggs et al (2002) suggested that users were likely to trust online advice systems based on three factors: source credibility, advice personalisation and advice predictability. Source credibility refers to the completeness of information provided in the site including where the information comes from, while advice personalisation refers to whether information provided is tailored to user needs. Advice predictability refers to whether information presented reflects user’s knowledge and prior experience. This situation leads to trust in adaptive systems.

Adaptive systems can personalise to users based on the activities they have done in the environment. Systems are able to adjust their behaviour to the expectations of users’ requirement based on the current situation of users (user model). It begins by observing and modelling users and this model will be updated in accordance with current behaviours. From the user model, systems will infer system behaviour that is suited to the users’ current situation. This will benefit users because they will get information based on their needs, and avoid information that is not relevant to them. In short, an adaptive system is capable of matching the appropriate output, using the implicit inferences based on interaction with the user. Because of these advantages, adaptive systems have been developed and implemented in different areas. Each area applied different techniques in terms of user modelling and adaptation.

Despite the advantages gained from adaptive systems, there are issues that need to be considered. The modelling process may provoke a user to question the issue of privacy as every action is recorded and noted by the system without their permission. The adaptation process may produce questions of whether user will follow the system’s recommendation, as this may relate to user trust in the system. Schmidt-Belz (2005) suggested that user trust in adaptive systems not only relates to privacy issues but also user control, consistency, and system competence. Based on qualitative empirical methods, Schmidt-Belz (2005) provides a set of user requirements as guidelines to design a trustworthy adaptive system. The requirements are:

- Users need access to inspect their model as well as the ability to switch off the inspections.
- Users should be allowed to inspect and have the ability to edit the model
- Users sometimes want to be free from being personalised and filtered. System may provide the option to switch off the adaptive behavior and offer relevant feedback to users.
- Users should be allowed to understand the modelling and reasoning of the system.
- Adaptivity is not provided to substitute bad usability design in the system but rather users should be helped to understand the adaptivity.
- The pro-active services (e.g. spam) must be unobtrusive, easy to switch off and only provided upon user subscription.
- Users should be provided with clear benefits from the personalisation implemented in a system designed with a high level usability.

From the above requirements, we can see that user trust in adaptive systems is closely related to user understanding of the system and level of control provided for them. The following subsections describe trust in several areas in adaptive systems.

### 2.2.1 Adaptive News Systems

The internet is widely known as a source of information that is accessible anywhere. Information increases continuously and this causes information overload to the reader. Yet the reader does not like to read the entire news items which are displayed daily. Therefore adaptive news systems have been developed as a mechanism to filter the news based on user requirements. Personalisation in adaptive news is to help users reach the content of the news that relevant to them. Identification of this relevant information for each user is identified by the system through model of user interest. This model is built based on user interaction with the system. The system will then recommend or categorise related information for a user to reach easily. User modelling and adaptation techniques for personalised news have been used in the systems such as SeAN (Ardissono, Console, & Torre, 2001) and Daily Learner (Billsus & Pazzani, 2000). SeAN is an adaptive system using multi-agents for accessing online electronic news. It has three main objectives: first, to select topics and news in the server that are highly relevant to users, second to adapt detail level of news items to user characteristics, and third to select the most appropriate advertising for each page and user. Daily Learner offers nine different categories of news which are *Top Stories, Politics, World, Business, Technology, Science, Health, Entertainment* and *Sports*. Users can select stories under the intended category and leave comments or rate the stories, whether they are interesting or not. Users can also notify the agent about the topic that was known or request more information about the stories. In general, users can rate the story as interesting, not interesting or known. Users are not forced to rate the news story but rather it is the user's own choice. After this initial training phase, the system is capable of producing a story according to user interest based on categories selected by the user. A list of related titles will be displayed in accordance with the current user model.

Personalised adaptive news is becoming increasingly important because most of the portal available in World Wide Web provides access to news and this is not limited to company related communications only. For instance, for companies that operate primarily through the web, they provide news related to companies and news that may be of interest to their clients. The main purpose of this personalised news is to attract web users and to gain their loyalty (Ardissono et al., 2001). Recently, adaptive news systems have been expanded to provide a more transparent system (Wongchokprasitti & Brusilovsky, 2007; Ahn, Brusilovsky, Grady, He, & Syn, 2007). This means that the content of models is opened to the user for inspection.

NewsMe (Wongchokprasitti & Brusilovsky, 2007) makes itself transparent by allowing users to rate news stories. Users may label news of interest as 'Tracked News' and news to be avoided as 'Blacklist'. Users may choose not to leave any feedback for the articles that have been read and the system will assume users do not have a clear view of the articles. Feedback received from users is used to build the user model and influence the way the recommendation is given to users. NewsMe also allows users to update their profile by moving the articles to another label or remove articles directly from their profile. Wongchokprasitti & Brusilovsky (2007) found that excessive manipulations of the user model may degrade system performance and that system feedback is efficient enough to match explicit feedback (from the user).

Adaptive news systems also provide user control where they can edit their models and improve the adaptation process. YourNews (Ahn et al., 2007) is an adaptive personalised news system that allows users not only to view their interest profiles in the news but also to edit them. YourNews constructs user models based on user reading behaviour, and recommends the most relevant news story to users based on this model. In terms of user control, the system allows users to remove or add new keywords related to the articles. Users can see the effects of adding and removing the keyword as soon as it is done. Therefore, users can expect which news will be affected from the changes made. In addition, users can see the importance of keywords related to the article when the cursor is placed on the title of the article. Keywords that are important for an article will appear larger than the other keywords. Ahn et al. (2007) suggested that the trust will be higher in a system that is transparent and allows users to control the system by editing their profile. However such control should be used with caution as it may harm the performance of the system. Trust in adaptive news systems is examined using time spent reading the articles and the average rank of items clicked by the subjects (Ahn et al., 2007).

### 2.2.2 Recommender Systems

Recommender systems aim to provide users with items or information that might match their preferences, and prevent users from serving one that is not relevant to them. The system will build a user model (user profile) for all users during their interaction with the system. User profiles are built by collecting data obtained either through explicit or implicit data collection. Explicit data collection is done by asking users to rate items they like or dislike, while implicit data collection is done by observing user behaviors in the system and these behaviors are recorded in the system to be analysed. Users will then receive items or information that may be off interest based on their profiles. Burke (2002) classified three main components that work together to predict recommendations for users. They are background data, input data and algorithm. Background data is the existing information held by the system and input data is the information that should be contributed by users of the systems. This information is then combined and compared to the algorithm to generate recommendations. Figure 2.1 shows the relationship between these three components in order to produce recommendations.

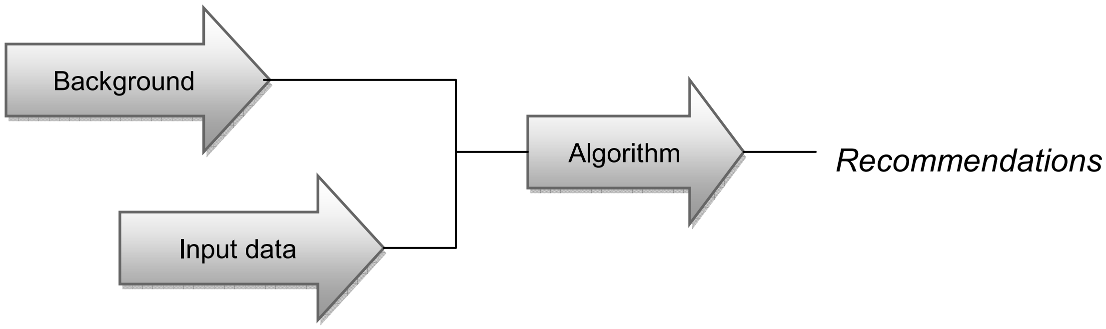



Figure 2.1: The relationship between the three components to generate recommendations

The recommendation techniques applied in an algorithm could be based on collaborative filtering, content-based, or a hybrid of these approaches to gain better performance (Burke, 2002, Adomavicius & Tuzhilin, 2005). Previous research showed that the accuracy of the recommendation algorithm could determine the users trust in the recommender system (McNee, Lam, Konstan, & Riedl, 2003). User trust in recommender systems is essential because research indicates that users plan to return to trustworthy systems (Chen & Pu, 2005).

Herlocker, Konstan, & Riedl (2000) found that most users wanted an explanation feature added to the system. This is because explanations in recommender systems help users make precise decisions (Bilgic & Mooney, 2005). In addition, the ability of the system to explain why items were recommended to the users is likely to increase user trust (Sinha & Swearingen, 2002). Explanations provided in the system must be good because bad explanations prevent users from accepting individual recommendations (Herlocker et al., 2000). Sinha & Swearingen (2002) found that users gave a higher rate to a system that provides understandable recommendations.

Therefore explanation made the system more transparent and increased the probability of trust in the recommender system (Sinha & Swearingen, 2002).

Sinha & Swearingen (2001) found that more people prefer the recommendations made by friends than the systems. Other studies found that users prefer to accept recommendation from trusted recommendation systems (Swearingen & Sinha, 2001). To meet these preferences, Golbeck (2006) had built a recommender system that combines both of them which deployed in a system known as FilmTrust. The recommendations are made based on explicit trust contributed by users through social networks (*social-trust*). Therefore instead of presenting a list of items to users, FilmTrust suggests the extent of possibility that users may be interested in the items they have been found. Result shows that the accuracy of prediction based on trust is significantly better, and users prefer to use the recommender system with this approach.

### 2.2.3 Adaptive Educational Systems

An adaptive educational environment provides support and enhances learning by personalising the materials and teaching environment to the learner. Education can be used to tailor information presented to the current state of learners' knowledge, provide navigation support and guide learners in their learning process (Brusilovsky & Eklund, 1998).

InterBook (Brusilovsky & Eklund, 1998) is an example of an adaptive electronic textbook that provides adaptive navigation support. Adaptive navigation support provides a suitable learning path by adapting link based on the user's individual characteristics. The characteristics involve the learner's goal and knowledge. In InterBook, colours are used to represent different meanings of adaptive links. A white bullet means there is no new topic to be learned, a green bullet means the topic is recommended for learners to learn, a red bullet means the topic is not ready to be learned, while a checked bullet means the topic has been visited by learners. Evaluation of the system shows that participants prefer to use non-sequential paths with adaptive link annotations, and this reflects their trust in annotations. Participants are found more confident using the relevant materials under the annotated link. Participants are also willing to allocate more time to read a page that appears not ready for them, and this indicates participants understand the system's behaviour and trust the annotations' integrity (Brusilovsky & Eklund, 1998).

In designing and building future adaptive learning system, Zliobaite et al. (2012) have identified six key challenges. One of the challenges is to improve usability and trust in the system. Similar to other areas in adaptive systems as describe previously, transparency is needed in order to obtain user trust in adaptive learning system. The way of how learning and adaptation process implemented in the system should be disclosed to the users. Zliobaite et al. (2012) suggested that wide deployment of learning systems can improve users trust in the system, and trusting the system relates to users' understanding of the system behaviour.

Learner control is important if co-operation with the learner is needed in the learning. As discussed above, Kay (2001) highlights several risks may occur if some control of the model is giving to learners. The risks include inaccurate information entered by learners and they may over or under estimate their performance in self-assessment. Tanimoto (2005) also suggests the risk of tampering with the model by students, which could affect the validity of the learner model. However, being in control of their models in adaptive educational system can build user trust in the system (Vogiatzis, Tzanavari, Retalis, Avgeriou, & Papasalouros, 2005). Therefore, while control may help increase learner trust when they have the opportunity to influence the model contents if they disagree such control may also reduce system effectiveness. Furthermore, previous research suggests that students may be uncomfortable with direct editing of their model, but prefer a system that offers less direct control (Mabbott & Bull, 2006).

All three areas of adaptive systems described previously have shown that transparency is an important element to build user trust in the system. System should allow users to access information on how to implement the process of adaptation in the system. For example, in recommender systems they provide explanations on how an item is recommended to the users. Therefore, users can understand the underlying process involved and thus increase user trust.

Schmidt-Belz (2005) also includes transparency as one of the trust elements in adaptive systems. However, the elements of trust in adaptive systems are mostly drawn from the perspective of user models that is slightly different with learner models in adaptive educational systems. User models usually model user interest while in an educational context learner models usually model user knowledge. Very little research has been made to study user trust in adaptive educational systems. This thesis will therefore explore user trust in the context of adaptive education specifically for open learner models (OLMs). The next section will discuss why trust is relevant in OLMs.

## 2.3 Discussions

In Section 2.1.1 we presented four characteristics of trust accepted by most researchers as identified by Wang & Emurian (2005). In order to investigate trust in an open learner model (OLM)(described in Chapter 3), we map these characteristics to the environment as shown in Table 2.4.

Table 2.4: Mapping trust characteristics (Wang & Emurian, 2005) with OLM environment

| Characteristics | OLM environment |
|---|---|
| There must be a *trustor* (trusting party) and a *trustee* (party to be trusted) in any trust relationship. | Trustor in OLM is learners or students.<br>Trustee is OLM systems that infer learner knowledge. |
| Trust involves *vulnerability*. | In OLM, learners may be uncertain about their knowledge level and rely on the system to infer it. They also face a risky situation in terms of their knowledge level hence put them in vulnerable situation. For example:<br>• OLM infers learner knowledge based on learners' interactions with the system and if the system makes mistakes, the accuracy of the model inferred will be affected. Learners will be exposed to a vulnerable situation due to this incorrect inference.<br>• facility to edit their learner model may also put them in the incorrect level of knowledge |
| Trust will *affect actions* (mostly risk taking behaviours) | In situation where learners trust the system inference about the model, they may form either positive or negative actions. For example learners may study hard if they find the knowledge level is low, or they may do nothing because they become demotivated due to the system inference. |
| Trust is a *subjective matter* | Different learners will have different trust over their learner models in OLMs. It may result from their attitudes towards machine and technology, confidence in their self-assessment skills, etc. |

The mapping of trust characteristics to OLMs shows that each characteristic is appropriate with OLM environment and this indicates that a study of trust is also relevant in OLMs.

The potential risks in using OLM are when control is given to learners as described in Section 1.2. Other than that, learners can continue to answer the questions until the system shows that they have high knowledge in a particular topic, and then stop answering questions on that topic. This can happen because of concerns that the system's presentation of their knowledge will decrease if they continue to answer the questions. Thus, this situation can give a wrong presentation of knowledge to the instructors and also to other students especially when they are using the peer models (Section 4.1.1).

From the perspective of human-machine interaction, a theory of how trust can be built by users in automated systems has been produced (Muir, 1987,1994). This may also be applicable to OLMs. The following points seem particularly relevant:

- the level of trust will affect user decisions such as the choice of manual or automated control and whether they follow the system's advice;
- a minimum system performance is necessary for user trust.

If learners can recognise that their OLM is sufficiently accurate, and if they understand the overall purpose of the learner model for adaptation, they will likely maintain a higher trust in the system. This is particularly important where the learner can see, but not challenge the learner model contents. When users have greater control over their model contents, their level of trust in the system may help determine the extent to which they accept the system's representations. Learner models that can be challenged by the learner can be useful where it is accepted that the model may not always be entirely accurate. If learners recognise an incomplete or possibly partially inaccurate model as still useful in adaptive tutoring, their trust may be raised if they are allowed to change or challenge it in cases where they consider the representations are below the minimum level required for effective adaptation. Therefore, trust in this context may not necessarily be dependent on the accuracy of the system's inferences. A minimum system performance may still be achieved for the development of trust by involving the learner in the learner modelling process in systems where the modelling can benefit from direct input from the learner, as long as the learner accepts this role.

While primarily applied to other fields, the definition of trust by Madsen & Gregor (2000) can also be relevant in open learner modelling. The evaluation for this definition will be described in Chapter 6.

## 2.4 Summary

This chapter has introduced the concept of user trust and its importance to the success of the relationship. We have presented trust research in various field and come out with pre-condition that makes trust relevant in the situation. Then we focus on trust in online and adaptive systems. We mapped characteristics of trust accepted by most researchers who study trust to an open learner model

(OLM) environment. It shows trust is relevant in an OLMs environment. In OLM, learners are allowed to see their learner model, and more importantly, learners can see system's inferences about their knowledge in the environment. Therefore, user trust may be even more important than in an environment that keeps the model hidden from learners. Next chapter will describe OLMs environment and issue of trust that may involve the environment.

# Chapter 3

# OPEN LEARNER MODEL (OLM)

Open Learner Models (OLM) can help learners to see their models and keep track of their progress in a specific domain as described in Section 1.1. In this chapter, we consider the motivations of open learner models, the environment of OLM and its features. We then focus to look at the trust issues in OLMs.

## 3.1 Intelligent Tutoring Systems

Intelligent Tutoring System (ITS) is a computer-based teaching system that provides adaptive (individualised) teaching or tutoring. In order to provide instructional feedback to learners, ITS requires and depends on several components - the domain model (the knowledge of the expert); the student model (the knowledge of the learner); the tutoring model (the knowledge of teaching strategies); and the user interface (Nwana, 1990; Nkambou, Bourdeau, & Mizoguchi, 2010). The domain model represents subject-matter expertise. It comprises all knowledge of a particular domain to be delivered to students including the concepts, rules and problem-solving ability. The student model is the dynamic representation of the learner's knowledge, skills and expertise in a domain. The tutoring model is the part that designs and regulates instructional interaction with the learner. In other words, it is the method of teaching or coaching learners in a system. ITS assesses each learner's action in interactive environments and develops a model of their knowledge, skills, and expertise. ITS tailors the best instructional strategies to the learner based on the learner model inferred.

## 3.2 Learner Models

In an adaptive learning system like ITS, the learner modelling process plays an important roles in order to achieve the adaptability and personalisation in the system. The learner model is inferred by diagnosing learners' knowledge during their interactions with the ITS (Wenger, 1987; VanLehn, 1988). The interaction in the modelling process requires learners to answer a series of questions or problem solving on a particular domain. The term learner model (or student model) is used to describe an abstract representation of the learner within the computer program (Holt, Dubs, Jones, & Greer, 1994), which represents the learner's current state of knowledge.

The learner model is used to track any changes in student knowledge by not only observing the interactions but also engaging in various learning situations. Wenger (1987) suggested that the learner model has three tasks:

- In terms of information, the data gathered must be from learners and about learners. It can be in two forms: explicit (by asking students to solve specific problems) and implicit (by tracking student interactions with the system).
- In terms of representation, the data gathered must be used to create the representation of the student's knowledge and learning process.
- In terms of accountability, the data must be accounted by performing some types of diagnosis. The diagnosis includes the state of student's knowledge.

Previously, the learner model was hidden from learners and has been kept and used exclusively by the system to affect appropriate adaptation to the learner. However, it has been argued that allowing learners to view and access their models can encourage learners to be responsible in their learning process especially on the awareness of developing knowledge and its difficulties (Kay, 1997; Bull & Pain, 1995). Opening the model to learners can direct them to explore their current state of knowledge and promote independent learning. In addition, learners' self-knowledge is crucial particularly for life-long and self-directed learning, and giving learners accountability for their learning may lead to more effective learning (Kay, 1997).

## 3.3 Open Learner Models

Open learner models (OLM) is a field of research that promotes independent learning by externalising the learner model contents to the learner (Bull & Kay, 2007). The aims of OLM are to encourage reflection, independent learning and formative assessment/progress monitoring (Bull, Quigley, & Mabbott, 2006). Through the OLM, learners may access information about their current state of knowledge, difficulties in the subject area and any possible misconceptions where this information is modelled.

In recent years, there has been an increasing interests in opening the learner model as a means to support meta-cognitive processes such as planning, reflection and self-evaluation (Kay, 2001; Dimitrova, McCalla, & Bull, 2007; Kerly, Hall, & Bull, 2007; Mitrovic & Martin, 2007). Other than supporting the meta-cognitive skills, Bull & Kay (2007) identified purposes for opening the learner model to the learner. This includes improving learner model accuracy, promoting learner reflection, helping learners with planning and/or monitoring their learning, facilitating collaboration and/or competition between learners, supporting navigation, giving the learner right of access to their information, supporting learner control, increasing the learner trust in the system by showing the learner model contents, and used the learner model as assessment.

Bull & Kay (2007) mapped the above purposes with 11 elements that should be considered in open learner modelling, and established a framework for OLM known as SMILI☺ (Student Models that Invite the Learner In). The elements are divided into three categories indicating: *What is available? How is the model presented?* and *Who controls access*?

*What is available?*

- Extent of model accessible – defines the extent of learner model available to the user
- Match underlying representation – defines the extent of similarity between the OLM and the underlying representation of the learner model
- Access to uncertainty – defines whether the learner model represent uncertainty and whether the user can access the information
- Role of time – defines whether the user can access historical, current or predicted future information
- Access to sources of input – defines the level of access for various sources of input used to infer the learner model, and whether users can access where the data for inferring comes from.
- Access to model effect on personalisation - defines whether users know the effect of the learner model on their personalised interaction

*How is the model presented?*

- Presentation of the learner model – defines how the learner model is presented to the learner, and the level of detail that can be accessed
- Access methods – defines how the learner model can be accessed, whether it is only for viewing or whether user can interact with the model

(e.g through edit, provide additional information or negotiate the learner model)

- Flexibility of access – defines whether the learner model can be viewed in different formats and whether the user can choose the level of details.

*Who controls access*?

- Who initiates access to the learner model – whether it is the system or the learner
- Controls the accessibility to other users – defines the extent of control that the users have over their learner model

Table 3.1 shows the example how the elements are mapped to purposes of opening the model. Three indicators are used in this framework to indicate the significant of row elements for the purpose in that column. Indicator ‘X’ means the row element is critical, ‘=’ means its importance is questionable and a blank indicates the element does not play a significant role for that purpose.

Table 3.1: SMILI Framework: HOW is the model presented? (Bull & Kay, 2007)

| Elements \ Purpose | Properties | Description | *Accuracy* | *Reflection* | *Plan/ Monitor* | *Collab/ Comp* | *Navig-ation* | *Right of access, control, trust* | *Assess-ment* |
|---|---|---|---|---|---|---|---|---|---|
| *7. Presentation* | Textual (i.e...) | | | | | | | | |
| | Graphical (i.e...) | | | | | | | | |
| | Overview | | X | X | X | = | = | X | X |
| | Targeted/all Details | | X | X | X | X | X | X | X |
| | All Details | | = | = | = | | | X | |
| | Support to use | | X | X | X | X | X | X | |
| *8. Access method* | Inspectable | | X | X | X | X | X | X | X |
| | Editable | | = | | | | | X | |
| | Addition | | X | | | | | X | |
| | Student persuade | | X | = | | | | = | X |
| | System encourage | | = | = | | | | | |
| | Negotiated | | X | = | | | | = | X |
| *9. Flexibility of access* | Complete | | = | = | = | = | = | X | = |
| | Partial | | X | X | X | X | X | X | X |

The elements included in SMILI☺ indicate that in general, development of OLMs includes similar features but different functions, which are usually based on the purpose of the system. In this research, we are interested in investigating user trust in relation to three purposes of opening the model to users:

- *increasing learner trust in the system by showing the learner model contents* – we are interested in investigating user trust in externalisation of the learner model
- *supporting learner control* – we are interested in investigating user trust when learner control is available in the system and which type of learner control the users more trusted in
- *facilitating collaboration and/or competition between learners* – we are interested in investigating user trust in peers model.

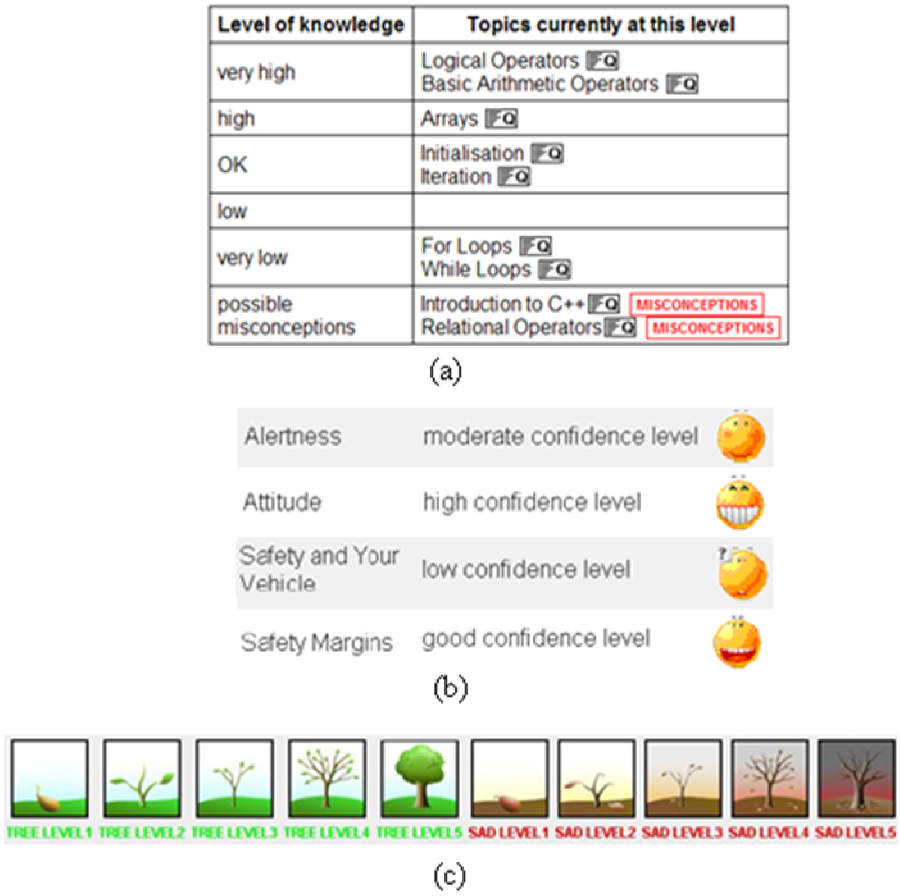
In order to investigate user trust as listed above, we shall describe OLM features in the next section in three categories: externalisation of the learner model, learner control over the learner model and OLM for other users.

### 3.3.1 Externalisation of the Learner Model

Externalisation of learner models is a critical part to be considered in OLM. Opening the models to learners means it involves the presentation of the underlying model used by the system. The underlying model may be in a different form from than that presented to the learner because it is usually complex or in a format that can only be understood by the system. For example, VisMod (Zapata-Rivera & Greer, 2004) is using a complex Bayesian network for the modelling but presenting the model to the learner in a structured graphical view; CALMsystem (Kerly et al., 2008) is using a weighted numerical model and presenting the model in a range of smiley faces that can be easily understood by children; while both SQL-Tutor and e-KERMIT (Mitrovic & Martin, 2007) are using a constraint-based model and externalise the model using skill meters.

A variety of ways to present the model is usually based on the purpose of why the system is built and who is the user of the OLM. For example in Subtraction Master (Bull & McKay, 2004) the use of a range of smiley faces is appropriate for children and may attract and encourage them to explore their knowledge. They could easily understand the information in a pictorial form and thus the learning process becomes more effective. Due to different purposes and different users within OLMs, various ways are used to present the model ranging from simple to more structured representations.

Simple representations often display learner knowledge using skill meters as described in Section 1.1. The early usage of skill meters can be seen in the ACT Programming Tutor (Corbett & Anderson, 1995), a practice environment in which students write short programming language. Examples of simple representations that similar in content to skill meters are the number of arrows in a target to represent a level of understanding of a concept (Brusilovsky & Sosnovsky, 2005); a list of topics ranked according to level of knowledge (Bull et al., 2006); the growth of trees to indicate the level of knowledge and misconceptions that may exist (Lee & Bull, 2008) and a range of smiley faces shown alongside text descriptors to represent the level of knowledge (Kerly et al., 2008). Figure 3.1 shows examples of simple views in OLM.



| Level of knowledge | Topics currently at this level |
|---|---|
| very high | Logical Operators FQ<br>Basic Arithmetic Operators FQ |
| high | Arrays FQ |
| OK | Initialisation FQ<br>Iteration FQ |
| low | |
| very low | For Loops FQ<br>While Loops FQ |
| possible misconceptions | Introduction to C++ FQ MISCONCEPTIONS<br>Relational Operators FQ MISCONCEPTIONS |



Figure 3.1: Examples of simple views: (a) ranked list (Bull et al., 2006); (b) smiley faces (Kerly et al., 2008); (c) growth of trees (Lee & Bull, 2008)

Structured views are usually more complex and provide detailed information in the learner models. Just as the diversity of simple views, structured views also used different methods of presentation of the model contents. For examples: hierarchical tree structures (Kay, 1995; Mabbott & Bull, 2006); tree maps (Brusilovsky, Hsiao, & Folajimi, 2011; Kump, Seifert, Beham, Lindstaedt, & Ley, 2012); textual descriptions of knowledge and misconceptions (Bull & Pain, 1995); three dimensional network structures (Zapata-Rivera & Greer, 2004), and concept maps (Rueda, Larrañaga, Ferrero, Arruarte, & Elorriaga, 2003;

Dimitrova, 2003; Mabbott & Bull, 2006). While most presentations in simple views are usually based-on or derived from the skill meters, Bull & Kay (2010) stated that there are variety of ways for presenting the structured model but the most common method is probably the concept map. Figure 3.2 shows examples of the presented learner model using concept map in various OLMs.

The externalisation of learner models for some OLMs are available in multiple views. The multiple views in OLM may consist of a combination of simple views, a combination of structured views or a combination of simple and structured views (Bull, Gakhal, Grundy, & Johnson, 2010; Pérez-Marín, 2007). The implementation of multiple views in OLM is driven by several reasons such as:

- to encourage learners to reflect on their knowledge from different perspectives (Kay, 1997),
- to provide alternative views to be selected by learners according to their preferences (Mabbott & Bull, 2006; Xu & Bull, 2010),
- to complete various aspects of the model information where it is displayed in a different view (e.g. Pérez-Marín, 2007; Van Labeke, Brna, & Morales, 2007).

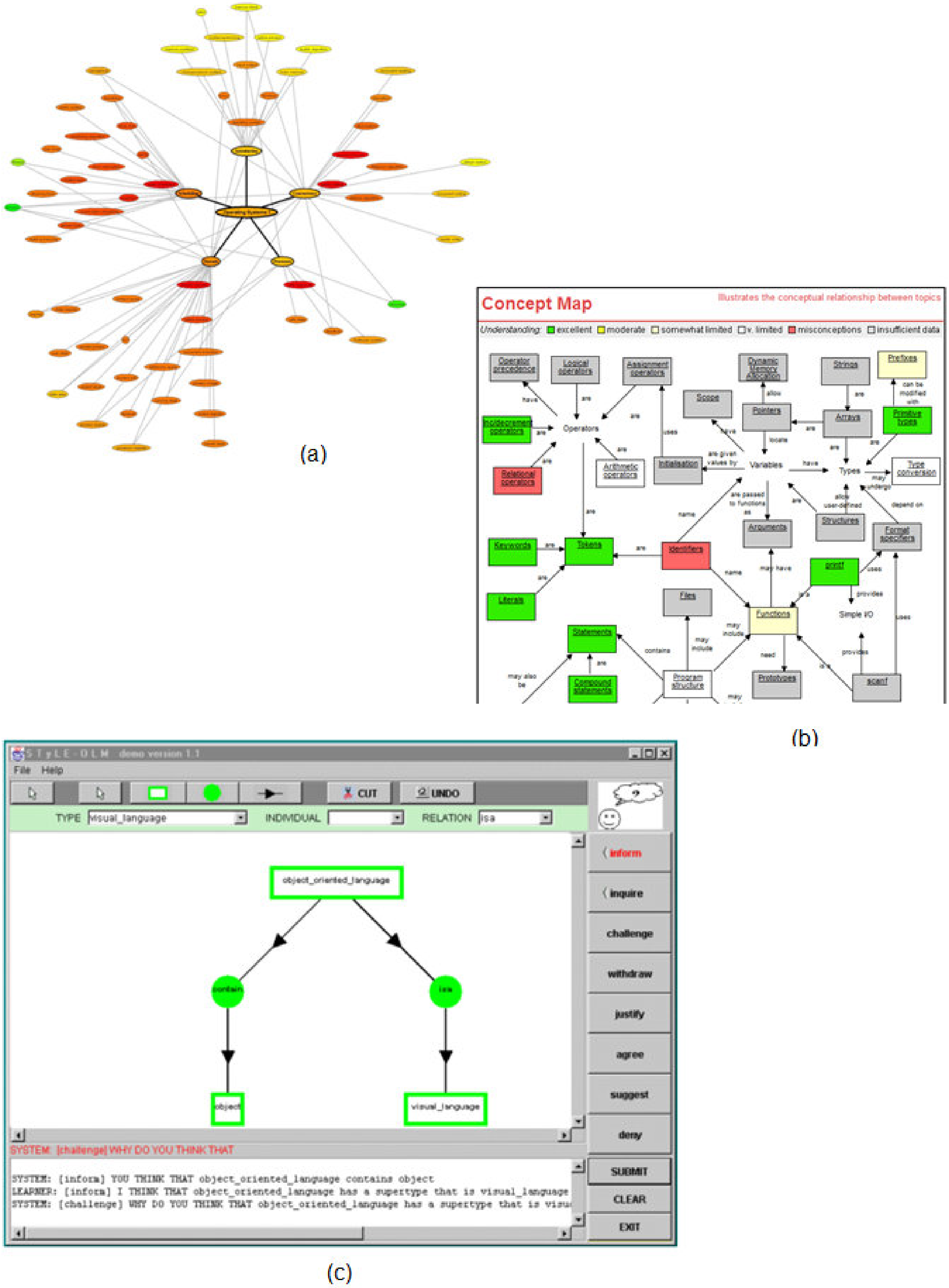



Figure 3.2: Examples of concept map used in OLMs: (a) Comov (Pérez-Marín, 2007); (b) Flexi-OLM (Mabbott & Bull, 2006); (c) STyLE-OLM (Dimitrova, 2003)

The possibility of multiple views in OLM is first raised by Kay (1997) as a useful way of encouraging students to think about their knowledge in different ways. She suggests organising the concepts in the Sam coach from different perspectives, for example of how well they match the user's favoured text editor, or according to the primitive text-editor functions.

OLMlets (Bull & Mabbott, 2006) is available in five simple formats including skill meters, graph, boxes, table and text. Among these formats, skill meters are the most common format used by the learners. For language awareness, OLMLA (Xu & Bull, 2010) offers four different formats for learners to choose to suit their preferences: index, function, example and skill meter (see Figure 3.3). Each of the views presented the modal verbs that are used by the user. Evaluation with the system found that participants accept the feedback of their language using OLM. Learners were able to used different learner views offered in OLMLA and claimed that the OLM is useful to represent their current rule use. Instead of using different formats, Zapata-Rivera & Greer, (2004) provides different visualisation techniques for learners to explore the learner models. Learners can use different display parameters in term of colour, size, proximity, link thickness and animation to represent causal relationships and marginal probability in an OLM using Bayesian network, VisMod (Zapata-Riviera & Greer, 2004). The use of multiple parameters has shown a strong influence in Bayesian network model, and some parameters have been found to be more effective than others (Zapata-Rivera, Neufeld, & Greer, 1999).

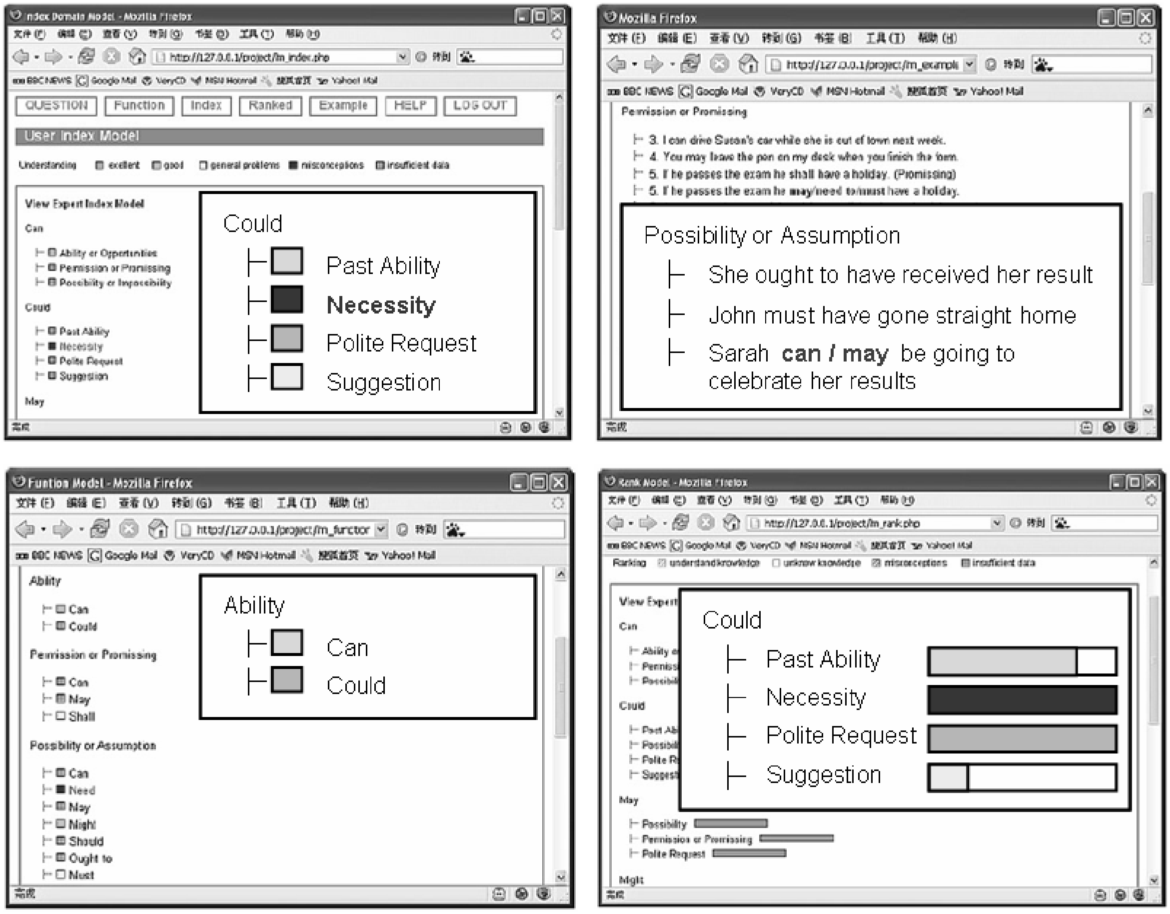



Figure 3.3: Multiple views in OLMLA (Xu & Bull, 2010): index (upper left), function (lower left), example (upper right) and skill meter (lower right)

Flexi-OLM (Mabbott & Bull, 2006) offers a selection of simple and structured representations of learner models. They are hierarchy, lecture, concept map, prerequisite, index, ranked and text summary (see Figure 4.4). Evaluation of the system has proven that users can easily select among the views, and use the views that are most useful to them. COMOV (Perez-Marin, 2007) also offers a range of simple and structured representations in its multiple views model including concept map, conceptual diagram, bar graph, table and text summary. In contrast with Flexi-OLM, each view in COMOV represents different information towards the learner models. Evaluation over four views (concept map, bar graph, table and summary) shows that all views are rated as informative by the participant and concept map was selected as a favourite representation than the others.

Table 3.2 summarises some examples of presentation of learner models in OLM. As can be seen, some systems provide simple views, some offer structured views, and some support the combination of simple and structured views.

Together with the diversity methods in externalising the learner models, colour is frequently used to support the presentation of learner models in OLM system (e.g Figure 4.1, Figure 4.4). Different colours are used to indicate knowledge level, area of difficulty and misconceptions. The use of different colours can draw learners' attention and help them to identify their knowledge directly. In presenting the learner models, colours are used together with other parameters especially size (e.g. Zapata-Rivera & Greer, 2004; Mitrovic & Martin, 2007). Other display parameters used in OLM systems are text (Bull & Pain, 1995; Paiva et al., 1995); quantity (Brusilovsky & Sosnovsky, 2005); position (Mazza & Dimitrova, 2003) and proximity (Gakhal & Bull, 2008).

Table 3.2: Externalisation of learner models

| OLM systems | Externalisation of LM | | |
|---|---|---|---|
| | Simple | Structured | Multiple views |
| ACT Programming Tutor (Corbett & Anderson, 1995) | ■ | | |
| AniMis (Johan & Bull, 2009) | ■ | | |
| CALMsystem (Kerly et al., 2008) | ■ | | |
| CosyQTI (Lazarinis & Retalis, 2007) | ■ | | ■ |
| COMOV (Perez-Marin, 2007) | ■ | ■ | ■ |
| C-POLMILE (Bull & McEvoy, 2003) | ■ | | |
| EER-Tutor (Mathews, Mitrovic, Lin, Holland, & Churcher, 2012) | | ■ | ■ |
| EI-OSM (Zapata-Rivera et al., 2007) | | ■ | |
| E-KERMIT (Hartley & Mitrovic, 2001) | ■ | | |
| ELM-ART (Weber & Brusilovsky, 2001) | ■ | | |
| Flexi-OLM (Mabbott, 2009) | ■ | ■ | ■ |
| Haptic Learner Model (Lloyd & Bull, 2006) | ■ | | |
| INSPIRE (Papanikolaou, Grigoriadou, Kornilakis, & Magoulas, 2003) | ■ | | |
| MusicaLM (Johnson & Bull, 2009) | ■ | | ■ |
| Mr Collins (Bull & Pain, 1995) | | ■ | |
| MyExperiences (Kump et al., 2012) | | ■ | ■ |
| OLMlets (Bull & Mabbott, 2006) | ■ | | ■ |
| QuizMap (Brusilovsky et al., 2011) | | ■ | |
| STyLE-OLM (Dimitrova, 2003) | | ■ | |
| Subtraction Master (Bull & McKay, 2004) | ■ | | |
| SQL-Tutor (Mitrovic & Martin, 2007) | ■ | | |
| SIV (Kay & Lum, 2005) | | ■ | |
| TAGUS (Paiva et al., 1995) | | ■ | |
| The Fractionator (Bull, Mangat, Mabbott, Abu Issa, & Marsh, 2005) | ■ | | ■ |
| UM toolkit (Kay,1995) | | ■ | |
| VisMod (Zapata-Rivera & Greer, 2004) | | ■ | |
| VCM (Cimolino, Kay, & Miller, 2004) | | ■ | |
| xOLM (Van Labeke et al., 2007) | ■ | | ■ |

In recent years, there has been an interest in providing more expressive presentation of learner models. In order to facilitate the learner in recognising learning difficulties and reconstructing the correct concept in a programming subject, Johan & Bull (2009) have presented learners' misconception using animation. Learners get more detail misconception information by using animation and step-by-step text description explaining the misconception. Figure 3.4 shows the misconception information in animation text and step-by-step text descriptions side-by-side. An evaluation of the system shows that learners are interested in using the animation and find it helpful to their learning. My-Pet-Our-Pet (Chen, Chou, Deng, & Chan, 2004) is another OLM using an animated avatar. In this system the animal characters which includes behaviour, expressions and emotions are used to represent the user's learning that includes the element of cognitive, social and affective.

MusicaLM (Johnson & Bull, 2009) is an OLM for learners of basic music theory. The learner models available in MusicaLM are in the format of text view, music notation and audio as shown in Figure 3.5. Evaluation of the system shows that participants are willing to use their OLM and that text view is used the most. Learners also made use of music notation and audio especially when 'incorrect knowledge' appears in their learner model.

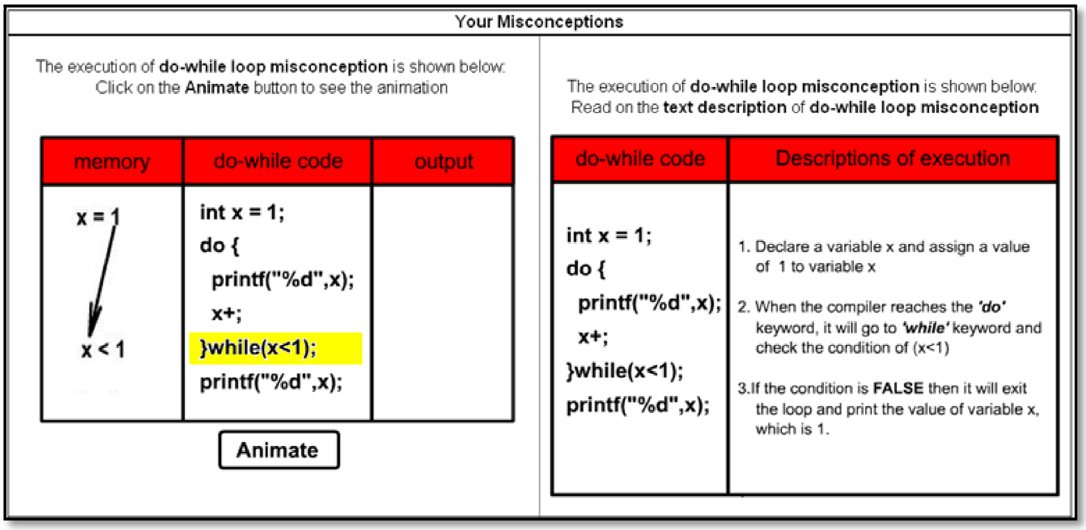



Figure 3.4: Misconception information in animation text and step-by-step text in AniMis (Johan & Bull, 2009)

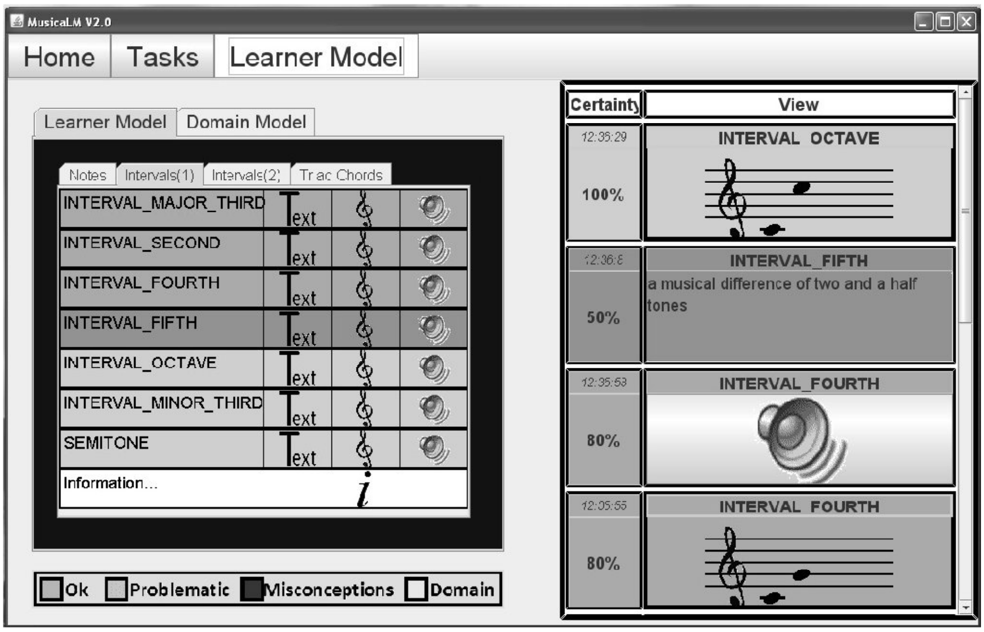



Figure 3.5: Learner models in MusicaLM (Johnson & Bull, 2009)

In OLM, the selection of LM presentation may vary according to purpose of the system, the target user group and focus of the externalisation (Mabbott, 2009). However the important aspect that should be considered in externalising the learner model is that it should be intuitive and understandable to the user

(Hartley & Mitrovic, 2001). Therefore the learning process becomes more effective because the user understand the information about their learning. In this research, we focus on OLM that offers multiple views that comprise both simple and structured views.

### 3.3.2 Learner Control over the Learner Model

Giving learners some control in learning may encourage them to be more responsible and autonomous. In OLMs, different learner controls are available and it may differ from one system to another (refer Section 1.2). Previous research shows that giving the learner some control (and allows the learner to influence the model) may lead to a more accurate model (Bull, Dong, Britland, & Guo, 2008).

An *inspectable* OLM is fully controlled by the system. The learner model is entirely dependent on system inference based on learner interactions with the system. Learner can see the model, but cannot change the contents of the model except in the usual way (e.g. by answering further questions). The primary goal is to allow the learner to see the model and help identify the amount of knowledge possessed and the possibility of knowledge gaps and misconceptions (Bull & McKay, 2004). In addition, an inspectable OLM also functions to help raise awareness of learner on their knowledge, prompting reflection, planning as well as formative assessment (Bull & Kay, 2010).

In *co-operative* models, the modelling process is jointly by both system and learners. Learners are required to provide complementary information requested by the system to be included in the learner model (Beck, Stern, & Woolf, 1997). This model uses learners' input in order to get a better representation of their skills, maintain an accurate model, and provide learners with a sense of control of their model by taking part in the modelling process.

The situation is quite different in the *add-evidence* models. Learners may contribute additional evidence to consider in the modelling process. In ELM-ART (Weber & Brusilovsky, 2001), learners can inspect and modify the learner model. ELM-ART implements an adaptive interactive textbook in order to provide online learning material. If learners already know the particular page or section, they can tell the system by providing some evidence. The evidence is provided either by solving programming problems, taking the test or doing some exercises. ELM-ART will only change the model when learners supply enough evidence to the system. TAGUS (Paiva, Self, & Hartley, 1994) also allows learners to inspect and when possible to change the learner model contents. Updating the learner contents in TAGUS involves four main services: add (identify new content to be considered in learner model), revise (modifies current learner model by including new information); tell (inform TAGUS about a new situation or evidence, but the system will decide what to do with the information); and contract (eradicate information from the model). In the situation where the information from different sources contradict with the existing model, TAGUS needs to decide the most reliable information using a trust function.

Learners may also *challenge* the models. This approach can be seen in EI-OSM (Zapata-Rivera et al., 2007), an OLM implemented based on a formal model of argumentation by Toulmin (1958). Toulmin's model includes six elements which play different roles in argument. They are *claims, data, warrants, backing, qualifiers* and *rebuttals* (Toulmin, 1958). *Claims* is the subject of the argument, *data* is the information that supports the claims, *warrants* is the generalisation that allows conclusions from data to claims, *backing* is information that supports the warrants, *qualifiers* is the degree of confidence of the conclusions, and *rebuttal* is the assertion that defeats the basic argument (the *claims, data* and *warrant*). EI-OSM uses a simplified version of Toulmin's argument structure to externalize, organize and evaluate assessment claims and supporting evidence. Elements of Toulmin's argument structure used in the EI-OSM are claims, data, warrants, backing and rebuttal. EI-OSM used evidence-based argument structures (i.e add new arguments and supporting evidence) from a variety of sources to organize information in the learner model. Students may challenge aspects of an argument displayed by the system. Instead of responding to arguments that come from the system or teacher, student may propose a different argument or individual supporting evidences (e.g further explanation, or evidence that is not included in the system). However, the decision to determine which evidence has the highest strength to influence the argument lies in the hands of teachers. Supporting evidence that has been approved by the teacher is considered stronger than the one that is provided by students without prior approval. The challenge approach has also been implemented in xOLM (Van Labeke et al., 2007). xOLM consists three phases of interactions: (a) learners explore the model and select a topic for discussion, (b) system justifies its judgment on the topic selected by the learner, (c) learners may challenge some aspects of system's judgement on the model. As learners can see the justification of the selected topic, they may question the learner model. If this happens, the system will give learners three options for further justification: 'agree', 'disagree' and 'move on'. The system's belief will be strengthened if learners select 'agree'. If learners select 'disagree', they have to respond to further information including the confidence of their assessment. This response will be calculated into the model. Learners can override the system's belief if they state high degree confidence in their assessment. The discussion will end if learners select 'move on'.

*Editable* learner models allow learners to modify the content of the models. OLM allows this interaction because of reasons such as improvement of knowledge at some point of time resulting from individual reading or studying outside the system, or learners might have forgotten recalled information or materials. Therefore, learners are entirely responsible for their learner models and can directly update theirs as soon as their knowledge changes. Editing can be done by simply changing the system's belief and changes will affect the model. Examples of OLM that use this method are C-POLMILE (Bull & McEvoy, 2003), SASY (Czarkowski, Kay, & Potts, 2005) and Flexi-OLM (Mabbott & Bull, 2006). In C-POLMILE, learners may use the system in the desktop PCs or Pocket PCs without having to synchronise the model. Therefore, learners may update the model manually by directly editing the percentage of knowledge or delete the list of problematic topics and misconceptions. In SASY, learners are allowed and even encouraged to view and edit their models. Learners may directly edit the models by adjusting values in the ‘view profile’ link. In Flexi-OLM, learners may edit their models if they are aware of any changes in knowledge. The system provides evidence or information in support of its belief (Mabbott & Bull, 2006); however, learners may proceed with the edit if it is contrary to their belief.

Learners may also change their model contents by *persuasion.* In contrast to editable OLM where learner model will change directly, in persuasion OLMs learners have to demonstrate their competence before the system agrees with the changes (new model) as requested by learners. Learners usually have to take some short tests by answering a series of questions on the specific topic to demonstrate their skills. However, this model will remain unchanged if the learners are unable to show their skills in the topic. In this situation, the final decision still remains with the system even if the learners initiated the system first in an attempt to change the system’s belief. A previous study shows that students are uncomfortable with an editable OLM but prefer to have an OLM that offered less direct control as in negotiate and persuade OLM (Mabbott & Bull, 2006).

In order to achieve a learner model agreed by both learner and system, a more collaborative approach is used in which the learner model is developed through *negotiation*. The process of negotiations usually ranges from request information, offer information, justify, challenge, argue, confirm and accept. An early negotiated learner model has been implemented in Mr. Collins (Bull & Pain, 1995). Both learners and the system are involved in a discussion to produce agreed model content, where each party maintains a separate belief. The system's belief is based on recent learner's interactions, while learners state their confidence each time they answer the question. Therefore both parties can challenge the other's belief and can provide justification to support their belief. The differences between the beliefs are clearly represented in the model. In contrast, STyLE-OLM (Dimitrova, 2003) maintains only one representation, in which the model is jointly constructed to reflect the agreement of both parties. During negotiations, the agreement reached can be added to the model and any conflicts that arise will be resolved through discussion or removed. Interest in the negotiation learner model has change the way the negotiation is conducted which include menu selection (Bull & Pain, 1995), dialogue games (Dimitrova, 2003) and most recently chatbots (Kerly & Bull, 2008). A chatbot is implemented in CALMsystem to discuss the learner model using natural language. Discussions in CALMsystem can be initiated by the learner or the system. The system will initiate the discussion if there is a difference between beliefs, or the learner does not seem engaged with the system.

Some examples of OLMs and their learner control over the learner model are shown in Table 3.3. All systems listed are inspectable, parallel with the main purpose of opening the model to students to enable them to inspect. However in a system where the learner model is available for learners to view, the accuracy of the model presented is crucial. In addition, the approach is very useful for learners' process of learning. Therefore, some OLMs offer learners some control to help the system infer a more accurate learner model by several types of controls.

With a given control, we are keen to investigate user trust in editable and persuaded OLM. This is because in editable, learners have full control of their learner model and can directly change the model contents. Therefore, accuracy of the learner model is questionable especially if the learner tampers the features. The persuasion OLM gives a learner more medium control and can be used to compare user trust between full-control and medium control of the learner model.

Table 3.3: Learner control over the learner model

| OLM systems | Learner control | | | | | | |
|---|---|---|---|---|---|---|---|
| | Inspectable | Co-operative | Add-evidence | Challenge | Editable | Persuaded | Negotiated |
| ACT Programming Tutor (Corbett et al., 1995) | ■ | | | | | | |
| AniMis (Johan & Bull, 2009) | ■ | | | | | | |
| CALMsystem (Kerly et al., 2008) | ■ | | | | | | ■ |
| CosyQTI (Lazarinis & Retalis, 2008) | ■ | | | | | | |
| COMOV (Perez-Marin, 2007) | ■ | | | | | | |
| C-POLMILE (Bull & McEvoy, 2003) | ■ | | | | ■ | | |
| EI-OSM (Zapata-Rivera et al., 2007) | ■ | | ■ | ■ | | | |
| E-KERMIT (Hartley & Mitrovic, 2001) | ■ | | | | | | |
| ELM-Art (Weber & Brusilovsky, 2001) | ■ | | ■ | | | | |
| Flexi-OLM (Mabbott, 2009) | ■ | | | | ■ | ■ | |
| Haptic Learner Model (Llyod & Bull, 2006) | ■ | | | | | | |
| INSPIRE (Papanikolaou et al., 2003) | ■ | | | | | | |
| MusicaLM (Johnson & Bull, 2009) | ■ | | | | | | |
| MFD (Beck et al., 1997) | | ■ | | | | | |
| Mr Collins (Bull & Pain, 1995) | ■ | | | | | | ■ |
| Narcissus (Upton & Kay, 2009) | ■ | | ■ | | | | |
| OLMlets (Bull & Mabbott, 2006) | ■ | | | | | | |
| STyLE-OLM (Dimitrova, 2003) | ■ | | | | | | ■ |
| SASY (Czarkowski et al., 2005) | ■ | | ■ | | ■ | | |
| Subtraction Master (Bull & McKay, 2004) | ■ | | | | | | |
| SQL-Tutor (Mitrovic & Martin, 2007) | ■ | | | | | | |
| Sam coach (Kay, 1997) | ■ | | ■ | | | | |
| TAGUS (Paiva et al., 1995) | ■ | | ■ | | | | |
| The Fractionator (Bull et al., 2005) | ■ | | | | | | |
| UM toolkit (Kay,1995) | ■ | ■ | | | | | |
| VisMod (Zapata-Rivera & Greer, 2004) | ■ | | | ■ | | | |
| VCM (Cimolino et al., 2004) | ■ | | ■ | | | | |
| xOLM (Van Labeke et al., 2007) | ■ | | | ■ | | | |

### 3.3.3 Open Learner Models to Other Users

Kay (1997) and Hansen & McCalla (2003) have suggested that learner models are not only for learner viewing, but also to show other users. Students can optionally have the option to release all or parts of their learner model to their selected peers named or anonymous in OLMlets (Bull & Britland, 2007) and UMPTEEN (Bull et al. 2007). All peer models accessible to a user can then be viewed together. Releasing the model to *peers* has been found to be useful to help learners identify difficult areas and to initiate collaborations with peers (Bull & Britland, 2007). In OLMlets, students can access data on *group* knowledge for each topic, with a star indicating their own knowledge as shown in Figure 3.6. Students can identify their position in the group and encourage healthy competition among peers, which motivate them to set a new goal (Bull et al., 2007). Learners can also compare their performance with the rest of their peers in a class in QuizMap (Brusilovsky et al., 2011). QuizMap allows learners to identify their strengths and weaknesses compared to their peers. The integration of social adaptive navigation supports in QuizMap guides learners to discover stronger peers to help them in learning and vice versa.

The other OLM that supports group learning is Narcissus (Upton & Kay, 2009). In order to facilitate effective group functioning, Narcissus supports group work based on evidence of contributions by each member. Students can see all the activities that contribute to the group, which made the group model scrutable. This method helps students to identify the main part of the activity in group learning. In addition, the group model is not for the student only but also can be seen by the tutor (*instructor*), which helps solve problems that may occur in the group.

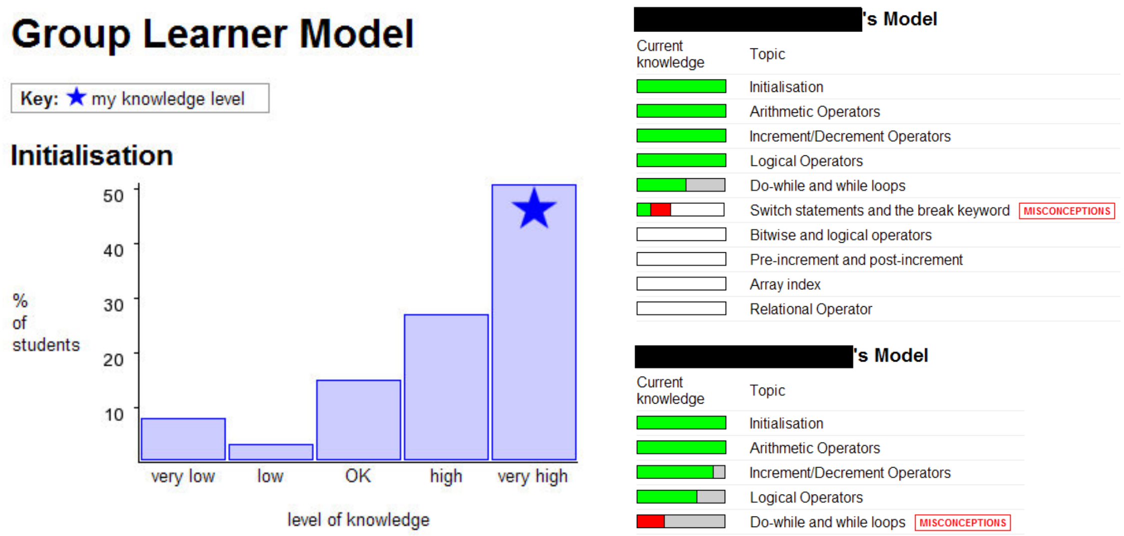



Figure 3.6: The OLMlets group comparison view, and individual peer models view (Bull & Britland, 2007)

An OLM open for instructors (or teachers) offers them information about the progress of the learners. Zapata-Rivera & Greer (2001) suggested that the instructors may adapt their teaching to individual learners or groups based on information in the learner models. In Subtraction Master (Bull & McKay, 2004), the learner model for the individual learners is displayed in a simple form in accordance with the intended use for children. A series of smiley faces is used to represent children’s skills at different levels of difficulty in subtraction. In order to help individual children, more detailed information is provided to the teachers in the system. Similarly, instructors in DynMap (Rueda et al., 2003) are presented with detailed information while the students are presented with the simpler format. Instructors can access learner models in UMPTEEN (Bull et al., 2007). However, they can only see the learner models that are released to them. Unlike the Subtraction Master, the model shown to the instructors in UMPTEEN is the same as the model seen by the learners. CosyQTI (Lazarinis & Retalis, 2008) also provides learners' information for instructors in order to help the instructors to understand their learners, as well as review and possibly redesign their teaching strategy. CosyQTI can inform the instructor if there are changes in the level of a learner's knowledge by sending an email or if the instructor is using the system, a dialog box will appear. Apart from accessing learner models, instructors in EI-OSM (Zapata-Rivera et al., 2007) are given the authority to assign the strength value for available arguments, and the possibility to override the decisions based on available evidence. Other OLMs that allow the instructor to see the learner models are INSPIRE (Papanikolaou & Grigoriadou, 2008), CourseVis (Mazza & Dimitrova, 2007), PDinamet (Gaudioso et al., 2009) and REPro (Eyssautier-Bavay et al., 2009). Table 3.4 shows examples of OLMs that open the learner models for others to see.

Table 3.4: OLMs open to other users

| OLM systems | OLM open to: | | | | |
|---|---|---|---|---|---|
| | Peers | Group | Instructors | Parents | Designer |
| CosyQTI Lazarinis & Retalis, 2008) | ■ | | ■ | | |
| CourseVis (Mazza& Dimitrova, 2007) | | | ■ | | |
| EI-OSM (Zapata-Rievera et al., 2007) | ■ | | ■ | ■ | |
| Fraction Helper (Lee & Bull, 2008) | | | | ■ | |
| Narcissus (Upton & Kay, 2009) | | ■ | ■ | | |
| INSPIRE ((Papanikolaou & Grigoriadou, 2008) | | | ■ | | |
| OLMlets (Bull & Britland, 2007) | ■ | ■ | ■ | | |
| PDinamet (Gaudioso et al., 2009) | | | ■ | | |
| QuizMap (Brusilovsky et al., 2011) | ■ | ■ | | | |
| REPro (Eyssautier-Bavay et al., 2009) | | | ■ | | |
| Subtraction Master (Bull & McKay, 2004) | ■ | | ■ | | |
| TAGUS (Paiva et al., 1995) | | | | | ■ |
| UMPTEEN (Bull et al., 2007) | ■ | | ■ | | |
| VisMod ( Zapata-Riviera & Greer, 2004) | | | ■ | | |

OLM also opens the learner models to other users like parents (Lee & Bull, 2008) and system designers (Paiva et al., 1995). Opening the models to parents allows them to see their children's learning progress as offered in Fraction Helper (Lee & Bull, 2008). Meanwhile, learner models open to the system designers can help them with the learner modelling process during the development (Paiva et al., 1995). From Table 3.4, most OLMs open the models for the instructor to inspect to help learners in their learning process. However in this research we focus on investigating user trust in peers models.

## 3.4 Discussion: Trust in OLMs

Trust is an important issue particularly when there may be potential risks (Mayer et al., 1995), and the topic has been of great interest to researchers in many fields as described in the previous chapter. In open learner modelling, apart from issues of privacy and the protection of personal data, the kind of risks that might apply result from learner control over their models (refer section 1.2). Such inaccuracies introduced into a learner model may affect the appropriateness of subsequent adaptations to the user. Inadequate adaptations may weaken learner trust in the system if they do not realise that these inaccuracies result from their own decisions. However, it has been suggested that students may be less comfortable with simply editing the model: they may prefer to use an OLM that offers less direct control (Mabbott & Bull, 2006). For example, when persuading the OLM, the learners can disagree with the model and demonstrate their competencies in order to affect a change in the model – i.e. they have the opportunity to challenge their model, but the system makes the final decision over whether the model will be changed. It seems, that some learners may trust an OLM to infer their knowledge to a greater extent than they trust themselves to identify it. We hypothesise, therefore, that persuading the learner model may be a more 'trustable' feature than direct editing of it.

With inspectable learner models, students can view (some of) the information about themselves without the possibility of suggesting alterations to it. Trust in the system's representations of the learner's understanding may be particularly relevant here – even if some learners do trust the model generally, if they see even one thing with which they disagree, this may reduce their trust in the system as a whole. Trust in the accuracy of the model may therefore be even more important if learners have no control over its contents.

A different aspect of trust is relevant when considering whether users may be likely to release their learner models to others. The facility to release the learner model can be useful both for individual learning where learners can identify their position in the group, and for collaboration where students may identify peers who could help them or may wish to work together with them on a subject (Bull & Britland, 2007; Bull et al., 2007). However, this relates to right of access to personal data and learner control over this data (Kay, 2001). Furthermore, sharing personal information makes one vulnerable to loss of privacy, information misuse or even identity theft (Zimmer et al., 2010). Some students are keen to release their learner models to peers, suggesting a level of trust not only in their learner models, but also in the manner in which other users might use their model data. In addition, some learners might release their models to others even though they believed the learner model was incorrect, especially when there is a choice for them to release the model anonymously. This situation may affect the effectiveness of having collaborations between learners. Here, the issues of trust are important because they need to identify which learners they should trust for having a good collaboration.

## 3.5 Summary

In this chapter, we began with learner modelling in ITS and then focus on OLM and its features. Opening the learner models involves the method of externalising the model to the learners. The externalisations range from the simple to more structured and detailed format. The ways of presentation may be influenced by several factors including the modelling techniques used, the target user and the purpose of presentations. Despite factors that lead to the format of the externalisation of the learner model, learners' understanding of the presentation is important as learners may reflect about their learning when they understand the model. OLM also gives learners the control over their models in order to provide more accurate learner models. The level of control over learners access to OLM is varied from more control to less or no control. While giving learners access may produce a more accurate model, learners may also 'abuse' the learner model. This may happen if learners give incorrect information directly to their model. Other than that, OLM is not only for learners to inspect but also the other users including peers, group, instructors, parent and the system designer to see (view). Learners may also release their learner model to other users, and to view the models of those who have released theirs. The model that can be viewed by instructors and parents allow them to monitor learners' progress.

However, opening the model to the learners may increase their perceptions of how a system evaluates their knowledge and updates the model. This raises questions of trust related to whether the learner believes the evaluations are correct, and whether they trust the system as a whole. For example, can OLM make a system more trustable because users can see the information it is using to adapt to them; or can it make a system less trustable? Which features of an OLM might make a system more 'trustable'? In the next chapter we investigate learner trust with reference to the complexity of the OLM, level of control over the model, and the release of the model to others.

# Chapter 4

# INVESTIGATING TRUST IN OPEN LEARNER MODELS

In Chapter 3, we discussed open learner models and why the trust is relevant to OLMs. In order to investigate trust in OLMs, we conduct an initial study to identify which OLM features may help to increase levels of trust in a system. In this study we are using two OLM systems - OLMlets (Bull et al., 2006) and Flexi-OLM (Mabbott & Bull, 2006). Specifically, we investigate learners' trust in simple and detailed OLM views, learner control over their model, and the option to release the learner model to others.

## 4.1 The OLM Systems

In our investigation of user trust, we choose OLMlets (Bull et al., 2006) and Flexi-OLM (Mabbott & Bull, 2006) as example OLM systems. We describe each system by considering the following features: complexity of model presentation; level of control over the model contents; and release of the model to other users. We hypothesized that issues of trust is related to the features in OLMs.

### 4.1.1 OLMlets

OLMlets (Bull et al., 2006) is an example of simple learner model presentation, developed as a means to help students identify their strengths and weaknesses as a starting point for their independent study in a range of subjects. It has five learner model presentation formats to allow learners to view their understanding to suit their preferences: skill meter, graph, text, table, and boxes surrounding topic names as shown in Figure 4.1.

Different colours are used in the skill meter, graph and boxes to indicate knowledge level, areas of difficulty and misconceptions. Misconception statements can be accessed by clicking on the misconception links, for example: "you may believe that the '=' operator can be used for comparison". Clicking on numbers below the heading displays an additional set of representations depicting instructor's expectations for learners' knowledge at that stage of their course for comparison.

In terms of learner control over the learner model, OLMlets can be viewed, but learners cannot change the contents of the model except in the usual way (by answering further questions). In other words, OLMlets only allows learners to inspect their learner model. However learners can optionally release all or parts of their learner model to instructors and other students of their choice (named or anonymously).

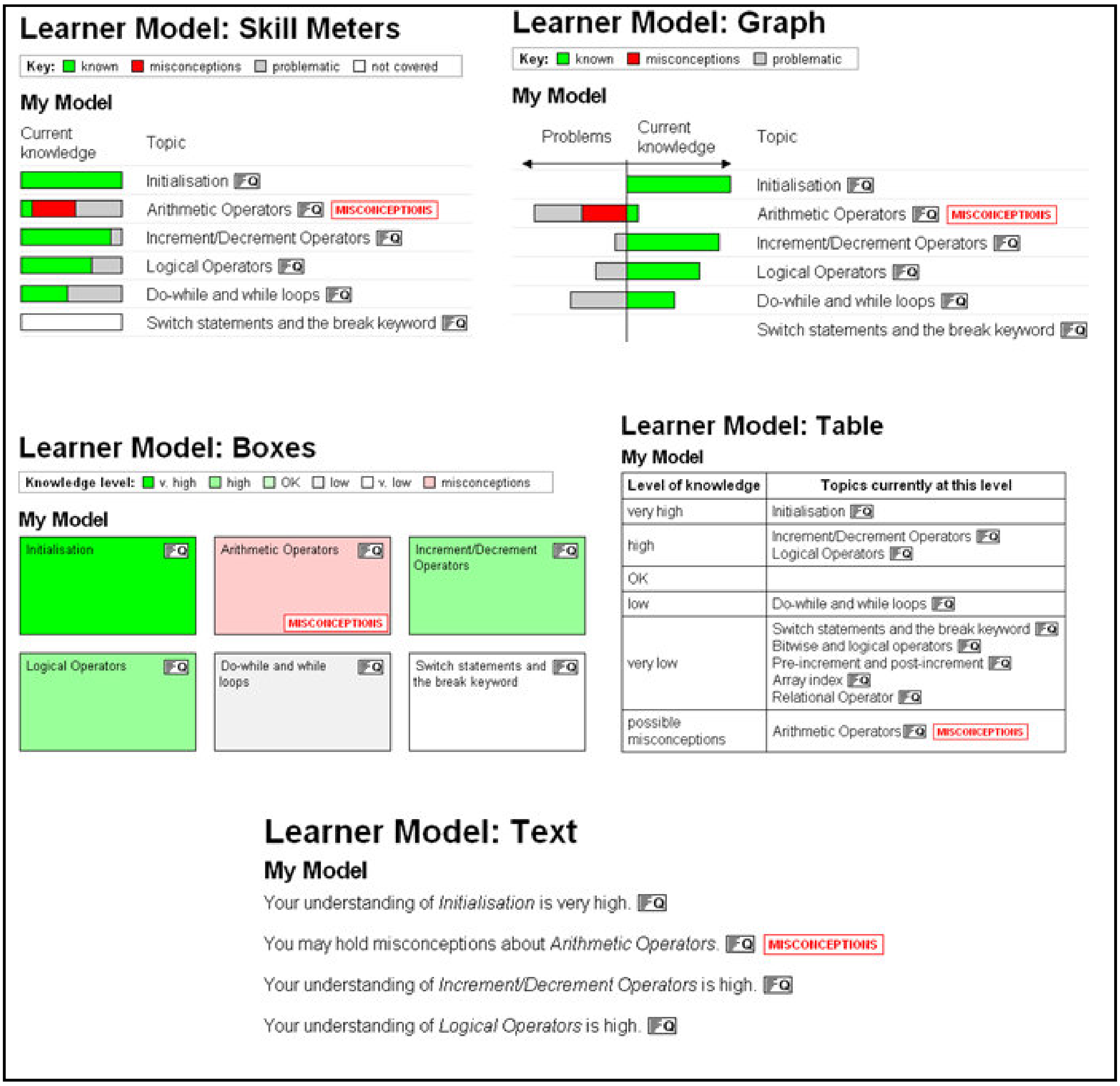



Figure 4.1: Individual learner model views in OLMlets

Learners can set and identity model access using the interface shown in Figure 4.2. If the anonymous mode is selected, the model is identified by the user number, for example ‘User 108’ instead of learner’s name. All peer models accessible to a user can then be viewed together as shown in Figure 4.3.

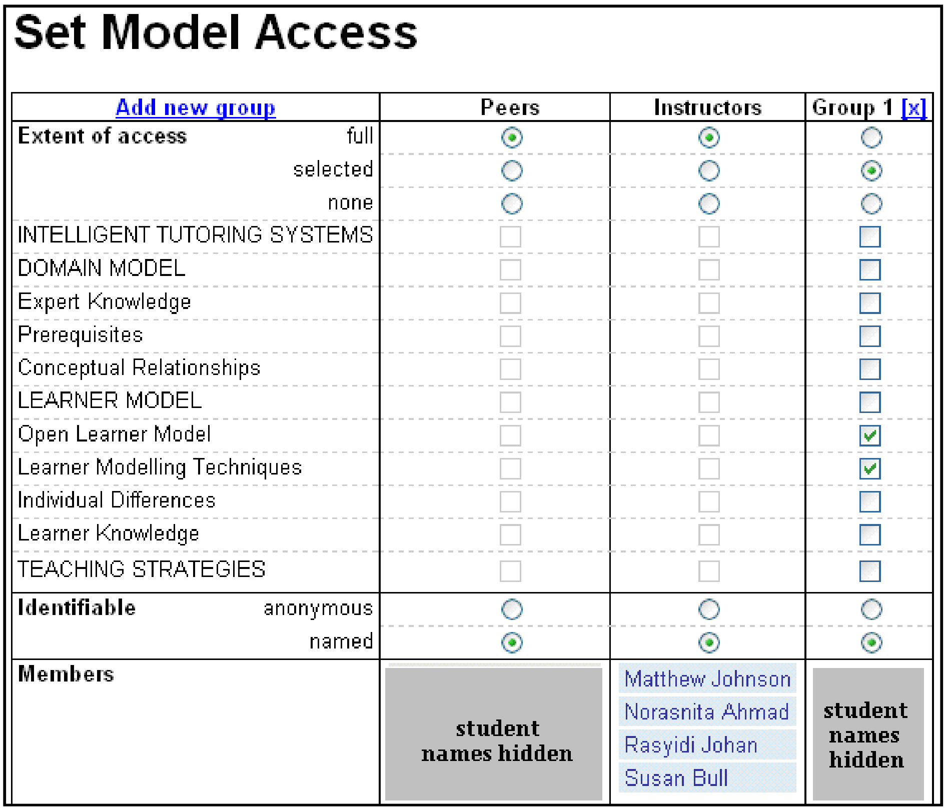



Figure 4.2: Set model access and identity

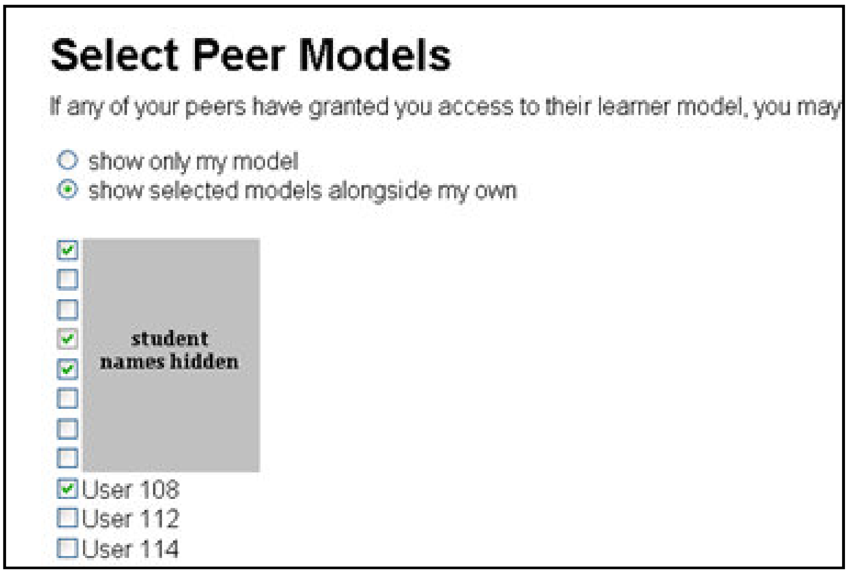



Figure 4.3: Select peers model

Learners can access data on the group's knowledge for each topic, with a star indicating their own knowledge (see Figure 3.7). The peer models can be useful to help learners identify areas of difficulties generally, and to initiate collaborations with peers (Bull et al., 2006).

### 4.1.2 Flexi-OLM

Flexi-OLM (Mabbott & Bull, 2006) is the example of OLM that includes simple and complex model presentations. The seven formats are: hierarchy of concepts, lecture structure, concept map, pre-requisites, alphabetical index, list ranked according to knowledge, and text summary (Mabbott & Bull, 2006) as shown in Figure 4.4. As with OLMlets, learners can use the representations that suit them best. Flexi-OLM uses colours to indicate student understanding, problematic areas and misconceptions, with misconception descriptions, and breakdowns of knowledge accessible from the concept links. Flexi-OLM aims at helping students identify the state of their knowledge in order to help them focus on their studies appropriately.

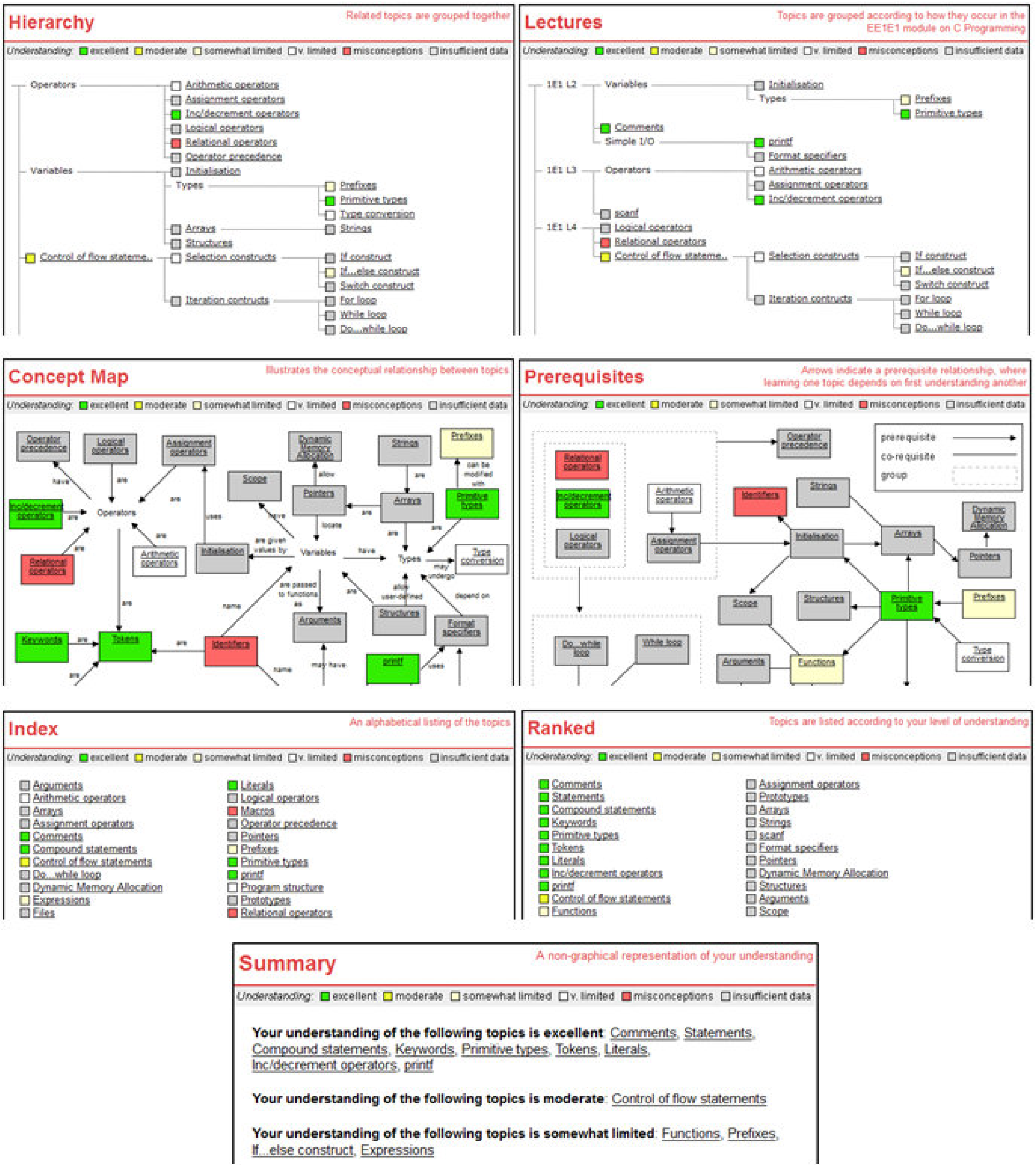


Figure 4.4: Multiple views in Flexi-OLM (Mabbott & Bull, 2006)

Besides being inspectable, Flexi-OLM also allows learners to edit or try to persuade the system of their knowledge if they disagree with the system representations (Mabbott & Bull, 2006). Learners can edit their model by simply changing the knowledge level. The system will provide evidence for its views but will accept the changes if the learner wishes to override the system's viewpoint. Figure 4.5 shows the learner's level of understanding for topic 'Tokens' is *very limited* (a) and he/she wishes to change the model to *excellent* (b). System will provide some evidence for current knowledge and provide some instructions if the learner wishes to continue the process(c) and will change the level to a new desired level directly (d).

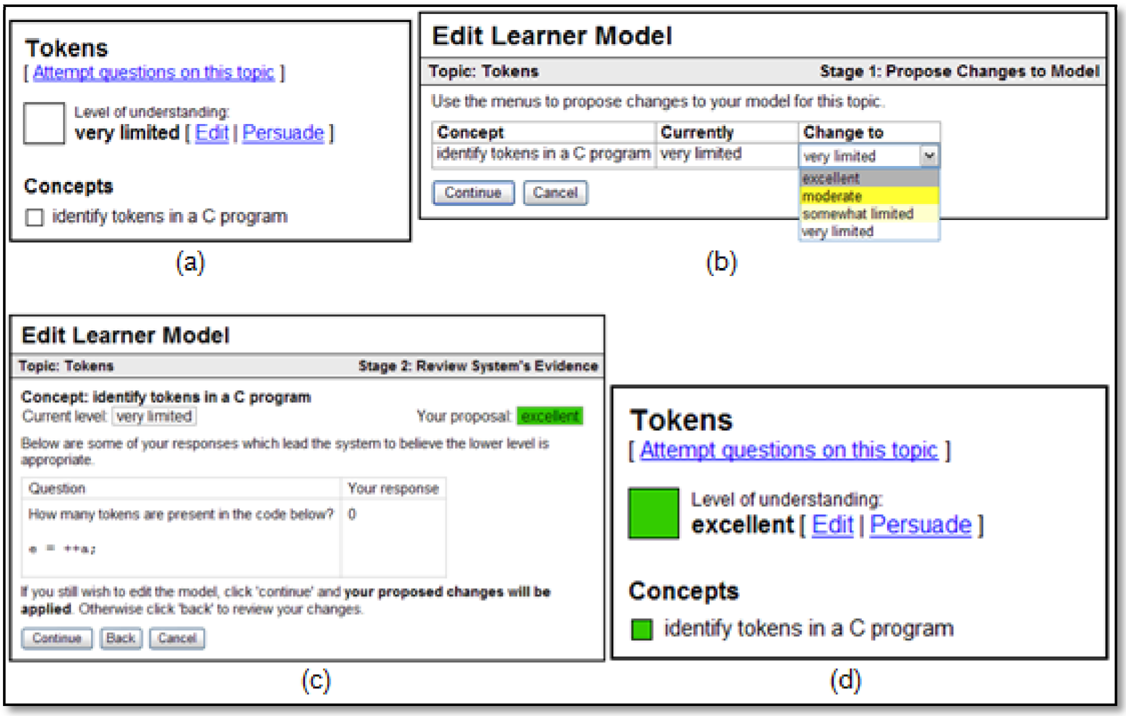



Figure 4.5: Edit the learner model in Flexi-OLM (Mabbott & Bull, 2006)

Persuading the system means students need to demonstrate that they have (or do not have) the skills by answering a few additional targeted questions about a topic. Only if students convince the system the model will be altered based on changes in their proposed model.

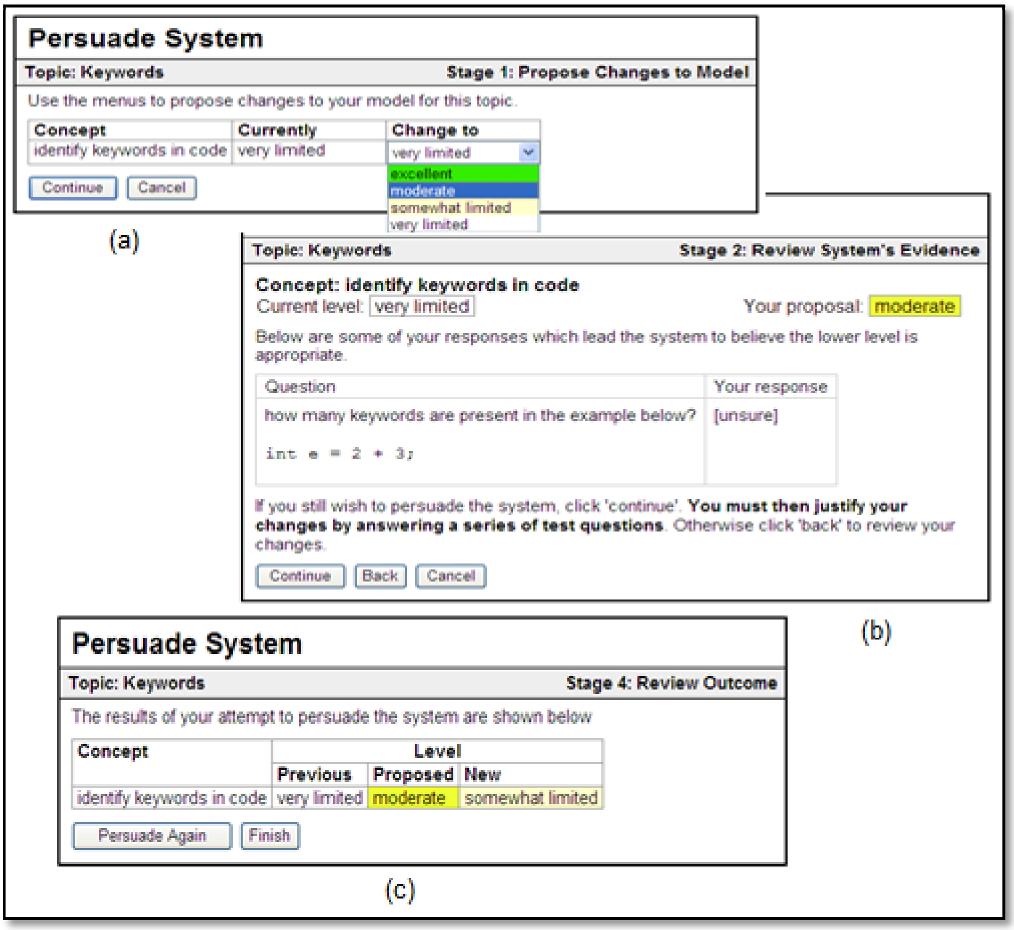



Figure 4.6: Persuading the learner model in Flexi-OLM (Mabbott & Bull, 2006)

In persuading, the first two steps are used in editing. Figure 4.6 shows the learner requests to change his/her knowledge topic from *very limited* to *moderate* (a) and the system provide evidence for its beliefs (b). Then the learner needs to demonstrate some additional knowledge for further questioning, and lastly the system comes out with the new level *somewhat limited* (c) because the learner does not demonstrate the extent he/she has claimed.

## 4.2 The Study

We describe an experimental study using the two OLMs presented above, to help identify which aspects of OLMs may increase user trust in a system. Specifically we investigate advanced level students' trust in simple and detailed OLM views, learner control over their model, and the option to release the learner model to others. We hypothesized that users trust in OLMs system.

### 4.2.1 Participants, Materials and Method

Participants were 9 Masters students and 9 beginning PhD students (students were in their first 3 months of study in PhD programme): a total of 18 participants. A study with the master students was conducted during a lab session for the ‘Educational Technology’ course, while a study with the PhD students performed at their leisure. No reward was given to the students who participated in this study. All students had no experience with OLMlets and Flexi-OLM. Therefore, students were introduced to both systems before using them. The domain for OLMlets and Flexi-OLM is the C programming language and students may choose any topics to initiate the interaction with the system.

Students begin with using OLMlets and followed with Flexi-OLM. For each system, they were instructed to answer questions, explore the learner model views and the system-specific features (use of peer models; persuading and editing). Then, they continued to use the OLMs to suit their approach to learning. Interaction with each system lasted around one and a half hours, including completion of a post-use questionnaire for each system (Appendix: Questionnaire1). Responses were given on a five point scale (strongly agree, agree, neutral, disagree, strongly disagree).

### 4.2.2 Results

Table 4.1 presents the results of students' stated trust in an OLM with reference to the issues considered (complexity of the model presentation; level of learner control over the model contents; and release of the model for peer viewing). As this is the preliminary study of investigating trust in OLM, the results presented here are very general. At this stage, some aspects are not being studied yet, but will be presented in Chapter 6 and 7.

Table 4.1: Learner trust in open learner models (in percentage)

| | | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|
| | | *<Strongly Agree … Strongly Disagree>* | | | | |
| ***Complexity of model presentation*** | | | | | | |
| **OLMlets** | Understand overview of knowledge level | 39 | 11 | 50 | 0 | 0 |
| | Believed overview learner model was accurate | 17 | 33 | 28 | 22 | 0 |
| | Trust overview (simple) model information | 22 | 56 | 22 | 0 | 0 |
| **Flexi-OLM** | Understand detailed model information | 33 | 33 | 28 | 6 | 0 |
| | Believed detailed learner model was accurate | 28 | 50 | 17 | 6 | 0 |
| | Trust detailed (complex) model information | 28 | 28 | 39 | 0 | 6 |
| ***Level of learner control over model contents*** | | | | | | |
| **Flexi-OLM** | Trust because can edit model | 6 | 17 | 39 | 22 | 17 |
| | Edited features believed correct | 11 | 33 | 22 | 17 | 17 |
| | Edited features believed incorrect | 11 | 6 | 28 | 39 | 17 |
| | Trust because can persuade system to change model | 17 | 39 | 22 | 17 | 6 |
| | Tried to persuade features believed correct | 28 | 22 | 28 | 22 | 0 |
| | Tried to persuade features believed incorrect | 28 | 6 | 39 | 22 | 6 |
| ***Peer models*** | | | | | | |
| **OLMlets** | Trust because can compare to peers | 11 | 39 | 44 | 0 | 6 |
| | Trust because can compare to instructor expectations | 17 | 44 | 33 | 0 | 6 |
| | Believed correct and opened to peers | 39 | 28 | 33 | 0 | 0 |
| | Believed correct and opened to instructor * | 41 | 29 | 24 | 6 | 0 |
| | Believed incorrect and opened to peers * | 18 | 24 | 29 | 18 | 12 |
| | Believed incorrect and opened to instructor * | 17.6 | 17.6 | 29.4 | 23.5 | 11.8 |

(* indicates one student did not respond, therefore total response is 17)

In terms of the complexity of model presentation, 66% of users claimed to understand the detailed learner model views (rated 5 and 4), while half (50%) understood the overview representations. 78% of learners agreed that the detailed views were accurate but only 56% of learners trust in the detailed views. While for the overview information, 50% of learners agreed that the overview information was accurate and 78% of learners trust in the overview information. In all cases some learners were not positive about these issues with regards to overview and detailed model presentations.

For the level of learner control over model contents, the facility to edit the learner model did not appear to foster trust, whereas there was a higher percentage of users who placed trust in the persuade feature. Many users edited and tried to persuade their learner model when they considered it correct more than when they believed it to contain errors - especially for editing.

In terms of peer models, the ability to compare one's own model to peer models and instructor expectations increased some learners' trust in their own model (50% in the case of peer models; 61% with reference to instructor expectations). The majority would release what they believed to be a correct model to instructors (70%) and peers (67%), while fewer would release what they considered an incorrect model.

### 4.2.3 Discussion

This section discusses the results according to the issues under investigation: (i) learner trust in relation to complexity of the model presentation; (ii) level of learner control over the contents of their learner model; and (iii) use of peer models.

#### 4.2.3.1 Complexity of Model Presentation

Presentation of the learner model may play an important role in the likely uptake of OLMs, as learners must to some extent, understand the model externalisations in order to use them effectively. In our study, two thirds of learners claimed to generally understand the information in the detailed model views, but only half stated that they understood the overview information. Given that learners have different preferences for detailed model presentations (Mabbott & Bull, 2006), it is not surprising that some learners rated this unfavourably. It may be that these users had one or two preferred views (out of seven - which is sufficient for successful use), but in general they found the majority of views less helpful. However, what surprises us is that so many users claimed not to understand the simple representations. We hypothesise that this is because users can easily and precisely see the model update in the simple view.

Learners are accustomed to receiving simple feedback that reflects an overall score. As OLMlets models knowledge over the most recent five responses for each topic, with heavier weighting on the more recent of these responses, the skill meters (and other views) change in noticeable (and perhaps unexpected) ways. Therefore, it may be that users did understand that a 'more filled' skill meter represented greater understanding on a topic, but did not realise that the recent responses affected weightings in the model. This issue is related to the question of the user being able to predict the system's adaptive behaviour based on their actions in the environment (Jameson, 2007).

In line with the above, only half of the students believed that the overviews of their knowledge were accurate. This may be due to the fact that modelling occurs over several questions, a single (or a few) correct responses will not immediately eradicate any problems shown in the learner model - although the weighting of problematic issues will decrease. Similarly, a misconception will not immediately disappear from the model once learners recognises their misconception: the weighting of the misconception will first decrease before it disappears completely. Thus, learners may know that they no longer have a misconception even though it is still shown as possible held. Nevertheless, despite half of the students neither fully understanding how the model was updated nor believing it as accurate, most learners still trust their overview model. The reverse was true for the detailed model views: while more understood the representations and had confidence in their accuracy, a lower number claimed to trust them. Perhaps the complexity of the views, although fostering confidence in the model, made them harder for some students to *use* and therefore, trust in their utility for supporting students' learning might be reduced.

#### 4.2.3.2 Level of Learner Control over Model Contents

We find learners are more comfortable with a system that has greater control over the model contents, than one which provides full control to themselves (Mabbott & Bull, 2006). Our results suggest this extends to their trust in the learner model. Learners do not simply trust their own amendments to the model, but have greater trust in a method that requires them to demonstrate their skills (or lack of skills) before the model is changed. The interesting thing is that users edited and attempted to persuade attributes they considered correct, more than those they believed incorrect (despite the limited time of the evaluation where models could only be partially constructed, thus leaving areas not showing high knowledge where learners may actually have been proficient). This may have been due to some curiosities in this particular experimental setting. It may also be because learners thought there was little point in interacting with their learner model if it was inaccurate. Perhaps, they considered it a waste of time to try to change the model contents if the system was likely to continue making what they perceived as incorrect inferences. Indeed, users may have gained trust in the persuade feature by observing that Flexi-OLM will not change an accurate representation to an inaccurate one.

#### 4.2.3.3 Peer Models and Instructor Expectations

Half of the users gained trust in their model by comparing it to the peer models. Perhaps, this is because they could identify their position in the group, matching what they would expect to see, at a given level of their knowledge. Of course, half did not state that their trust was related to the ability to explore others' models. It would be interesting to find out whether these users found their relative position to be different from their expectations, or whether they simply did not regard this information as important for trust. Previous users have used peer models extensively (Bull, Mabbott & Issa, 2007), but some did prefer not to consult this information. It is unlikely that the latter students would consider the ability to use peer models to increase their trust in the system. The figure for the facility to compare to instructor expectations was a little higher - for some this confirmation of their position in relation to what they were expected to have achieved appeared useful for increasing trust. It would be worthwhile investigating whether this generally gave them a greater sense of where they should be, and trust was related to this feeling of understanding what their progress actually meant.

Most learners were willing to open their learner model to peers and instructors if they believed the model inferred by the system was accurate. However, some still released what they considered an inaccurate model to others. Since students could release their models anonymously, any reluctance to use the model would not be due to possibility of others identifying them with inaccurate data. The situation a perceived model to be inaccurate may affect use of the model in initiating or supporting collaborations between learners: if learners have released their own 'incorrect' model (according to their belief) to other users, will they trust other models less? Will this make them less inclined to seek help according to the contents of peer models? Another obvious issue is that peers might make their own model - trust in colleagues is particularly important in this kind of context.

## 4.3 Implications

We have raised many questions related to trust in OLMs. In terms of the complexity of the model, learners seem to understand detailed presentations better; however they seem to have greater trust in an overview. We have suggested that learners may not have understood the manner in which the overview model was updated, but since they did seem to trust it, this suggests understanding the manner in which the model is inferred, may not be crucial in creating trust. In Chapter 3, we describe a variety of externalisations used in OLMs ranging from simple to detailed and structured presentation. Despite the existence of a variety of OLMs, some have had extensive use (e.g. Bull et al, 2006; Mitrovic & Martin, 2007; Weber & Brusilovsky, 2001), to date there has been little investigation into the extent to which learners may trust different types of OLM representations. Therefore, our questions in investigating this issue are:

- *Do students understand and trust open learner model externalisations?*
- *Do students trust simple or more structured view?*
- *Are there any features that makes open learner models view more trustable?*

In terms of learner control, some learners edited or endeavoured to persuade their models even though they believed the model content was correct, but fewer students challenged what they perceived to be incorrect attributes. We have hypothesised that this may be due to lower trust in the system's ability to continue modelling them correctly after the model was changed. To consider this issue further, our questions are:

- *Do learners use and trust the edit function in OLM?*
- *Do learners use and trust the persuade function in OLM?*

Finally, many learners appear to trust their model because they could compare it to instructor expectations and some also because they could compare to peer models. It would be useful to investigate how trust might be developed amongst learners who have access to each other learner models. Therefore we will focus on learner trust in peer models and our questions regarding this issue are:

- *Do learners use and trust peer models?*
- *Do learners trust the named learner model or anonymous learner model?*

Trustable OLMs are likely to be important to encourage users to continue using them, in order to gain the educational benefits that can be derived (e.g. metacognitive skills such as supporting planning, reflection, and formative assessment). In studying trust, different fields have established different definition of trusts that are appropriate for the fields as discussed in Chapter 2. Therefore, to investigate trust in OLM, a definition of trust in OLMs needs to be established. While primarily applied to other fields, the definition of trusts by Madsen & Gregor (2000) can also be relevant in open learner modelling. When studying trust in open learner models, we adapt and define trust in the learner model as *the individual user's belief in, and acceptance of the system's inferences; their feelings of attachment to their model; and their confidence to act appropriately according to the model inferences* (Ahmad & Bull, 2008). The formulation of trust definition in OLM is described in Chapter 6. Based on this definition, the key issues investigated for user trust in OLM are:

- *The extent to which students trust (and accept) the OLM system on their first use.*
- *The extent to which students continue using the OLM optionally after their initial use.*
- *The extent to which students trust (and accept) the OLM after longer term of use.*

Therefore the research question related to this study is: *"What are the elements of trust in open learner models?"*

In this chapter we have investigated trust issues in OLMs using two systems, OLMlets and Flexi-OLM, and the results gathered are totally based on learners' responses to the questionnaires. At this stage we did not have any access to the log files that seem important to investigate trust issues in OLM. With log files, the correlation between learners' responses to the questionnaires and what is actually logged by the system can be seen. Therefore, we extend OLMlets to a system that combines features that might build user trust in OLM as identified in this study, and we call it tOLMlets. With tOLMlets, we can access the logs files for all interactions in the system.

## 4.4 Summary

This chapter has considered trust issues in OLMs, focusing on (i) complexity of model presentation; (ii) level of learner control over the model; (iii) the facility to view peer models and release one's own model to peers. Results suggest that different users may find different features of OLMs important for developing trust. As designing trustable OLMs may be crucial for their maintained use, a key issue is how to design an OLM that might be trustable for a variety of users. Therefore, we have come out with several questions relating to trust in OLM and also decided to extend OLMlets to a system known as tOLMlets. We further investigate trust in OLM and for each feature identified we use an extended system called tOLMlets. The descriptions of tOLMlets will be provided in the next chapter.

# Chapter 5

# tOLMlets

In Chapter 4, we have described the investigation of user trust in OLM using two OLM systems, OLMlets (Bull et al., 2006) and Flexi-OLM (Mabbott & Bull, 2006). Initial results suggest that different users may find different features of OLMs which are important for developing trust. In this chapter, we present tOLMlets to consider these issues further, where *t* refers to trust. As mentioned in the previous chapter, tOLMlets is an extension of OLMlets (Bull et al., 2006). It comprises some features of simple OLMs and peer models based on OLMlets and detailed OLM representations and learner control based on Flexi-OLM. As with OLMlets and Flexi-OLM, tOLMlets was developed with the aim of encouraging metacognitive skills and independent learning, by showing students representations of their strengths and weaknesses in a subject.

## 5.1 Why OLMlets?

OLMlets (Bull et al., 2006) has been developed to support students learning and help them to reflect on their knowledge (including lack of knowledge and misconceptions) immediately. With OLMlets, students are also expected to plan their future learning event and be more responsible for their learning. The learner model environment in OLMlets is programmed using the PHP scripting language and hosted in Apache web server. It is connected to the MySQL relational database engine where all model data in OLMlets including subject domain topics, questions, answers, misconceptions and system logs are stored. This application is running on a Sun Solaris system (Bull, Gardner, Ahmad, Ting, & Clarke, 2009). Users can access the system through graphical user interface (GUI). Figure 5.1 shows the general architecture of the OLMlets.

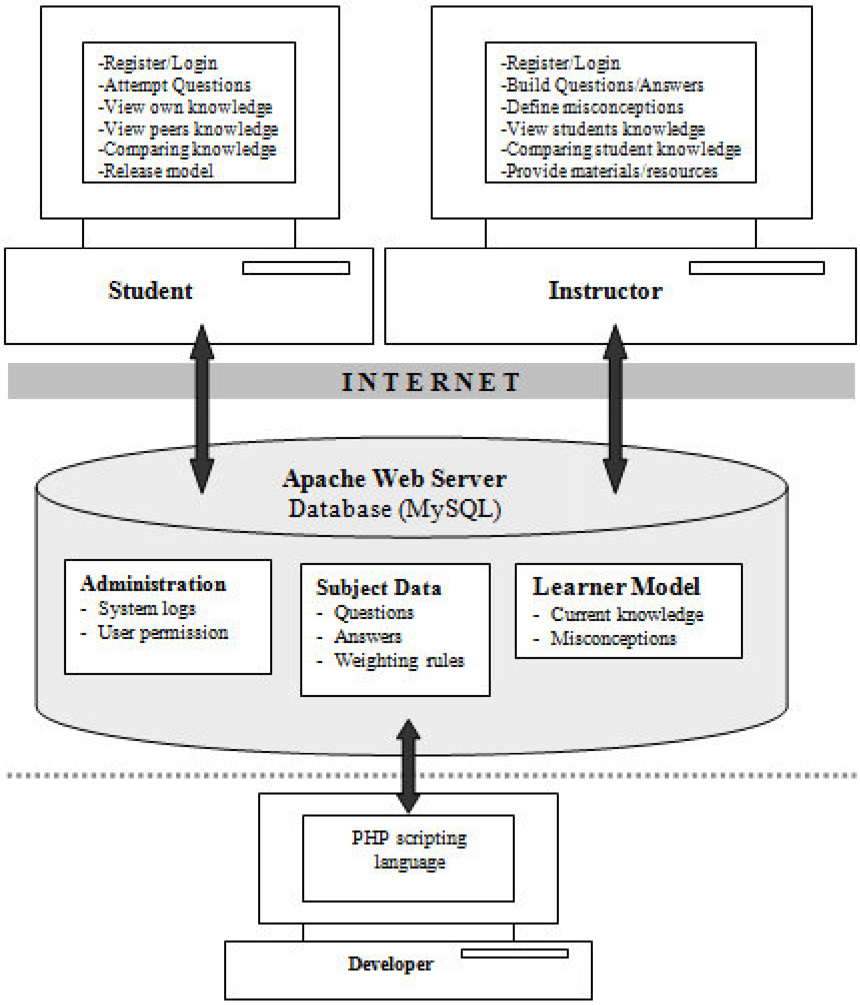



Figure 5.1: General architecture of OLMlets

In this research we decided to extend OLMlets as a system that combines features, which may contribute to trust in OLM as identified in Chapter 4. In addition to the fact that OLMlets is owned and hosted in the School of Electronic, Electrical & Computer Engineering, University of Birmingham, the decision to extend OLMlets was influenced by the following factors: the extensive use of OLMlets in university courses indicates that this system is useful and successful in the environment, the modelling technique used in OLMlets, and the fact that OLMlets provides other functions than just viewing owned model, but also allows students to see peers models and release theirs for others to view. The next section will describe each of these factors further.

### 5.1.1 The Extensive Use of OLMlets

OLMlets has been used extensively in the actual learning environment (Bull et al., 2006; Bull & Britland, 2007; Bull et al., 2009). OLMlets is used alongside a lecture course to support learning for university students. Evaluation using the system shows that users have  good interactions with the system in which students attempt questions, quite often view their model, and view the comparisons of their knowledge with peers and instructors expectations (Bull et al., 2006; Bull & Britland, 2007). OLMlets is also a practical resource for learning while helping to stimulate students to take part in the formative assessment. Over time, the use of OLMlets to support learning for university student is increasingly widespread. In the early deployment, OLMlets only supported five university courses for engineering students (Bull et al., 2006), but it continued to grow and support up to 18 courses (Bull et. al., 2009). Extensive use of OLMlets in the actual learning environment and the responses shown by users indicate that OLMlets has been successful in supporting students learning. This makes OLMlets as a good choice for studying trust in OLM.

### 5.1.2 The Modelling Technique in OLMlets

OLMlets supports a variety of courses for engineering students as described in the previous section because the modelling technique used is rather simple. It can be used by any subject as long as appropriate multiple-choice questions can be constructed even though the structure and conceptual relationships of each subject is different (Bull & Mabbott, 2006).

OLMlets uses a weighted numerical to construct a model of learners' knowledge (Bull & Mabbott, 2006). The construction of this model requires students to answer multiple-choice questions. The learner's knowledge level in each topic is managed by the system as a continuous value between 0 and 1. A value of 0 indicates that no knowledge exists, and a value of 1 indicates mastery of knowledge may exist. The possibility of misconceptions is also stored as a continuous value between 0 and 1 in the misconceptions library; where 0 indicates no misconceptions and 1 indicates a high probability that students hold misconceptions. The misconceptions library is defined by the instructor. The system identifies a misconception by comparing learners' input to the system with the misconceptions library. The model for each learner is displayed for the last five attempts on the questions. Taking into account that the learner's understanding may change from time to time, the heavier weighting is given to the most recent attempts (each is assigned a weighting of 0.3 times the previous response). For the purpose of opening the model for users to see, these values are converted to representations that are easily understood by users.

OLMlets uses two ranges of knowledge level to externalise the model. For the skill meter and graph, these values are changed to 'known', 'misconception', 'problematic' or 'not covered'. While for the boxes, table and texts, these values changed to 'very high', 'high', 'ok', 'low', 'very low' or 'misconception' (see Figure 4.1). OLMlets is a domain-independent OLM. It depends entirely on the input of questions set by the instructor and the learner model is built as defined based on instructor input. In order to extend the system for investigating issues of trust in OLM, the simple modelling technique used in OLMlets is an advantage because it is easy to understand the modelling process and thus quicken the process. Furthermore, Muir (1987) suggests that user trust in a system can be built using the minimum system performance, therefore, simple modelling technique used in OLMlets to study trust in OLM is not a problem as long as it can function properly.

### 5.1.3 Features of Comparing to Peer Model

In OLMlets, learners can view not only their own model but also can access to peers models that are released to them (Bull & Britland, 2007). Features to view models of other users are not only implemented by OLMlets but also by other OLM systems (refer to Section 3.3.3). These features have several advantages, such as students may seek collaboration with peers, while instructors and parents can view student learning progress. In the pilot study, it is found that users gained trust in their model and able to compare it to the peer models. Hence, this research focuses on the model that involves interactions among students (peers models).

## 5.2 Extensions to OLMlets

OLMlets is currently available in five simple views which are skill meter, graph, boxes, text and table (Bull et al., 2006). As discussed in Chapter 3, OLMs are not limited to the simple views, but also more structured and detailed. Initial work suggests students may trust an OLM specifically the presentation of the LM. The simple views in OLMlets (Bull et al., 2006) may be trusted even if users do not fully understand them or have complete confidence in their accuracy. Whereas the structured views in Flexi-OLM (Mabbott & Bull, 2006) were less trusted by some learners although the LM is understood better and considered more accurate. The above results were with two OLMs with different architecture. Users may have a different perception of each system and thus affect their trust in the presentation of the learner model. Therefore, we added a structured view in OLMlets, and made both simple and structured views available in a single system known as tOLMlets to further investigate user trust in OLM presentations. Section 5.2.1 will describe these further.

In terms of interactions, OLMlets allows learners to attempt questions and examine their models. Learner models are inferred solely by the system based on the responses of learners, and learners do not have control over their model. However, giving some controls to learners can raise issues of trust towards the accuracy of the model (refer section 1.2). Therefore, control features are added and available in tOLMlets in order to further investigate learners' trust in the models if learners are given such controls. Section 5.2.2 will describe these further.

### 5.2.1 Externalisation of the Learner Model

The development of a structured view in tOLMlets is based on the structure of the concept map. This is because most OLMs that implemented a structured approach are using a concept map for presenting the learner model (e.g. Rueda et al., 2003; Dimitrova, 2003; Mabbott & Bull, 2006; Pérez-Marín, Alfonseca, Rodríguez, & Pascual-Nieto, 2007). The more recent research can even generate the concept map learner model automatically from learner answers (Pérez-Marín & Pascual-Nieto, 2010). Therefore, in order to investigate user trust in the presentation of a learner model, we chose a structured approach that is commonly used in OLMs to be applied in tOLMlets, alongside some of the simple views.

The contents of the learner model in a structured view will change in line with changes in other views available in OLMlets. Boxes containing topic's names will be filled with different colours according to learner's knowledge. This is similar to the 'boxes' view in OLMlets (see Figure 4.1), but with more structured layout which is linked based on the relationships between topics in the course. When students hold misconception, the related box will be filled with red colour and a small box with word 'misconception' will appear on the left of the screen. Clicking on this box will reveal brief description of the misconception as shown in Figure 5.2.

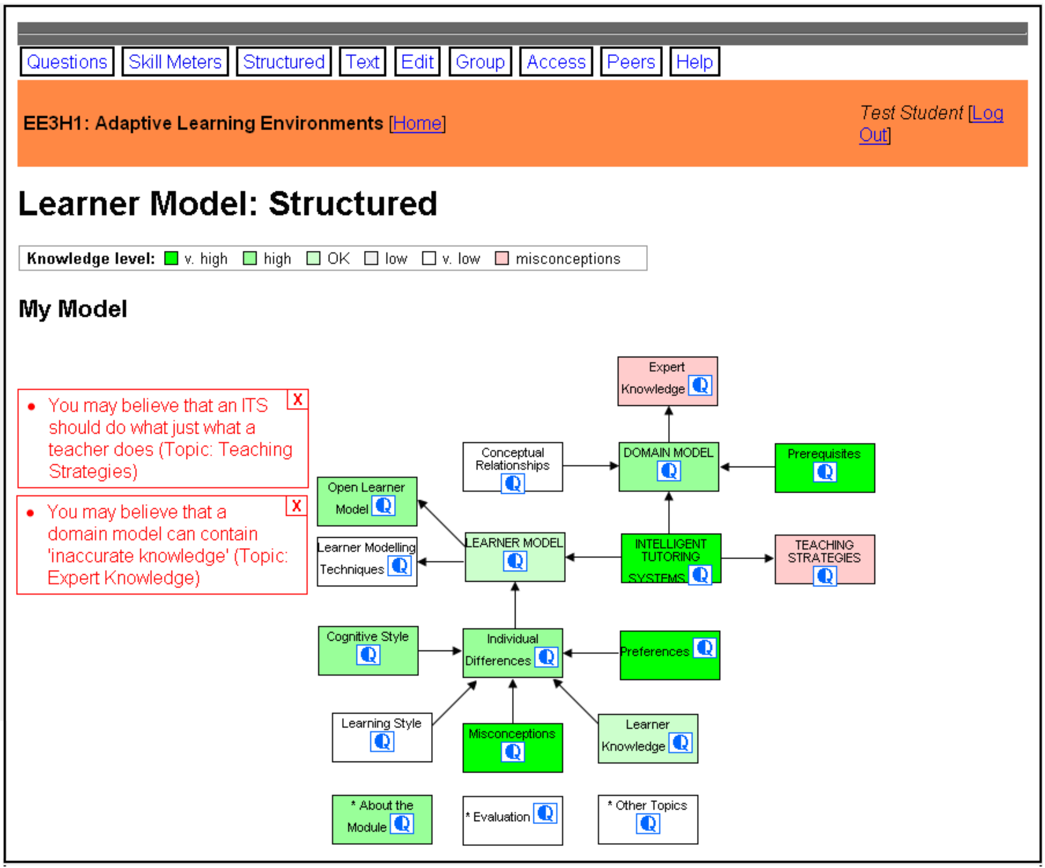



Figure 5.2: Structured view in tOLMlets

## 5.2.2 Learner Control over the Learner Model

In open learner modelling, aside from issues of privacy and protection of personal data, the kind of risks that may occur is from learner control over their model (refer section 1.2). Hence, to study user trust in learner control over the learner model, we implement edit and persuade features in tOLMlets. We describe these functions in the next section.

### 5.2.2.1 Edit

OLM allows learners to edit the model content considering that learner may improve their knowledge outside the system as explained in Section 3.3.2. In tOLMlets, learners may perform edit function by selecting the edit tab in the system and the interface shown in Figure 5.3 will be displayed. Let say the learner wants to change the knowledge level for topic 'Domain Model'. He or she can start the step by clicking '[edit]' beside the topic's name.

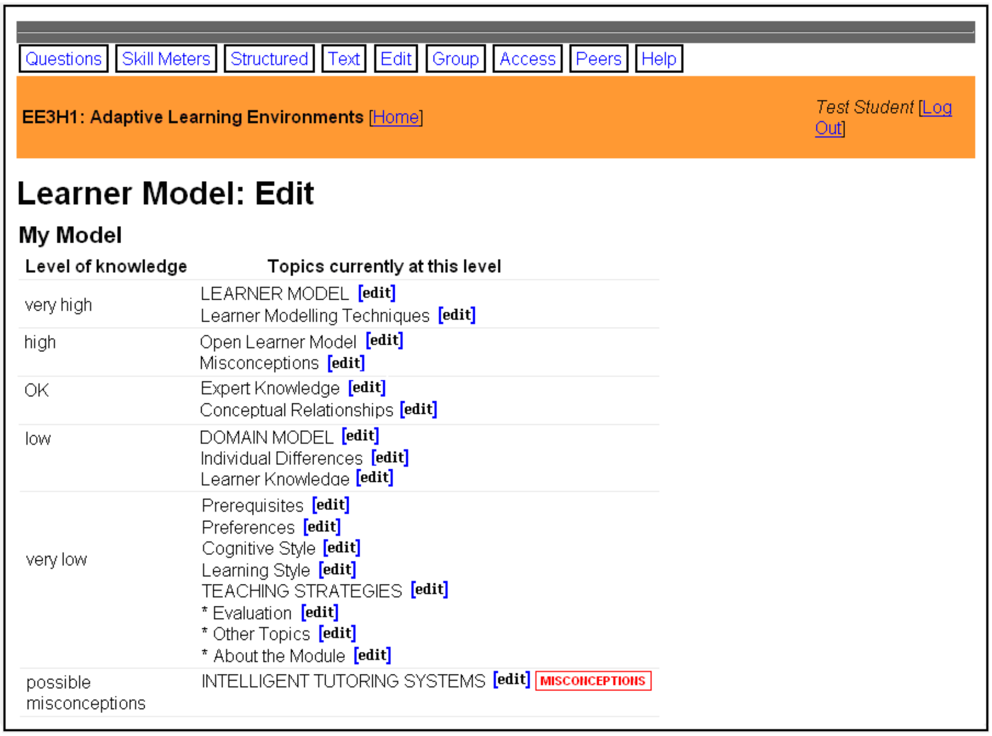



Figure 5.3: Learner selects the topic to edit

Next it will take the learner to second interface as shown in Figure 5.4. This interface displays the learner's current knowledge on the selected topic (Domain Model), together with the evidence that has contributed to this knowledge. Providing the evidence of the current state of the model in the edit function has found to be more useful to students than those without (Mabbott, 2009). The ability to view the evidence not only encourages users to edit, but also makes them more confident to edit. Therefore providing an edit function with evidence is a useful way to explore trust in OLMs.

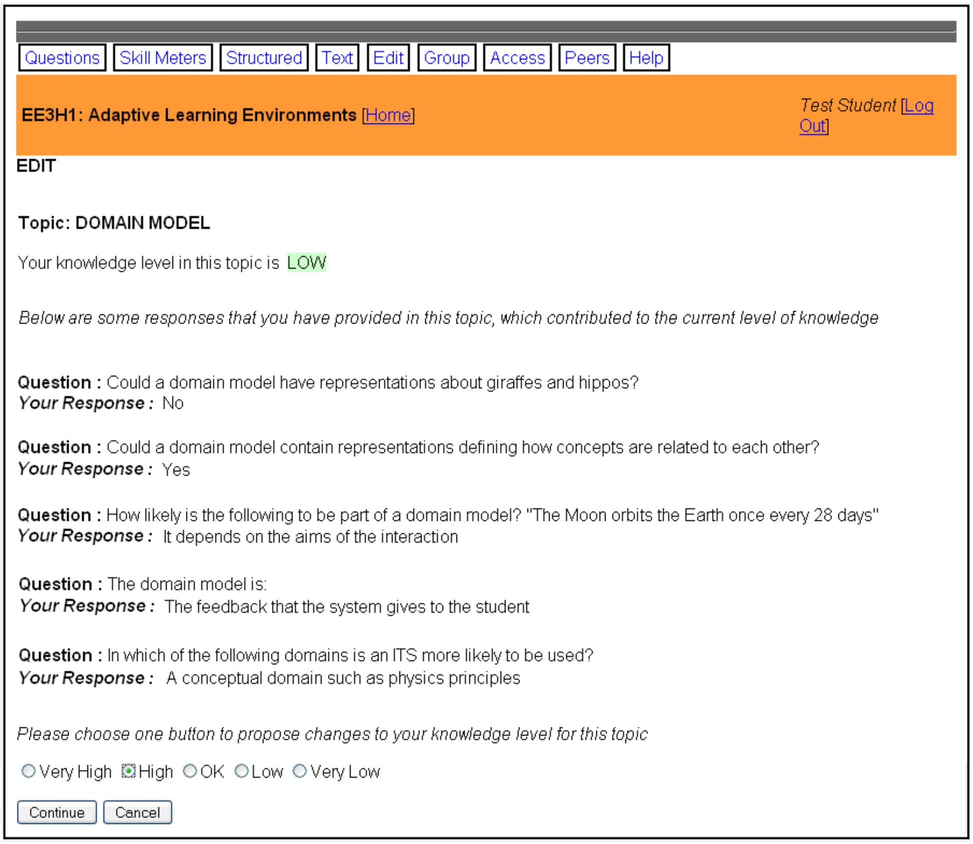



Figure 5.4: Interface showing current level of knowledge and some evidences

If learners wish to change the model, they may select a new knowledge level and tOLMlets will automatically replace it. Let say learners wish to change the current knowledge level under the topic 'Domain Model' from 'low' to 'high' (see Figure 5.4); they simple click the '[continue]' button.  This change will be displayed either in the edit page or in the view options (skill meter for this example) as shown in Figure 5.5.

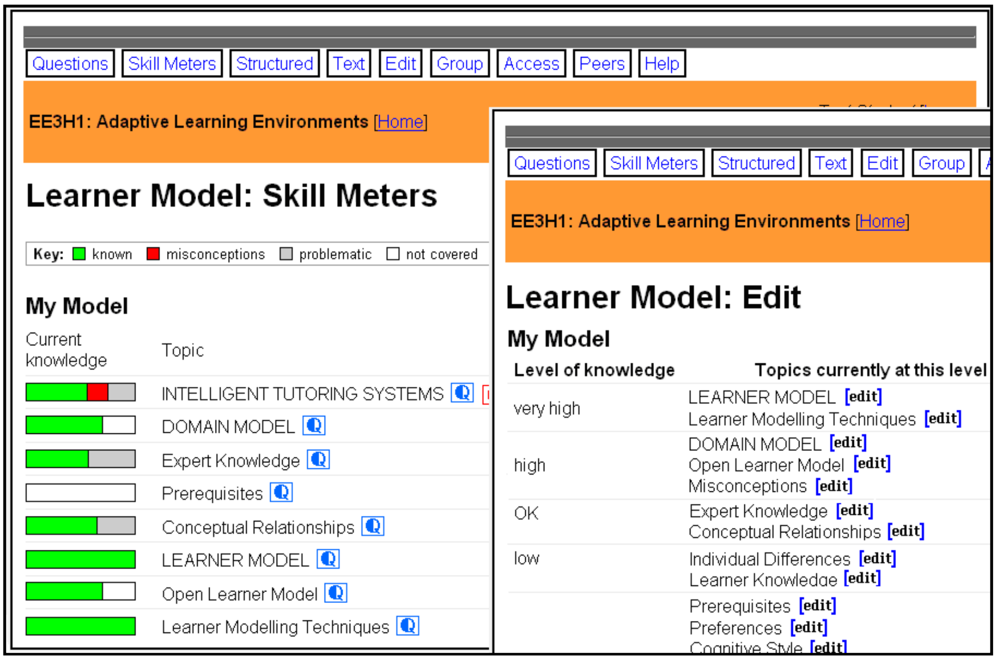



Figure 5.5: The knowledge level after learner edit the model content showed in skill meter (left); and in edit page (right)

#### 5.2.2.2 Persuasion

In addition to direct edit, persuasion features is also built in tOLMlets. It is based on persuasion features in Flexi-OLM (Mabbott & Bull, 2006). In order to persuade the system, learners start the process by choosing the topic (see Figure 5.6) and the new level of knowledge that they desired (see Figure 5.7). In this example learner choose to persuade the topic ‘Intelligent tutoring System’.

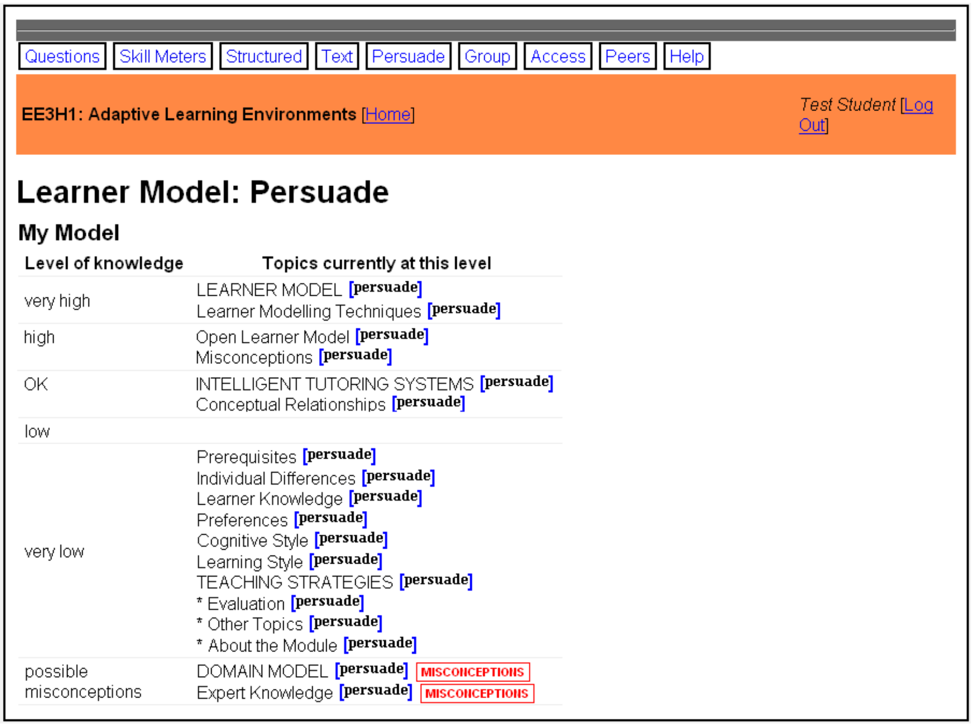



Figure 5.6: Interface for select which topic to persuade

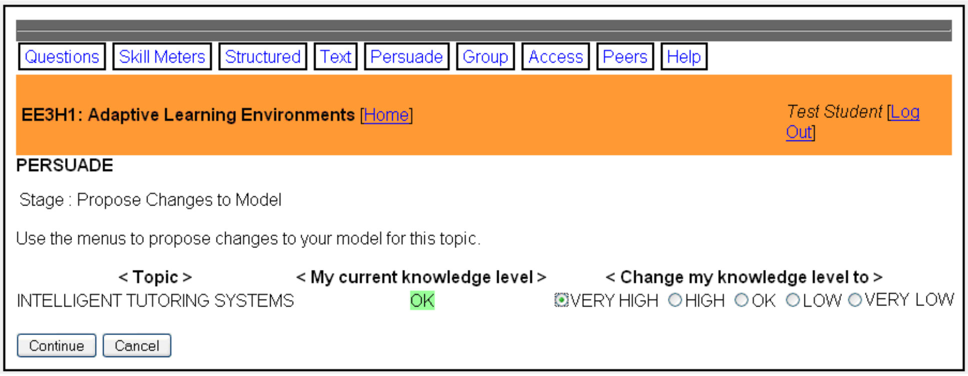



Figure 5.7: Interface for select a new level of knowledge

Learners are shown the evidence that contribute to their current knowledge as shown in Figure 5.8. This is very similar to Figure 5.4. After reviewing the evidence, if learners still wish to change the content model, they need to take a short test about the topic to demonstrate their skills (see Figure 5.9).

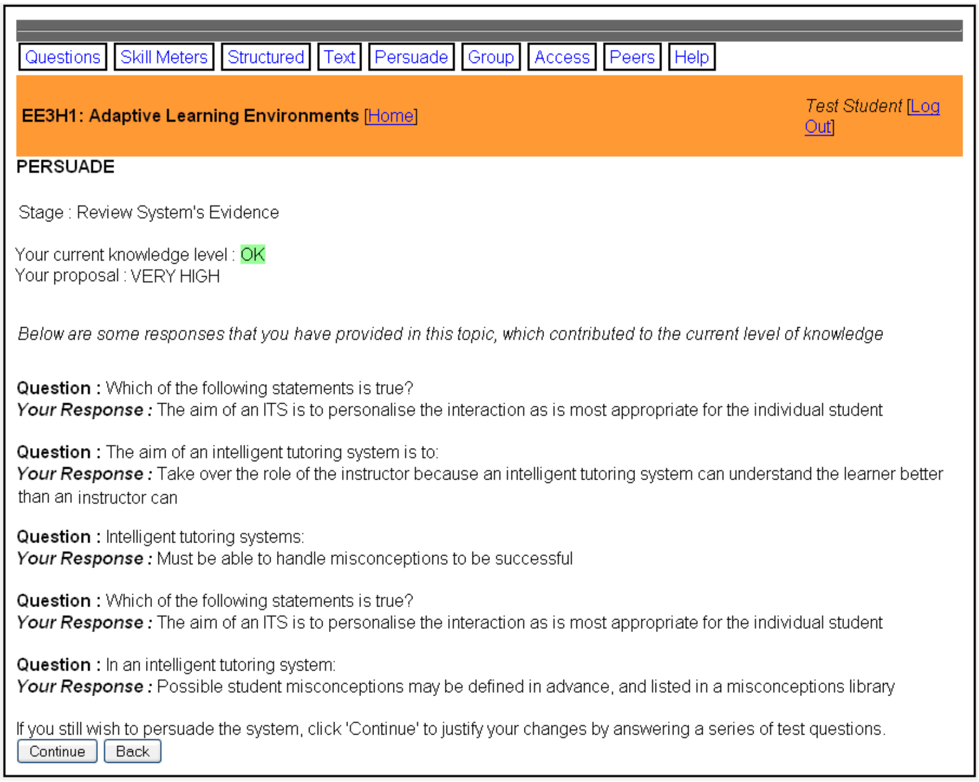



Figure 5.8: The evidence of current knowledge

The contents of the model will not be changed as desired by learners unless they prove their skills. tOLMlets will maintain or change the content model based on learners response to the system in a short test. Let say learners want to persuade the system to change the model under the topic ‘Intelligent Tutoring System’ from ‘OK’ to ‘very high’ (see Figure 5.7), and after taking a short test it is found that learners only have knowledge that is categorised as ‘high’, the learner knowledge in this topic will change from ‘OK’ to ‘high’ and not to ‘very high’ as desired (shown in Figure 5.10). Learners can view the changes (of the new level) in the learner model views that are available in tOLMlets, or in the ‘persuade’ page itself (see Figure 5.11)

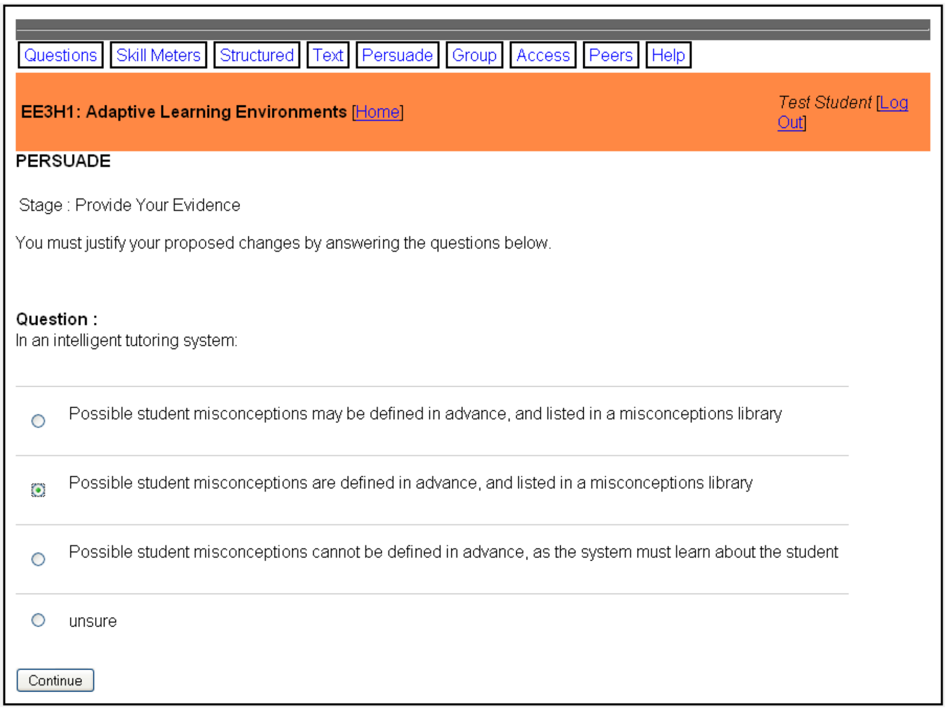



Figure 5.9: Short test to convince tOLMlets

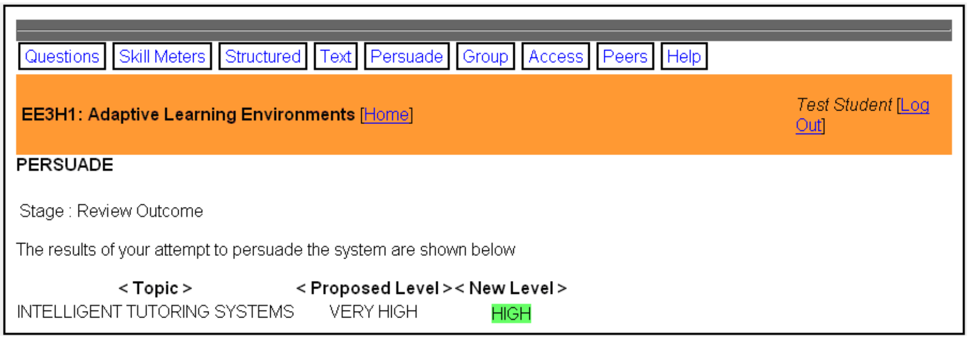



Figure 5.10: Reviews the outcome after the attempt to convince tOLMlets

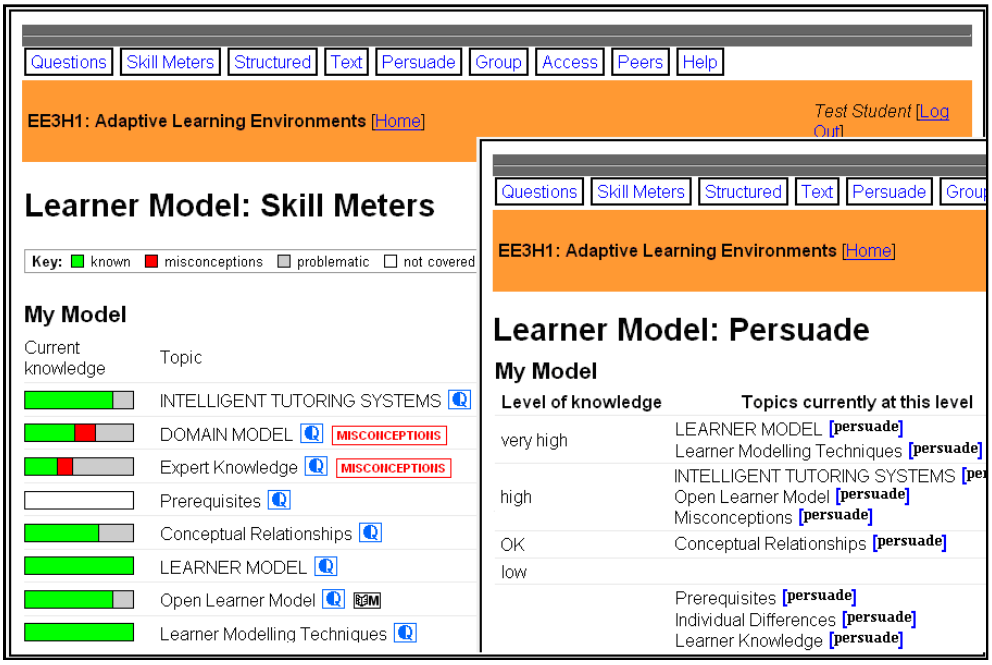



Figure 5.11: The level after learner persuade the model displayed in skill meter (left); and in persuade page itself (right)

Table 5.1: Comparison between OLMlets, Flexi-OLM and tOLMlets features

| | **OLMlets** | **Flexi-OLM** | **tOLMlets** |
|---|---|---|---|
| Externalisation of learner model | Simple | Simple<br>Structured | Simple<br>Structured |
| Learner control over the learner model | - | Edit<br>Persuade | Edit<br>Persuade |
| OLM to other users | Peer<br>Instructor | - | Peer<br>Instructor |

Table 5.1 shows the comparison between OLMlets, Flexi-OLM and tOLMlets features. Apart from simple presentation, tOLMlets also provides learners with structured presentation of learner model. In tOLMlets, learners can change the learner model if they do not agree with the system inference as in Flexi-OLM. Learners may edit the model directly if they are confident about their learner model, or otherwise, use the persuasion function and try to persuade the system to change the model. In terms of other users that can see the model, OLMlets and tOLMlets allow access from peers and instructors. tOLMlets

inherits this feature from OLMlets and the description of this feature can be found in Section 4.1.1. In order to investigate user trust in OLM, tOLMlets now represents all three features considered in this research.

## 5.3 Summary

In this chapter we extend OLMlets to tOLMlets to investigate issues of trust in OLM instead of developing a new system. The selection is made on the basis that the system is widely used, applying simple modelling techniques and having additional features for others to access the model (that focus to peers model in this research).

There are different types of OLM representation as discussed in Chapter 2. However until now there has been little investigation into the extent to which learner may trust different types of OLM representation. OLMlets provides students with five simple views, and in the extended version, tOLMlets, we incorporate both simple and structured views in one system. This allows us to investigate user trust towards simple and structured view of the learner model.

In Chapter 2, we also discussed various types of control in OLM system. Different types of controls over the learner model will affect the model inferred by the system. Giving learners some control over their learner model may produce a more accurate model or vice versa. This invited to the question of the model produced, and may involve user trust towards the resulting model. Therefore, we implemented features for student to control their model in tOLMlets. In order to investigate trust, we add a full control feature of the model (through edit the model directly) and a limited control feature through persuasion. Features that are implemented in tOLMlets are features that usually available in other OLM systems. Therefore this makes tOLMlets represent most common features in OLM and allows us to investigate user trust in the OLM. Next chapter will describe the evaluation of user trust using the system.

# Chapter 6

# EVALUATION: USER TRUST IN OLM

In this chapter, we investigate users' trust in OLM as a whole system based on two modes of studies: laboratory study and deployed study. We start with the evaluation of the definition of trust in the learner model as mentioned in Chapter 2. The definition consists of 3 main components: (i) user belief and acceptance of information inferred by the system; (ii) user feeling of attachment with the system; and (iii) user confidence to act appropriately based on information inferred. We evaluate user trust on each of these components. Next we assess the relationship of user trust with several items that may influence trust in the system. The key issues investigated are:

- The extent to which learners trust (and accept) the OLM system on their first use.
- The extent to which learners continue using the OLM optionally after their initial use (preliminary use).
- The extent to which learners trust (and accept) the OLM after long-term use of the system.
- The relationship between learner trust and several criteria that may influence trust in OLM.

## 6.1 Users' Trust in OLMs

We did the study in two settings: laboratory and deployed study. In the laboratory study learners were using tOLMlets in a short period about two hours lab session. While in the deployed study learners were introduced to tOLMlets in a lab session and they may continue using the system for 6 weeks. We hypothesized that users trust in OLM system as a whole.

### 6.1.1 Participants, Materials, Method

This subsection will explain the participants, materials and method involved in the study.

#### 6.1.1.1 Laboratory study

Participants were 42 MSc. students from the School of Electronic, Electrical and Computer Engineering, University of Birmingham. All participated during a course entitled 'User Models & Models of Human Performance' (UMMHP). The students were introduced to tOLMlets by using the system in an about two-hour laboratory session. Some participants had experience using the previous version of tOLMlets (OLMlets), while most of them were new to the system.

Participants began the session with the registration and logged in into the system. Upon the login, students were presented with an 'empty' learner model showing the topics of the UMMHP course. They were instructed to answer questions provided in the system to build the learner model and view the learner models available for them. Students were asked to consider using the other functions provided in the system such as releasing their model to peers, viewing peers model available to them, and viewing the group model. The system logged all interactions.

At the end of the session, participants completed questionnaires regarding their interaction with the system. The questionnaires comprised statements requiring participants to indicate their level of agreement on a 5-point Likert scale with further open-ended questions (Appendix: Questionnaire2).

#### 6.1.1.2 Deployed study

Participants were third-year undergraduate students taking a course called ‘Adaptive Learning Environments’ in the School of Electronic, Electrical and Computer Engineering, University of Birmingham. A total of 26 students were enrolled in the course. Participants were introduced to tOLMlets in a laboratory session in the second week, and they were asked to continue using the system to support their learning throughout the course. The system was available for six weeks and students could use the system in their own time. The final state of the model the students achieved was counted and it contributed 5% to the overall course marks. At the end of week seven, questionnaires with the same components in Section 6.2.1.1 were used and distributed to get participants insight towards their use and trust in the system.

### 6.1.2 Results: Logs data

In this section we present students' interactions with tOLMlets.

#### 6.1.2.1 Laboratory study

Participants attempted between 14 and 267 questions, with the average number of questions attempted being 83 (*SD*=58). Table 6.1 shows the number of questions answered before the first inspection of the model. The majority of the learners attempted the questions before viewing the model, except for the six learners. They started with inspecting the blank model before attempting the questions.

Table 6.1: Number of questions attempted for the first time

| Questions attempted | 0 | 1 | 2 | 3 | 4 | 5 | 6+ |
|---|---|---|---|---|---|---|---|
| Number of students | 6 | 6 | 3 | 2 | 1 | 7 | 17 |

The learner model was inspected a total number of 2597 times, between 16 and 141 by an individual user. The average number of inspections was 62 (*SD*=35). Table 6.2 shows that more than a quarter of students inspected the learner model once before continuing with further questions.

Table 6.2: Number of models viewed for the first time

| Model viewed | 1 | 2 | 3 | 4 | 5 | 6+ |
|---|---|---|---|---|---|---|
| Number of students | 17* | 4 | 6** | 1 | 3 | 11 |

* 3 views the blank model; ** 3 views the blank model

The number of questions answered between inspections also varies among users. Table 6.3 shows that some users inspect the model after every question while others wait after a few questions.

Table 6.3: Frequency of questions attempted between inspections

| Questions attempted | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 - 26 |
|---|---|---|---|---|---|---|---|---|---|---|
| Number of attempted | 734 | 122 | 89 | 54 | 51 | 40 | 24 | 16 | 12 | 81 |
| Percentage (%) | 60 | 10 | 7 | 4 | 4 | 3 | 2 | 1 | 1 | 7 |

The frequency of inspecting the model after each question is high, which is 734 times. Most participants inspected the model after they have tried each question. The maximum number of questions before the model was inspected was 26 questions.

#### 6.1.2.1 Deployed study

A total number of 26 students logged into the system. Table 6.4 shows the total number of logins over six weeks when the system was available. These include logins when the students were first introduced to the system. Students log into the system frequently in the fifth week when the system was available.

Table 6.4: Number of logins per student

| | No. of login | Mean | SD |
|---|---|---|---|
| S1 | 8 | 1.3 | 1.9 |
| S2 | 18 | 3.0 | 2.5 |
| S3 | 10 | 1.7 | 3.1 |
| S4 | 14 | 2.3 | 4.3 |
| S5 | 5 | 0.8 | 1.2 |
| S6 | 13 | 2.2 | 3.9 |
| S7 | 10 | 1.7 | 2.3 |
| S8 | 16 | 2.7 | 4.6 |
| S9 | 18 | 3.0 | 2.8 |
| S10 | 9 | 1.5 | 1.6 |
| S11 | 9 | 1.5 | 2.7 |
| S12 | 14 | 2.3 | 3.4 |
| S13 | 8 | 1.3 | 2.0 |
| S14 | 21 | 3.5 | 1.2 |
| S15 | 7 | 1.2 | 1.2 |
| S16 | 3 | 0.5 | 0.5 |
| S17 | 14 | 2.3 | 3.0 |
| S18 | 3 | 0.5 | 0.8 |
| S19 | 3 | 0.5 | 1.2 |
| S20 | 12 | 2.0 | 1.7 |
| S21 | 8 | 1.3 | 1.5 |
| S22 | 19 | 3.2 | 2.8 |
| S23 | 7 | 1.2 | 1.2 |
| S24 | 9 | 1.5 | 1.5 |
| S25 | 9 | 1.5 | 2.3 |
| S26 | 15 | 2.5 | 1.8 |

Table 6.4 also indicates that all students logged in multiple times. The minimum number of logins was 3 and the maximum number of logins was 21. Half of the participants logged into the system more than ten times.

Participants were able to attempt a large number of questions and made more inspections on the learner models due to a longer timescale compared to a laboratory study. Participants attempted between 191 and 1340 questions, with a mean of 439 (*SD*=277). Learner models were inspected a total number of 9836 times, while the highest number of inspections made by an individual user was 1114. The mean number of inspections was 378 (*SD*=234). The number of questions answered before the inspection of the model varies among students. They inspected the learner model after attempting between 1 to 20 questions. However, most of them ended up checking the model after every question.

### 6.1.3 Results: Questionnaires

In this section, we present questionnaire results related to use and trust in the OLM system. For the laboratory study, all 42 responses were available while for deployed study only 16 (out of 26 users) responses were available. Some participants did not attend the session in week 7 (during which users filled in the questionnaires) and some did not return the questionnaires. In order to get the questionnaires back, we asked the participants via email, however without luck, no one is replying to the email. For clarity of comparison we present the results in percentages.

First, we present users' response based on the definition of trust in learner models (refer Section 1.2) that involves three key points: (i) individual user's belief in, and acceptance of the system's inferences; (ii) feelings of attachment to their model; and (iii) their confidence to act appropriately according to the model inferences. Results are presented in Table 6.5, Table 6.6 and Table 6.7 respectively.

#### 6.1.3.1 Acceptance of the system inferences

Table 6.5 shows user response on acceptance of the system's inferences for the laboratory study and deployed study.

Table 6.5: Acceptance of the system inferences (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | **5** | **4** | **3** | **2** | **1** | **Mean** | **SD** |
| **Laboratory study (N=42)** | | | | | | | |
| *Believed tOLMlets when:* | | | | | | | |
| user uncertain about owned knowledge | 19 | 50 | 24 | 7 | 0 | **3.8** | 0.8 |
| it shows a *high* level of knowledge | 17 | 40 | 40 | 2 | 0 | **3.7** | 0.8 |
| it shows a *low* level of knowledge | 14 | 43 | 33 | 7 | 2 | **3.6** | 0.9 |
| it shows a *higher* level of knowledge than expected | 17 | 33 | 40 | 10 | 0 | **3.6** | 0.9 |
| it shows a *lower* level of knowledge than expected | 12 | 36 | 38 | 12 | 2 | **3.4** | 0.9 |
| **Deployed study (N=16)** | | | | | | | |
| *Believed tOLMlets when:* | | | | | | | |
| user uncertain about owned knowledge | 0 | 56 | 38 | 6 | 0 | **3.5** | 0.6 |
| it shows a *high* level of knowledge | 25 | 63 | 13 | 0 | 0 | **4.1** | 0.6 |
| it shows a *low* level of knowledge | 25 | 44 | 25 | 6 | 0 | **3.9** | 0.9 |
| it shows a *higher* level of knowledge than expected | 6 | 69 | 25 | 0 | 0 | **3.8** | 0.5 |
| it shows a *lower* level of knowledge than expected | 13 | 50 | 38 | 0 | 0 | **3.8** | 0.7 |

## Laboratory Study:

In the laboratory study, 69% of users believe the system evaluation when they are uncertain about their knowledge. Only 7% of users do not believe in system evaluation when they are uncertain about their knowledge, while 24% remain neutral in the circumstances. About half of the users believed in the system when a higher level of knowledge is shown or when a lower level of knowledge is shown.

The actual knowledge (from logs in laboratory study) shows that 40% of the users have more knowledge than the problematic knowledge (including misconceptions). 79% (33 users) provided the same rating whether tOLMlets shows high or low level of knowledge (22 agree, 10 neutral, 1 disagree). For 17 users who hold actual high knowledge (as recorded in the system), 10 of them claim that they believe tOLMlets when knowledge is high, while 7 claim that they believe tOLMlets when knowledge is low. For 25 users who hold actual low knowledge, the number who believe the system, whether it shows high or low level knowledge is the same which is 14 users. In terms of expectations about the knowledge, half of the users believe in the system when higher level of knowledge is shown. For the lower level of information than expected, nearly half of the users believe the system and 14% refuse to believe it.

## Deployed Study:

In the deployed study, results show that 56% of users believe the system evaluation when they are uncertain about their knowledge. 6% of users do not believe in system evaluation when they uncertain about their knowledge, while 38% remain neutral with the situation. The acceptance of the system inference is high when tOLMlets shows a higher level of knowledge with 88% of users believe the system. For the low level of knowledge 69% believe in the system inference. However 6% refuse to believe tOLMlets when low level of knowledge is displayed.

The actual knowledge (from logs in deployed study) shows that all 16 users have more knowledge than the problematic knowledge (including misconceptions). 13 users rated the same value for whether tOLMlets shows high or low level of knowledge (11 agree, 2 neutral). 14 users claim that they believe tOLMlets when knowledge is high, while 11 users claim that they believed tOLMlets when knowledge is low.

In terms of expectations about the knowledge, 75% of the users believe the system information when it shows a higher level of knowledge (*M*=4.1, *SD*=0.6) and 63% believe when it shows a lower level than what they expect (*M*=3.9, *SD*=0.9). There are no users who do not agree with both cases. Next is the results for feeling of attachment to the model.

### 6.1.3.2 Feeling of attachment to the model

The feeling of attachment to the model is shown in Table 6.6.

Table 6.6: Feeling of attachment to the model (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | **5** | **4** | **3** | **2** | **1** | **Mean** | **SD** |
| **Laboratory study (N=42)** | | | | | | | |
| *Continue using tOLMlets if:* | | | | | | | |
| the information was *higher* than expected | 17 | 40 | 38 | 5 | 0 | **3.7** | 0.8 |
| the information was *lower* than expected | 12 | 31 | 38 | 19 | 0 | **3.4** | 0.9 |
| **Deployed study (N=16)** | | | | | | | |
| *Continue using tOLMlets if:* | | | | | | | |
| the information was *higher* than expected | 19 | 31 | 31 | 19 | 0 | **3.5** | 1.0 |
| the information was *lower* than expected | 44 | 19 | 31 | 6 | 0 | **4.0** | 1.0 |

#### Laboratory Study:

In the laboratory study, 57% of users claim they continue using the system when the information displayed by the system is higher than what they expected. Meanwhile 43% of users continue using the system although the information is lower than what they expected. 5% of users refuse to continue use the system when the knowledge is higher than expected, and the percentage increases to 19% when the knowledge is lower than expected. The percentages of users who remain neutral are the same in both cases. More users continue using tOLMlets if the information is higher than expected (*M*=3.7, *SD*=0.8) compared to when the information is lower (*M*=3.4, *SD*=0.9). This difference is significant ($t$=2.21, $p$<.05).

## Deployed Study:

In the deployed study, there is higher percentage of users who continue using the system when the information is below expectation than when it shows higher information than expected. However 19% of users will not use the system when the knowledge shown is over expectation, and the percentage decreases to 6% when it is below expectation. Same as in laboratory study, the percentages of users who remain neutral are the same in both cases. However, in this study more users continue using tOLMlets if the information is lower than expected (*M*=3.5, *SD*=1.0) compared to when the information is higher (*M*=4.0, *SD*=1.0). This difference is significant ($t$=1.94, $p$<.05).

Next, we assess users' actions when they find the information in tOLMlets is lower than expected.

#### 6.1.3.3 Actions when information in tOLMlets is lower than expectations

Figure 6.7 shows that users will do something about their learning if the information in tOLMlets is low.

Table 6.7: Actions when information in tOLMlets is lower than expectations (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | **5** | **4** | **3** | **2** | **1** | **Mean** | **SD** |
| **Laboratory study (N=42)** | | | | | | | |
| *If tOLMlets information is lower than expected:* | | | | | | | |
| search for new information | 40 | 38 | 19 | 2 | 0 | **4.2** | 0.8 |
| answer more questions to better understand the topics | 29 | 36 | 29 | 7 | 0 | **3.9** | 0.9 |
| answer more questions to get the right answers (but not necessarily to understand the topics) | 7 | 43 | 31 | 5 | 14 | **3.2** | 1.1 |
| talk to friends about the difficulties | 26 | 36 | 33 | 2 | 2 | **3.8** | 0.9 |
| find somebody to help/discuss difficulties using the peer models | 24 | 31 | 38 | 7 | 0 | **3.7** | 0.9 |
| **Deployed study (N=16)** | | | | | | | |
| *If tOLMlets information is lower than expected:* | | | | | | | |
| search for new information | 31 | 44 | 19 | 6 | 0 | **4.0** | 0.9 |
| answer more questions to better understand the topics | 50 | 38 | 6 | 0 | 6 | **4.3** | 1.1 |
| answer more questions to get the right answers (but not necessarily to understand the topics) | 25 | 31 | 19 | 19 | 6 | **3.5** | 1.3 |
| talk to friends about the difficulties | 19 | 44 | 13 | 13 | 13 | **3.4** | 1.4 |
| find somebody to help/discuss difficulties using the peer models | 19 | 31 | 25 | 13 | 13 | **3.2** | 1.3 |

## Laboratory Study:

For the five options provided in the questionnaires, the majority of users in the laboratory study choose to search for new relevant information outside the system (e.g. through the library, internet). 65% of users will answer more questions in tOLMlets to get a better understanding about the topic. There are also users who answer more questions in tOLMlets in order to get the right answer. In addition, users will also discuss the difficulties they face with friends (62%), and 55% look for help by using the peer models available in the system.

## Deployed Study:

Meanwhile in the deployed study, the majority choose to answer more questions in tOLMlets to get a better understanding about the topic. This is followed by 75% of users seeking new relevant information outside the system. Finding somebody to help for the difficulties using peer models is the last action taken when information was lower than expected with only 44% of users choosing to do so.

Comparison of using peer models to discuss difficulties in the deployed study ($M$=3.2, $SD$=1.3) and in the laboratory study ($M$=3.7, $SD$=0.9) reveal a significant differences between the groups ($t$=1.72, $p<.05$). This is possibly due to the different levels of groups in the study. Users in laboratory study are master students that only take a year to complete their programs of study. Therefore, they may find that using peer models is a better option to discuss their difficulties because of the limitation in knowing their friends more closely. Meanwhile, users in the deployed study are undergraduate students where they know each other better because their period of study is longer than those in the master programs. Therefore they may prefer to discuss their difficulties face-to-face instead of using peer models.

#### 6.1.3.4 Users' definition of trust in OLM

Users were also asked to give a brief description of what trust in OLM means to them. Responses obtained are as follows:

Table 6.8: Users' definitions of trust in OLM

| **Laboratory study:** |
|---|
| ▪ *The system knows accurately how much I know, system gives the correct answers and does not mislead me*<br>▪ *How willing I am to act on the feedback from the system. For example, if I trust the model and misconceptions I am likely to act on it and research those areas to improve my learner model*<br>▪ *Trust means that the system correctly measures my learner model and has a correct domain model*<br>▪ *Questions the system gives are well related to the topic and the levels the system show can really show how I know about the topic*<br>▪ *Trust would be knowing the content, questions and answers are accurate and the model generated is created using the correct and relevant information gathered about the user* |
| **Deployed study:** |
| ▪ *It means a lot as the more I trust the learner model, the more frequently I would use it. Also I'm more likely to learn more after having trusted the system in the first place*<br>▪ *Trust means that the knowledge is being represented correctly*<br>▪ *How much I can believe and rely on the open learner model*<br>▪ *Confidentiality and privacy in the publication of my test data, and that of others*<br>▪ *Do I think what I'm being told is a correct representation of the truth* |

#### 6.1.3.5 Users' opinion related to the use and trust in tOLMlets

Next, we present users' opinions related to the use and trust in tOLMlets based on several criteria. Table 6.9 shows user opinions in tOLMlets in the laboratory study and deployed study.

Table 6.9: User opinions in tOLMlets (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | **5** | **4** | **3** | **2** | **1** | **Mean** | **SD** |
| **Laboratory study (N=42)** | | | | | | | |
| I trust the information in tOLMlets | 24 | 47 | 24 | 5 | 0 | **3.9** | 0.8 |
| tOLMlets is easy to use | 28 | 60 | 10 | 2 | 0 | **4.1** | 0.7 |
| I know what will happen the next time I use tOLMlets because I understand how it behaves | 36 | 52 | 10 | 2 | 0 | **4.2** | 0.7 |
| I am interested to see my knowledge information in tOLMlets | 38 | 26 | 28 | 7 | 0 | **4.0** | 1.0 |
| I like using tOLMlets in my learning | 26 | 38 | 33 | 2 | 0 | **3.9** | 0.8 |
| I understood the information given by tOLMlets | 41 | 52 | 5 | 2 | 0 | **4.3** | 0.7 |
| The information in my learner model is accurate | 33 | 60 | 7 | 0 | 0 | **4.3** | 0.6 |
| **Deployed study (N=16)** | | | | | | | |
| I trust the information in tOLMlets | 25 | 31 | 38 | 6 | 0 | **3.8** | 0.9 |
| tOLMlets is easy to use | 31 | 38 | 19 | 13 | 0 | **3.9** | 1.0 |
| I know what will happen the next time I use tOLMlets because I understand how it behaves | 56 | 25 | 19 | 0 | 0 | **4.4** | 0.8 |
| I am interested to see my knowledge information in tOLMlets | 63 | 31 | 6 | 0 | 0 | **4.6** | 0.6 |
| I like using tOLMlets in my learning | 38 | 19 | 31 | 6 | 6 | **3.8** | 1.2 |
| I understood the information given by tOLMlets | 63 | 25 | 13 | 0 | 0 | **4.5** | 0.7 |
| The information in my learner model is accurate | 31 | 56 | 13 | 0 | 0 | **4.2** | 0.7 |

## Laboratory Study

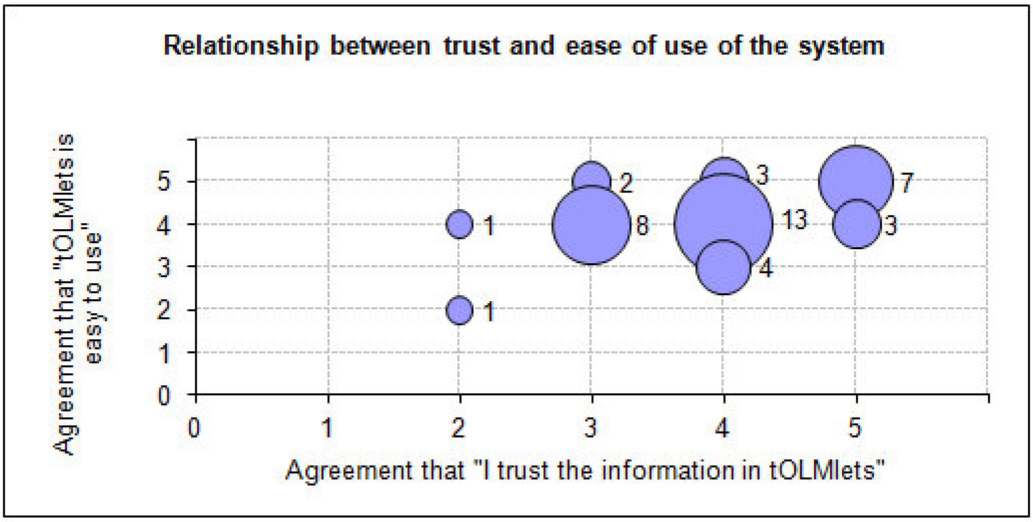
Table 6.9 clearly shows that the majority of users trust the information in tOLMlets. The majority of users also find that tOLMlets is easy to use and claim that they understand how the system behaves (*M*=4.2, *SD*=0.7). More than half of the users are interested to see their knowledge information in tOLMlets and like to use tOLMlets in their learning. In terms of the learner model, majority of the users claim that they understood the information (*M*=4.3, *SD*=0.7) and perceive the learner model is accurate (*M*=4.3, *SD*=0.6). In overall, users in laboratory study showed a very positive response about their opinions on tOLMlets.

## Deployed Study

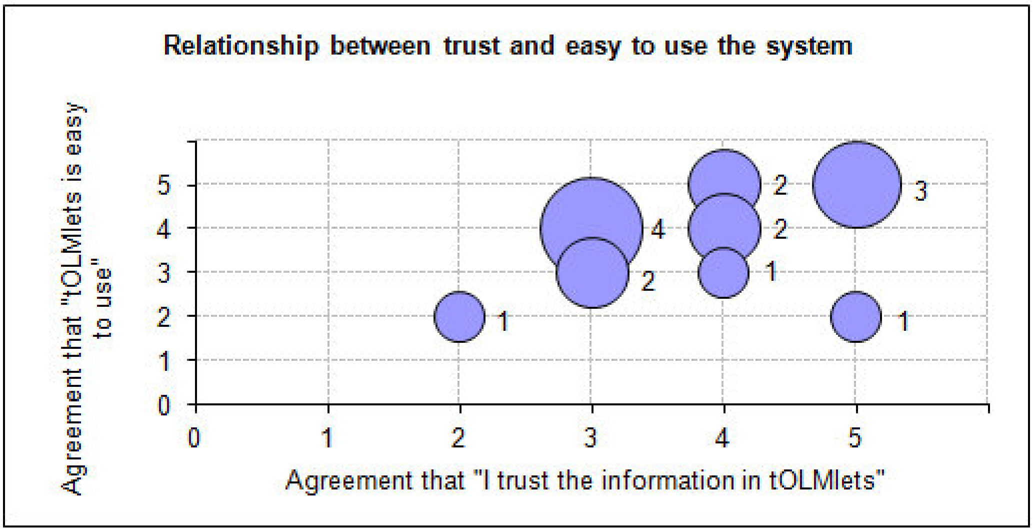
Meanwhile, for deployed study, more than half of users trust the information while 38% remain neutral, and 6% do not trust the information. 69% of users find that tOLMlets is easy to use and 94% claim they understand how the system behaves. The majority of users are interested to see their knowledge information in tOLMlets (*M*=4.6, *SD*=0.6) but only more than half of them like to use the system in their learning (*M*=3.8, *SD*=1.2). In terms of the model presented, a lower percentage is obtained compared to the percentage in the laboratory study. 88% claims that they understood the information and 87% perceive the learner model is accurate.

In order to consider patterns between the questionnaire items, we assess the relationship between trust and each criteria is listed in Table 6.9.

The relationship between trust and ease of use of the system for laboratory and deployed study is shown in Figure 6.1. There are relationship between trust and ease of use of the system for both settings. For laboratory study, 26 users agree (rated 4 and 5) that tOLMlets is easy to use and trust the system. Four users remain neutral with the ease of use of the system but trust the information provided. There is a significant correlation of 0.4 ($p$<.05) between trust and ease of use of the system in laboratory setting. Meanwhile for deployed study, 7 users agree tOLMlets is easy to use and trust the system. 4 users find tOLMlets is easy to use but remain neutral with trust on the system. There is a not significant correlation of 0.5 ($p$>.05) between trust and ease of use of the system in the deployed study.

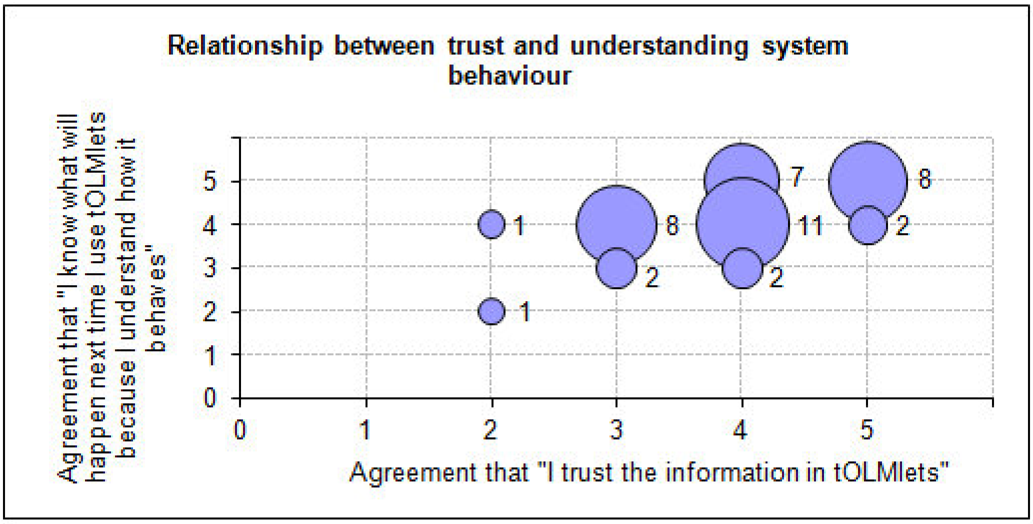



(a) Laboratory: Pearson Correlation = 0.4; p-value = 0.01

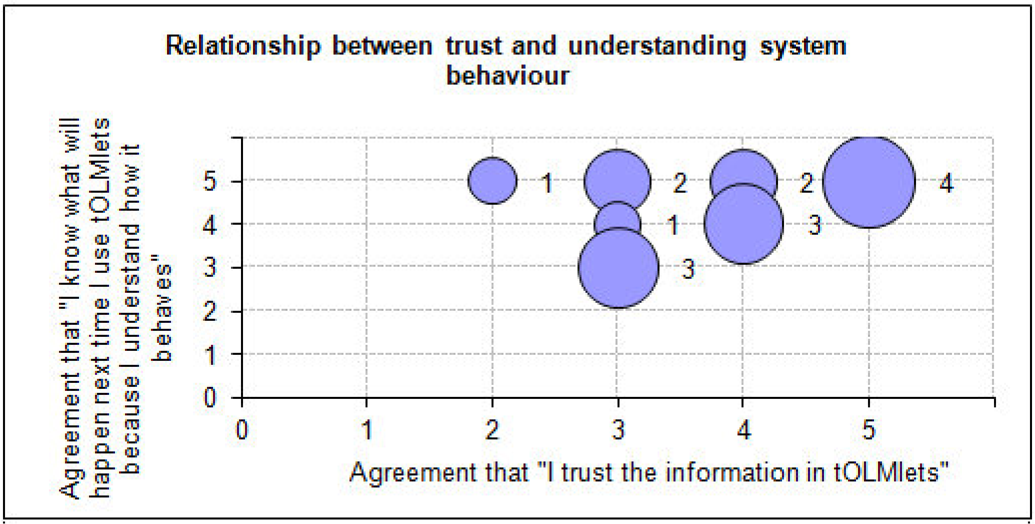



(b) Deployed: Pearson Correlation = 0.5; p-value = 0.07

Figure 6.1: Relationship between trust and ease of use of tOLMlets.
(In this and subsequent 'bubble-plot' figures, the bubble size reflects the number of participants providing the assessment-answer pair located at the centre of the bubble).



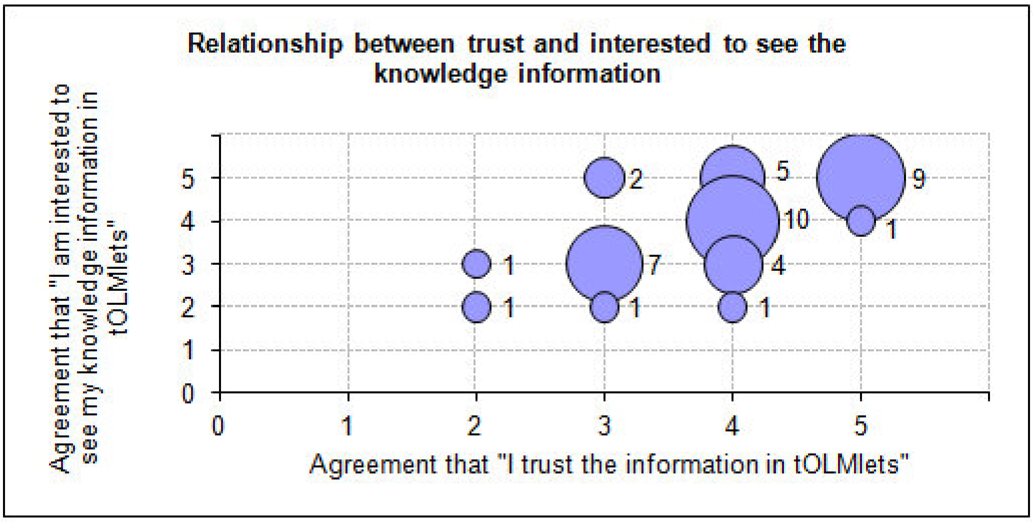

(a) Laboratory: Pearson Correlation = 0.6; p-value = 0.00



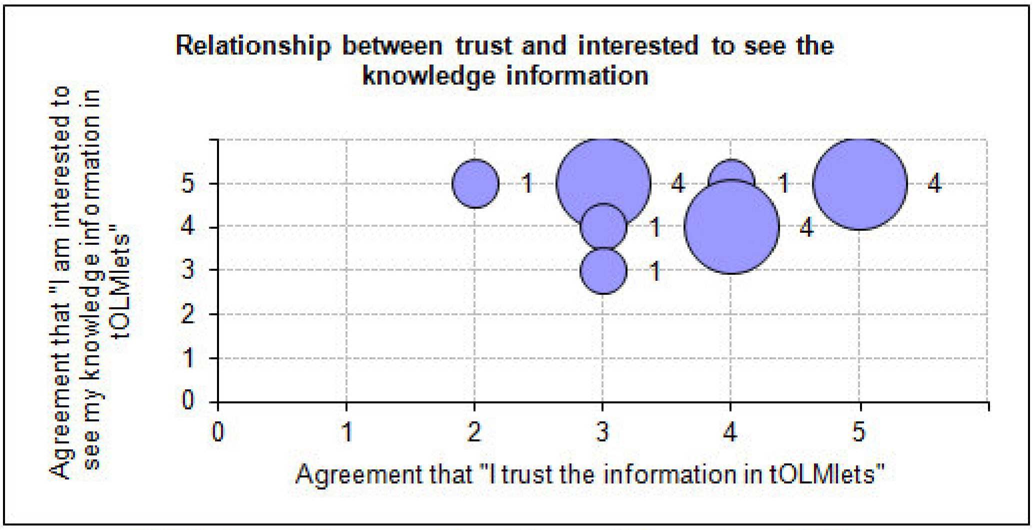

(b) Deployed: Pearson Correlation = 0.4; p-value = 0.12

Figure 6.2: Relationship between trust and understanding the system behaviour

Figure 6.2 shows the relationship between trust and understanding the system behaviour. For laboratory study, 28 users agree that they understood tOLMlets behaviour, and for deployed study 9 users claimed that they understood how the system behaves. There is a significant positive relationship (*correlation*=0.6; $p<.05$) between trust and understanding the system behaviour in laboratory study. Meanwhile, in the deployed study, there is a not significant positive relationship (*correlation*=0.4; $p>.05$) between trust and understanding the system behaviour.




(a) Laboratory: Pearson Correlation = 0.7; p-value = 0.00

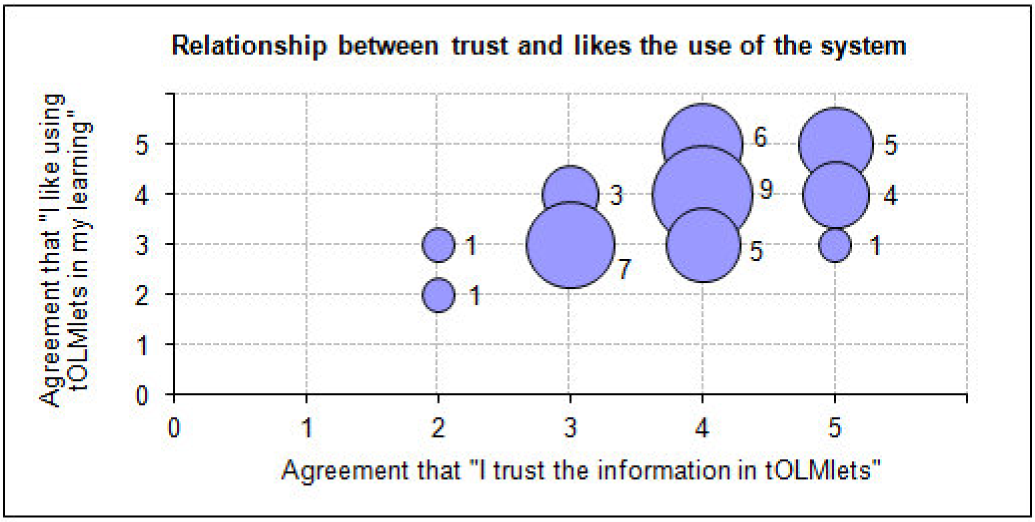



(b) Deployed: Pearson Correlation = 0.1; p-value = 0.15

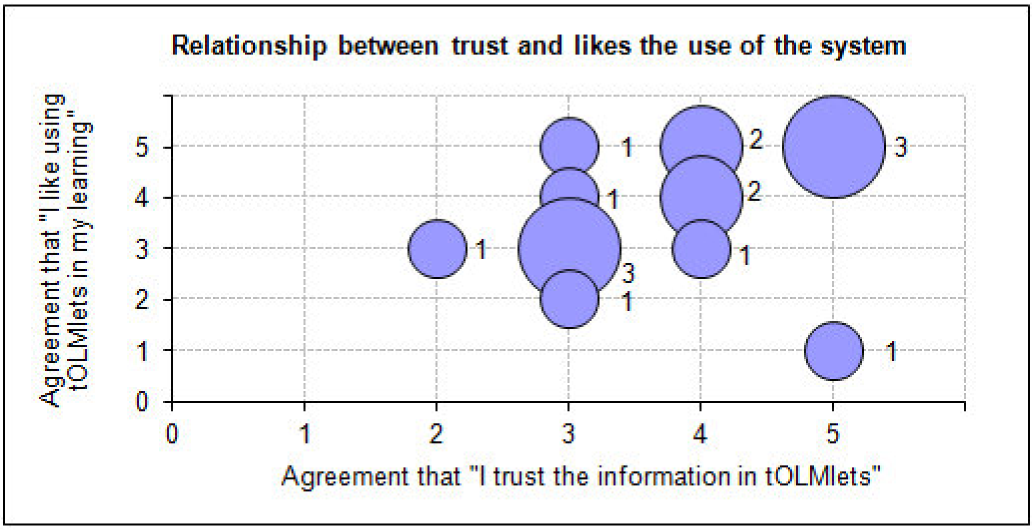
Figure 6.3: Relationship between trust and interest to see the knowledge information in tOLMlets

Figure 6.3 shows that in laboratory study trust has a strong and significant relationship with user interest in viewing the knowledge in open learner models (*correlation*=0.7; $p$<.05). 25 individuals agree that they trust and interest to see their knowledge in tOLMlets while 4 learners trust in the information but remain neutral whether they are interested to see the information or not. 7 learners chose to be neutral for both items. In contrast to the laboratory study, results in deployed study show a positive but very weak and not significant relationship (*correlation*=0.1; $p$>.05) between the two items.

In the lab study, results show that trust has a strong and significant relationship with users liking to use the system in their learning (*correlation*=0.6; $p$<.05) (Figure 6.4). 24 users claim they like using tOLMlets and trust the information. 6 users trust the information in tOLMlets but remain neutral whether they like using the system or not. In deployed study, there is a positive but not significant relationship between trust and users liking using the system in their learning (*correlation*=0.4; $p$>.05).

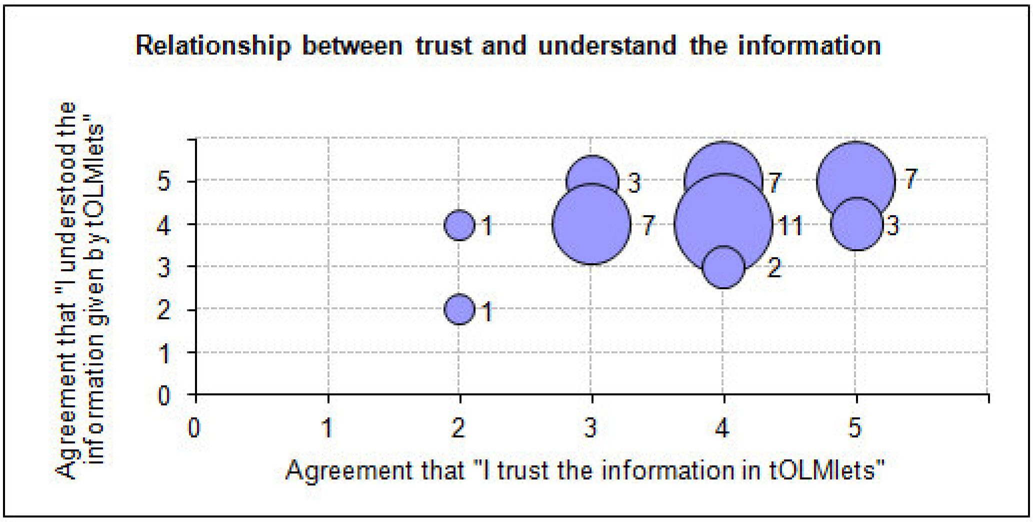



(a) Laboratory: Pearson Correlation = 0.6; p-value = 0.00

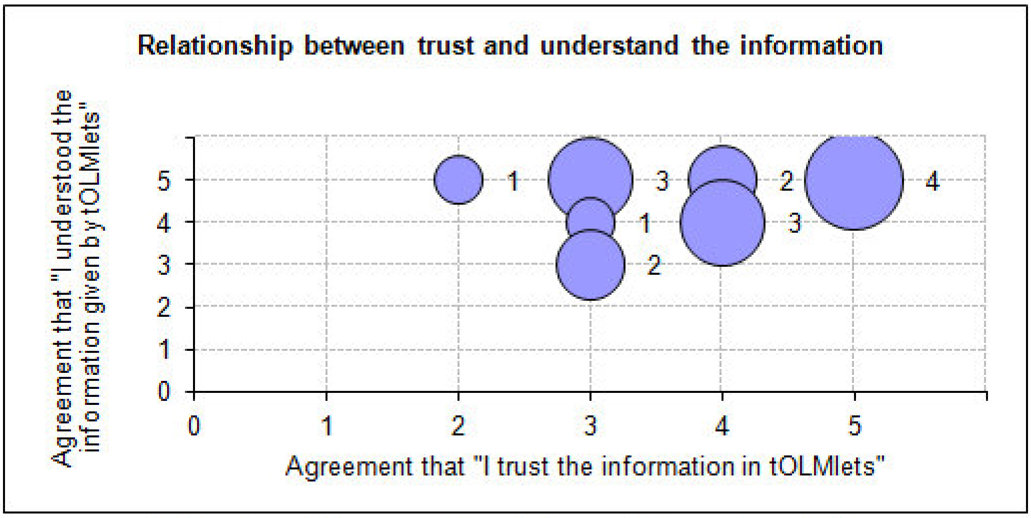



(b) Deployed: Pearson Correlation = 0.4; p-value = 0.12

Figure 6.4: Relationship between trust and like to use tOLMlets



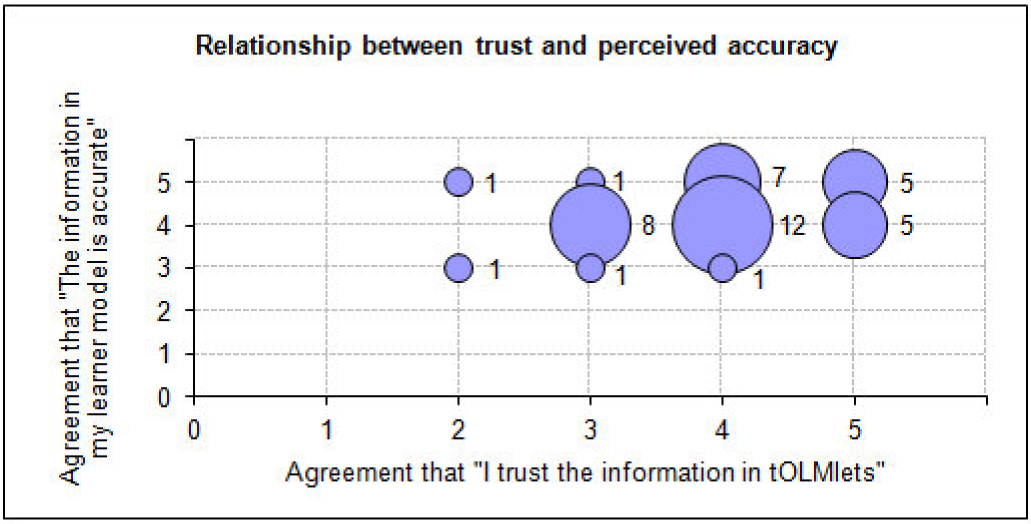

(a) Laboratory: Pearson Correlation = 0.4; p-value = 0.01



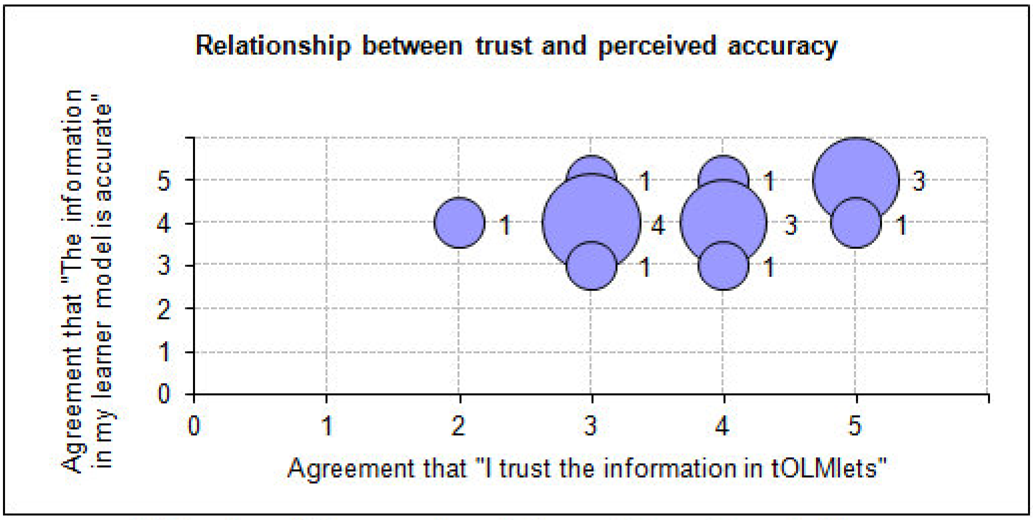

(b) Deployed: Pearson Correlation = 0.4; p-value = 0.12

Figure 6.5: Relationship between trust and understanding information displayed in OLM

Results also show that trust has a positive relationship with an understanding of the information displayed in OLM for both studies (see Figure 6.5). In laboratory study, 28 out of 42 users agree that they trust tOLMlets and understand the information given by the system. While in the deployed study, 9 out of 16 users trust and understand the tOLMlets information. Both studies show the same correlation which is 0.4, however there is a significant correlation in the laboratory study (*correlation*=0.4; *p*<.05) and a not significant correlation in the deployed study (*correlation*=0.4; *p*>.05).




(a) Laboratory: Pearson Correlation = 0.3; p-value = 0.02




(b) Deployed: Pearson Correlation = 0.4; p-value = 0.11

Figure 6.6: Relationship between trust and perceived accuracy of information displayed in OLM

Figure 6.6 depicts the relationship between trust and perceived accuracy of the model. In laboratory study, 29 out of 42 users agree that they trust tOLMlets and perceive the information in the learner model as accurate. Meanwhile, 10 users perceive their learner model is accurate but one user did not trust the information and 9 are neutral about it. In deployed study, half of the users agree that they trust tOLMlets and perceive the information in the learner model as accurate. 6 users perceive their learner model is accurate but one user did not trust the information and the rest remain neutral in trusting the information. Both settings show a positive correlation of 0.4, however there is a significant relationship in laboratory study ($p<.05$) and not significant relationship in the deployed study ($p>.05$). Next is the discussion of the results obtained.

## 6.2 Discussions

In terms of acceptance of the system's inferences, both studies show a sufficient level of belief. High and low level of knowledge displayed in the system show an impact on users feeling of attachment to the model, or in more general, on the engagement with the system. In the lab study, more users keep using the system when a higher level of knowledge than expected is displayed by the system. Meanwhile 41% continue using the system when information shown was below expectation. The opposite situation happens in the deployed studies where more users continue to use the system when the information displayed is lower than expected. This indicates a great engagement between users and the system as they continue to use the system in order to obtain a better information/model. In addition, it can be concluded that users in a short-term use of the system (laboratory study) will engage with the system when it shows a high level of information. Meanwhile for a long-term use (deployed study), more users will engage with the system when the information shown is below expectations. Here we may suggest that there is a different way of how users develop trust in open learner models in the short-term and the long-term of use of the system.

At the end of the questionnaires, we asked the users to provide the definitions of trust in OLM. The definitions obtained are similar with ours. Trust is related to the accuracy of the model presented, the willingness to accept system inferences and rely on it, and the willingness to act based on the system feedback about the learning. Users also claim that they were likely to have more trust in the first place.

The relationship between trust and several criteria assessed shows a positive relationship in both studies. One of the criteria is a perceived ease of use which is required for trust in internet activity (Gefen et al., 2003). In studying trust in open learner models, a perceived ease of use of the system shows a positive relationship to trust the information in the system. The result obtained in the lab study is slightly less than in the deployed system. This may be due to the duration of use of the system that may slightly affect the relationship between trust and ease of use of the system

Jameson (2007) suggested that users can predict the system's adaptive behaviour based on their actions in the environment. The duration of use of the system may also affect the level of trust as they understand how the system behaves. Trust in lab study has a strong relationship with the users' understanding of how the system behaves. However, in the deployed studies trust has only a weak relationship. This means that in the short term of usage, users may not realise how the model is being calculated and they think that they really understand the system behaviour. While in deployed study, users may realise how the calculation is done and they have more understanding of how the system behaves, as well as could predict them as suggested by Jameson (2007).

In the laboratory study, users' interests to see the knowledge information in the system shows a strong relationship with user trust. The same figure is obtained in the relationship between trust and users who like the use of the system, however, the short period of use affects the correlation in the relationship. Both studies show that trust has a positive relationship with the understanding in the information displayed in the system. This is in line with the purpose of opening the model in open learner model, which is to let users to inspect, understand the importance of information presented, and have a relationship with user trust. In terms of perceived accuracy of the learner model, results in deployed study shows a sufficient relationship with trust. This may be due to the use of a longer lead where learners are more aware of the accuracy of the information.

## 6.3 Conclusions

Back to the three keys investigated:

- *The extent to which learners trust (and accept) the OLM system on their first use.*

  Most learners in their first use of the system, have sufficient trust (and accept) the information inferred by the system. This is clearly shown especially when they are uncertain about their knowledge in the laboratory study.

- *The extent to which learners continue using the OLM optionally after their initial use.*

  Learners continue using the open learner models because it helps them in their learning. Although some of them do not trust the system, they continue using the system to know their level of knowledge evaluated by the system. However, giving some rewards based on the final model might influence student to continue use the system, especially in deployed study.

- *The extent to which learners trust (and accept) the OLM after longer term of use.*

Most learners in the longer term of use of the system have a sufficient trust in OLM. Even though trust is slightly lower compared to short term of use, most learners trust and accept the information in OLM.

- *The relationship between learner trust and several criteria that may influence trust in OLM*

  The relationship between trust and several criteria assessed shows a positive relationship in both studies.

In the next chapter, we will consider user trust with each feature provided in the open learner models.

# Chapter 7

# EVALUATION: USER TRUST IN OLM FEATURES

As described in Chapter 3, OLMs have various features including the complexity of the model presentation, the learner control over the model contents, and the facility to view peer models and release one's own model for peer viewing. This chapter describes the evaluations of each feature mentioned above. The chapter starts with the evaluation of user trust in the presentation of learner models in Section 7.1, followed by users trust in the learner control over the learner model in Section 7.2. Section 7.3 describes the evaluation of user trust in viewing peer's model and releasing their own model. The chapter ends with the conclusion of the finding in each section.

## 7.1 User Trust in Externalisation of Learner Models

Externalisation of the learner model may play an important role in the likely uptake of open learner models (OLMs), as students must to some extent understand the model externalisations in order to use them effectively. In

Chapter 3, we describe a variety of externalisation of learner models available in OLMs. In this section, we describe a study to investigate user trust in externalisation of open learner models that we categorised as simple and structured views. Using tOLMlets, we investigate learner consultations of the model views and their level of trust in each view. In this study, our key questions is whether learners may trust open learner model externalisations and identify certain features that make learner model presentation more 'trustable'. We hypothesized that user trust in externalisation of learner models. Our key questions are:

- *Do learners understand and trust OLM externalisation?*
- *Do learners trust simple or more structured view?*
- *Are there any features that makes OLMs view more trustable?*

### 7.1.1 Participants, Materials, Methods

Participants were 42 students from the University of Birmingham in Electronic, Electrical and Computer Engineering Department. These were the same participants as described in Section 6.1.1.1. Therefore, the same material and methods were used. Results reported in the next section are only for the laboratory study because we have similar data for the deployed study, and the results were very similar but for a smaller number of users.

### 7.1.2 Results

In this section we present the logs data of students' interactions with tOLMlets, and the questionnaires related to use and trust in externalisation of the learner model.

#### 7.1.2.1 Logs Data

The logs data in Section 6.1.2.1 are also applied here. Apart from logs data in Table 6.1, Table 6.2 and Table 6.3, the usage of each view in the system is presented in Table 7.1.

Table 7.1: Usage of each view

| Views | Total Inspections | Mean | SD | Range |
|---|---|---|---|---|
| Skill meter | 2047 | 49 | 25.6 | 12 - 101 |
| Structured | 397 | 10 | 6.4 | 0 - 25 |

All users inspect their learner model using the skill meter view, with a minimum of 12 inspections. However there are users who do not use the structured view to examine their learner model. A total inspections for skill meter is 2047 while for structured view is 397. Table 7.1 also shows the average number of inspections made of each view. The skill meter was viewed the most with a mean of 49 times per user (*SD*=25.6) followed by structured with a mean of 10 times per user (*SD*=6.4).

### 7.1.2.2 Questionnaires Results

Table 7.2 depicts user responses on the usefulness of each view in relation to four tasks: identifying knowledge, identifying areas of difficulty, identifying misconceptions (where defined) and identifying what to study next.

Table 7.2: Usefulness of each view (in percentage)

| *Views:* | Identify knowledge | Identify difficulties | Identify misconceptions | Identify next topic to be learned |
|---|---|---|---|---|
| Skill meter | 81 | 62 | 69 | 71 |
| Structured | 62 | 57 | 52 | 64 |

The majority of users find that all views are useful in terms of identifying the knowledge, areas of difficulty, misconceptions and which topic to study next. The skill meter shows the highest percentage in all four tasks with 81% of users finding it useful to identify knowledge (rated 4 and 5), 62% of users finding it useful to identify difficulties, 69% of users finding it useful to identify misconceptions and 71% of users finding it useful to identify next topics to be learned. Among four tasks assessed, the skill meter is very useful to identify knowledge (with 81% of users agree on this), while structured view is very useful to identify topics to be learned next. The skill meter is found more useful in identifying the knowledge (significant $t$=3.52, $p$<.05) and the misconception (significant $t$=2.71, $p$<.05) compared to structured view. No significant differences were found in the other two tasks (identifying difficulties and identify next topic to be learned) between the skill meter and structured view.

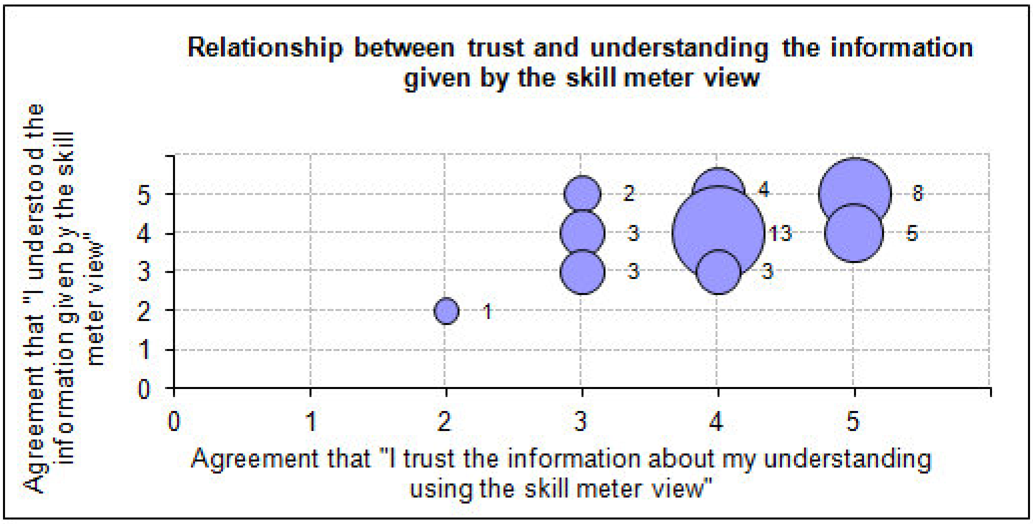
Next, we present user opinions regarding trust, understanding and accuracy of the learner model externalisation in Table 7.3. Results shows similar mean response between the skill meter and structured view. Most of the users claim to understand the information given by the skill meter, with a mean of 4.1 (*SD*=0.8). Meanwhile, in the structured view, the percentage of users that claim they understand the information given by the skill meter is slightly less (67%), with a mean of 4.1 (*SD*=0.9). 29% of the users are neutral about their understanding using the structured view while 5% of the users claim they do not understand the externalisation. In terms of accuracy, 76% of the users think that the information in the skill meter and structured view is accurate. There is no user who disagree that the structured view is not accurate. For trusting the information, more than half of the users trust the information in both views (79% in the skill meter and 74% in the structured view). For each criteria accessed, there is no significant differences between the skill meter and structured view.

Table 7.3: User opinions on understanding, perceived accuracy and trust of the learner model presentations (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
| I understood the information given by: | | | | | | | |
| the *skill meter* view | 33 | 50 | 14 | 2 | 0 | **4.1** | 0.8 |
| the *structured* view | 29 | 38 | 29 | 5 | 0 | **3.9** | 0.9 |
| The information in my learner model is accurate in: | | | | | | | |
| the *skill meter* view | 19 | 57 | 21 | 2 | 0 | **3.9** | 0.7 |
| the *structured* view | 21 | 55 | 24 | 0 | 0 | **4.0** | 0.7 |
| I trust the information in tOLMlets about my understanding using: | | | | | | | |
| the *skill meter* view | 31 | 48 | 19 | 2 | 0 | **4.1** | 0.8 |
| the *structured* view | 26 | 48 | 16 | 10 | 0 | **3.9** | 0.9 |

For each externalisation, we consider the relationship between trust and understanding, and between trust and perceived accuracy of the models.

In Figure 7.1, 30 users agree (rated 4 & 5) that they trust the information using skill meter and understand the information given by the skill meter. Trust in the skill meter is significantly correlated with the level of users understanding of the learner model (*correlation*=0.5, *p*<.05).




Pearson Correlation = 0.5; p-value = 0.00

Figure 7.1: Relationship between trust and understanding of information by using the skill meter view.

For the structured view (shown in Figure 7.2), 23 users claim to understand the information displayed and trust it. There are 8 users who trust the information using the structured view but remain neutral on whether they understand the information given. There is a significant correlation between understanding and trust in information displayed using structured view (*correlation*=0.4, $p<.05$). In the structured view, the number of users who trust the information but remain neutral or disagree with the understanding of view is more than those who understood the information but neutral or distrust the information.

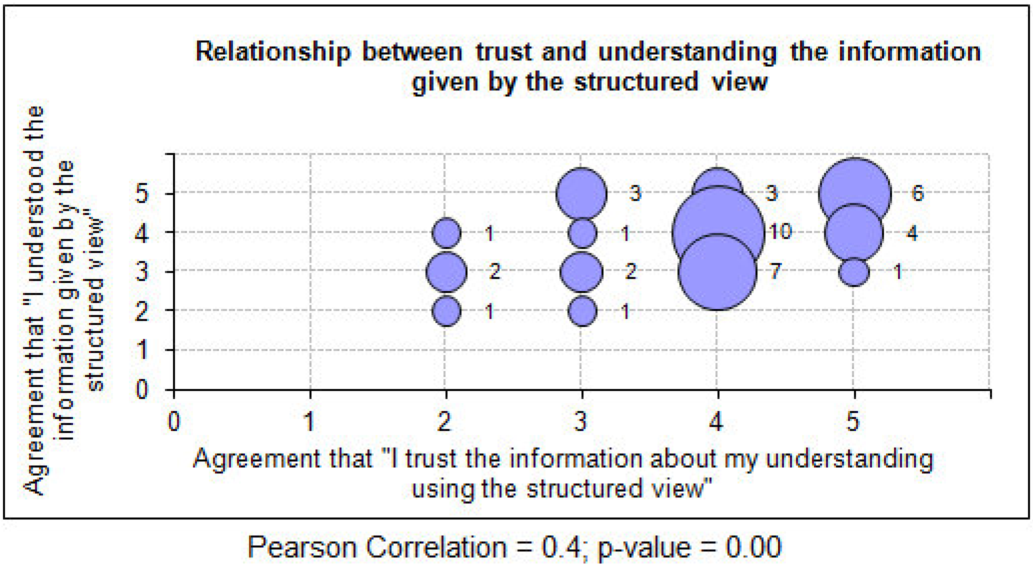
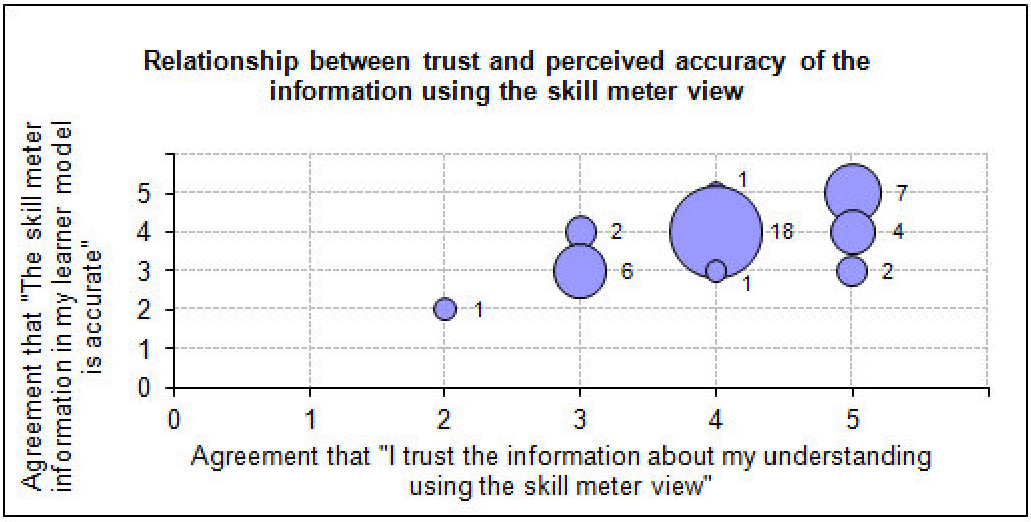


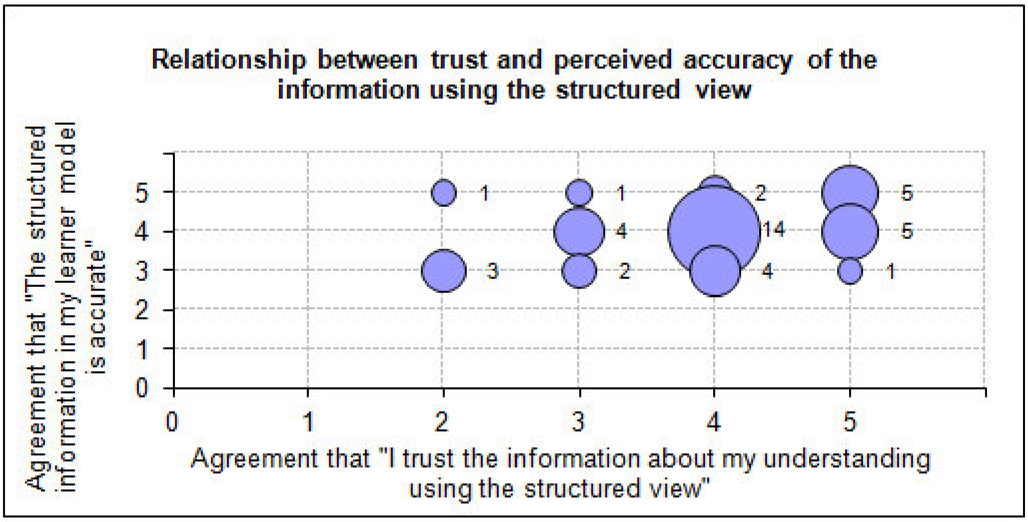

Figure 7.2: Relationship between trust and understanding of information by using the structured view.

In terms of the relationship between perceived accuracy and trust in the information displayed, all views show a positive relationship. Trust in the skill meter has a strong relationship with perceived accuracy of the model with a correlation value of 0.7 ($p$<.05). This is shown in Figure 7.3. 30 students perceived that skill meter shows accurate information and they trust the information displayed.




Pearson Correlation = 0.7; p-value = 0.00

Figure 7.3: Relationship between trust and perceived accuracy of the information using the skill meter view.




Pearson Correlation = 0.4; p-value = 0.02

Figure 7.4: Relationship between trust and understanding of information by using the structured view.

While trust in skill meter is correlated with understanding and perceived accuracy of the presented information, this is also the case for the structured view. In Figure 7.4, 26 users perceive the information about their understanding using the structured view is accurate and also trust the information. Trust is significantly correlated with the accuracy of the learner model presented by structured view with the correlation value of 0.4 ($p<.05$). The discussion of the result obtained is in the following section.

### 7.1.3 Discussion

In this study, learners generally get the benefit through the use of the learner model views available in the system. All views are useful to identify knowledge, difficulties, possible misconceptions and the next topic to be learned. Among the four tasks assessed, learners find structured view is very useful to identify a topic for the next learning. This maybe because the view is arranged based on the relationships between concepts in the subject. The relationships between topics are clearly shown in the structured view and thus help the learners to identify the next topics to be learned.

Learners claim to generally understand the information in the simple view and structured view. As learners have different preferences for model presentations (Mabbott & Bull, 2006), the number of usages for each view is different. However, there is no significant difference that can confirm that the students understand the information in simple view compared to structured view. The availability of simple and structured views in a single system may help learners to easily compare their understanding in both presentations. Meanwhile, a low percentage of learners claim that they understand the information in the structured view. Perhaps learners are having difficulty with the concept in the subject, and thus affect their understanding when viewing the information using the structured view. However, the number of learners who trust in the information although they disagree or are neutral with regards to understanding of the view is more than in the simple views.

In terms of accuracy, learners believed that both simple and structured views were accurate. However the strength of the relationship is different from one to another. The perceived accuracy of the skill meter view has a very strong relationship with learner trust in the view with a correlation of 0.7 ($p<.05$), while the relationship with the structured view is slightly weak with a correlation of 0.4 ($p<.05$).

Our evidence also proves that both simple and structured views contribute to trust in OLM system. Therefore, we propose that the use of various externalisations of the learner model not only complement each other in presenting a model (e.g Perez-Marin, 2007; VanLabeke et al., 2007) or as an alternative view in the system (e.g Mabbott & Bull, 2006; Johnson & Bull, 2009; Xu & Bull, 2010), but it also contributes to trust in the OLM system.

In the next section we will describe the evaluation of trust in learner control over the learner model.

## 7.2 User Trust in Learner Control over the Learner Model

Learner control is an important aspect of the OLM environments in order to develop more accurate learner model. It has been explained that there are many types of learner control in the OLM including cooperatives, add-evidence, challenge the model and negotiation with system about the model inferred. In this study we hypothesized that users will trust the control they get over the learner model.

Our key investigations are:

- *Do learners use and trust the edit function in OLM?*
- *Do learners use and trust the persuade function in OLM?*

### 7.2.1 Participants, Materials, Methods

In this study, participants were from two different groups of MSc. students from the School of Electronic, Electrical & Computer Engineering, University of Birmingham, UK. All participated during one of the laboratory session for a course called ‘User Model and Models of Human Performance’. Participants in Group A consist of 29 students and they were using the version of editable tOLMlets. Meanwhile, participants in Group B consist of 18 students and they were using the version of tOLMlets that allows the persuasion function.

Students were instructed to answer questions about topics available in tOLMlets to review their understanding of the course content, explore the learner model views, and use features of editing (for Group A) and persuading (for Group B) the model when they think necessary. The final model obtained by the students does not contribute to the course marks. Interaction with the system lasted around one and a half hours, including completion of a post-use questionnaire (Appendix: Questionnaire3. Responses were given on a five point scale (strongly agree, agree, neutral, disagree, strongly disagree).

## 7.2.2 Results

In this section we present the log data of user interactions with tOLMlets, and the questionnaires related to use and trust in learner control over the learner model.

### 7.2.2.1 Log Data

#### Edit

Table 7.4 shows the number of edits performed by the users in Group A. A total of 120 edits logged by the system. The maximum number of edits made by the user is 16 times. 23 users edit the information equal or less than six times, and 3 users edit the information between seven to eight times.

Table 7.4: Number of edits

| | 1 - 2 | 3 - 4 | 5 - 6 | 7 - 8 | 9 - 10 | > 10 |
|---|---|---|---|---|---|---|
| Number of students | 9 | 8 | 6 | 3 | 1 | 2 |

Table 7.5: Edit Level – current knowledge and the new level

| Current level | New level | | | | |
|---|---|---|---|---|---|
| | Very high | High | OK | Low | Very Low |
| Very high | - | 5 | | | |
| High | 15 | - | 4 | | |
| OK | 13 | 21 | - | 3 | |
| Low | 12 | 11 | 6 | - | |
| Very low | 4 | 9 | 6 | 3 | - |
| Blank | | 4 | 4 | | |

Table 7.5 shows the mapping between the current knowledge levels that users had and the new level after the editing. Most of the editing performed is to improve the knowledge level, or in other words to a higher level from the existing knowledge. The highest number of edit was made from level 'OK' to level 'High' which is 21 times, followed by edit from level 'High' to level 'Very High' which is 15 times. There is also a situation where users edit their model to a lower level from what is inferred by the system. Some users also edit from the

topic with a blank model (user not even attempt any question yet from the topic).

## Persuade

Table 7.6 shows the number of persuasion performed by the users in Group B. A total of 58 attempts of persuasion have been logged in the system. The maximum number of persuasion made by the user is 7 times. 17 users persuade the information equal or less than five times, and only 1 user persuade more than five times.

Table 7.6: Number of persuasion

| | **1** | **2** | **3** | **4** | **5** | **> 5** |
|---|---|---|---|---|---|---|
| Number of students | 2 | 5 | 4 | 4 | 2 | 1 |

Table 7.7: Persuasion Level – current knowledge and the proposed level

| **Current level** | **Proposed level** | | | | |
|---|---|---|---|---|---|
| | Very High | High | OK | Low | Very Low |
| Very high | - | 1 | | | |
| High | 8 | - | | | |
| OK | 10 | 7 | - | | |
| Low | 6 | 5 | 3 | - | 1 |
| Very low | 3 | 3 | 2 | 3 | - |
| Blank | | 2 | | 1 | 3 |

Table 7.7 shows the mapping between the current knowledge levels that users had and the proposed level for attempts to persuade. Similar to results in the

editing, most of the persuasion performed is to improve the knowledge level. However, not every persuasion made is successful. Table 7.8 shows the outcomes of attempts to persuade the system. Half of the attempts to change the knowledge level resulted in no change while around a quarter were completely successful.

Table 7.8: Outcome of persuading

| **Outcome (final model)** | **Total** |
|---|---|
| Lower than original | 4 |
| Same as original | 29 |
| Higher than original & lower than proposed | 10 |
| Lower than original & higher than proposed | 0 |
| Same as proposed | 14 |
| Lower than proposed | 1 |

#### 7.2.2.2 Questionnaires Results

##### Edit

Table 7.9 shows user responses related to the edit features in the OLM. In the situation where users believed the information in the system is inaccurate, more users edit the information (*M=3.5, SD=1.1*) compared to when they believed the information is accurate (*M=2.8, SD=1.1*). This difference is significant, *t*=3.91, *p*<.05. However 17% of the users edit the model even though they believed the information presented is accurate. Unfortunately we did not have any qualitative insight from the users because of the time constraints during the study.

Table 7.9: Edit the model when believed information accurate and inaccurate (in percentage)

| | <str. agree … str. disagree> 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
|---|---|---|---|---|---|---|---|
| Edit the information believed accurate | 10 | 7 | 45 | 24 | 14 | **2.8** | 1.1 |
| Edit the information believed inaccurate | 14 | 45 | 21 | 17 | 3 | **3.5** | 1.1 |

Table 7.10 shows the edit function in the situation when users trust or distrust the information. 62% of the users edit the information when they did not trust the model. The number of users who edits the model when they trust the information is relatively small which are only 10% of the users. There is a significant different, $t$=4.51, $p$<.05 between edit the information when users did not trust the model (*M=3.6, SD=1.0*) and when they trust the model (*M=2.4, SD=1.0*).

Table 7.10: Edit the model when trust and distrust the information (in percentage)

| | <str. agree … str. disagree> 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
|---|---|---|---|---|---|---|---|
| Edit the information when trust the model | 0 | 10 | 48 | 17 | 24 | **2.4** | 1.0 |
| Edit the information when did not trust the model | 14 | 48 | 21 | 14 | 3 | **3.6** | 1.0 |

Table 7.11: The usefulness and trust in editing the model (in percentage)

| | <str. agree … str. disagree> 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
|---|---|---|---|---|---|---|---|
| Usefulness | 31 | 28 | 31 | 10 | 0 | **3.8** | 1.0 |
| Trust | 17 | 28 | 31 | 14 | 10 | **3.3** | 1.2 |

Meanwhile in Table 7.11, 59% of the users agree that the edit feature is useful for their learning. 45% of the users trust the edit function in the system. The relationship between usefulness and trust in the editing the model is depicted in Figure 7.5.

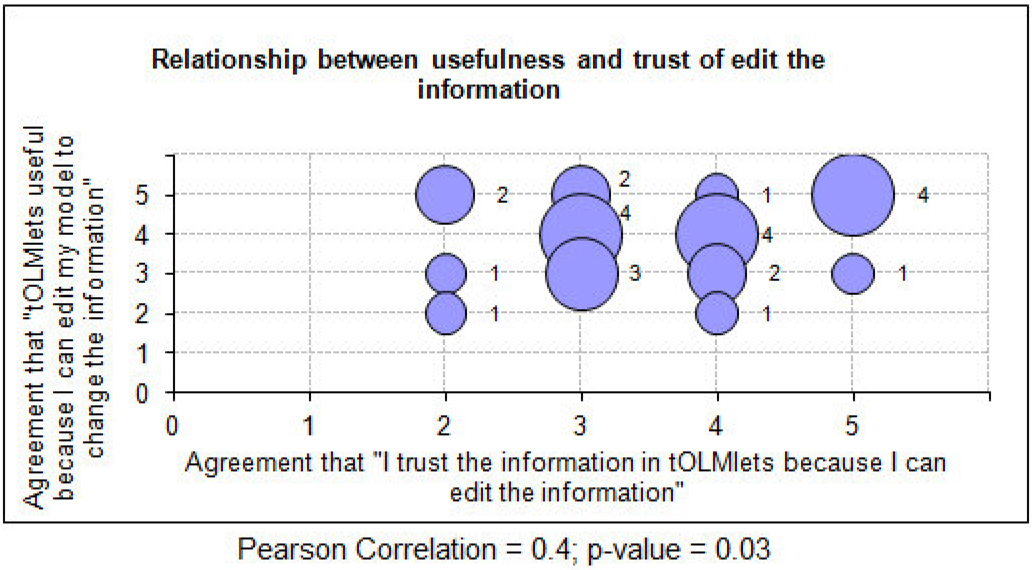



Figure 7.5: Relationship between usefulness and trust in editing the information.

9 users agree (rated 4 and 5) that the edit function in tOLMlets is useful and they trust it. Meanwhile, 8 users agree that the edit function is useful but did not trust the function. The relationship between usefulness and trust the edit function shows a positive significant relationship (*correlation*=0.4, $p<.05$).

## Persuade

For the persuasion function (as shown in Table 7.12) more users tried to persuade the information when they believed the information is inaccurate

(*M*=3.5, *SD*=1.0) compared to when they believed the information is accurate (*M*=2.4, *SD*=1.2), *t*=3.03, *p*<.05). This is similar to results in edit function where more users carry out the editing when they believed the information is inaccurate. Table 7.13 shows that 34% of users tried to persuade the model when they did not trust the information and 17% tried when they trust the information. Comparison of tried to persuade the model when user did not trust the information (*M*=2.9, *SD*=1.1) and when user trust the information (*M*=2.5, SD=1.0) revealed no significant differences between the situations *t*=0.92, *p*>.05.

Table 7.12: Tried to persuade the model when believed information accurate and inaccurate (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
| Tried to persuade the information believed accurate | 6 | 11 | 33 | 22 | 28 | **2.4** | 1.2 |
| Tried to persuade the information believed inaccurate | 22 | 28 | 28 | 22 | 0 | **3.5** | 1.0 |

Table 7.13: Tried to persuade the model when believed information trust and distrust (in percentage)

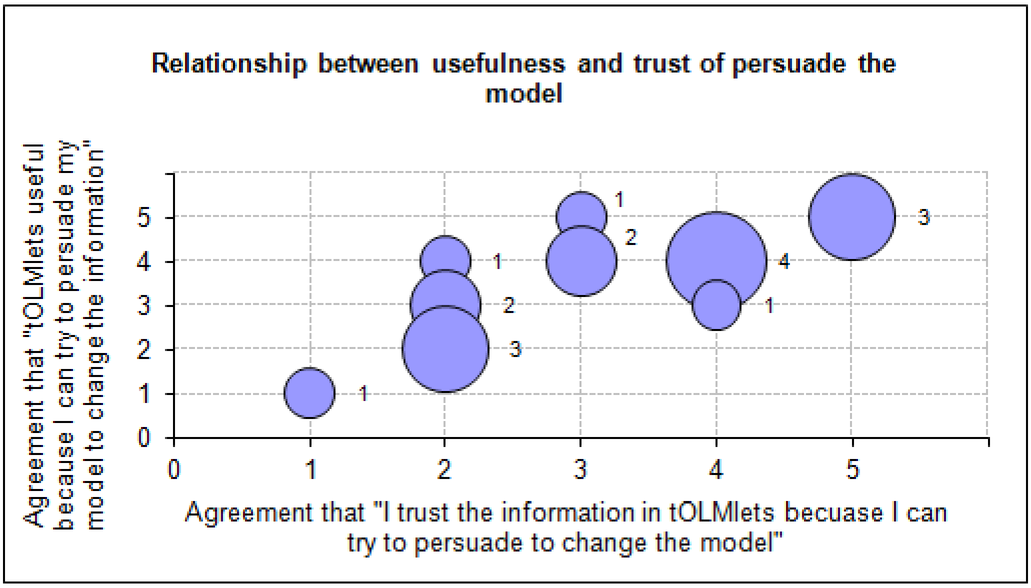
| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
| Tried to persuade the information when trust the model | 6 | 11 | 28 | 39 | 17 | **2.5** | 1.01 |
| Tried to persuade the information when did not trust the model | 6 | 28 | 28 | 28 | 11 | **2.9** | 1.13 |

Table 7.14 shows that 38% of the users agree that the persuasion feature is useful for learning and 27% of the users trust the function.

Table 7.14: Usefulness and trust for feature persuading the model (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
| Usefulness | 14 | 24 | 10 | 10 | 3 | **3.6** | 1.2 |
| Trust | 10 | 17 | 10 | 21 | 3 | **3.2** | 1.3 |

We assess the relationship between usefulness and trust in the persuasion function as shown in Figure 7.6. Results show that there is a strong and significant relationship (correlation=0.8; *p*<.05) between the usefulness and trust of the persuasion function in tOLMlets




Pearson Correlation = 0.8; p-value = 0.00

Figure 7.6: Relationship between usefulness and trust in persuasion.

After trying the persuasion function, the learner model is not necessarily changed to the new level as desired by the users. Table 7.15 shows users trust the persuasion function in certain situations. 61% of the users (rated 4 and 5) trust in the persuasion function if the model is changed to the higher level that is in line with user belief about their knowledge. In the situation when the model is changed to the lower level (in line with user belief), only 45% of the users trust it.

Table 7.15: Users trust the persuasion functions in certain situations (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
| model changed to higher level (in line with belief) | 11 | 50 | 17 | 17 | 6 | **3.4** | 1.1 |
| model changed to lower level (in line with belief) | 6 | 39 | 28 | 22 | 6 | **3.2** | 1.0 |
| model changed to higher level (not in line with belief) | 0 | 11 | 50 | 28 | 11 | **2.6** | 0.9 |
| model changed to lower level (not in line with belief) | 0 | 11 | 44 | 33 | 11 | **2.6** | 0.9 |
| model stayed at the same level | 6 | 22 | 44 | 22 | 6 | **3.0** | 1.0 |

Users seem to trust the persuasion function less if the model is changed to a level that not in line with their belief of knowledge, whether it is a higher or lower level. Meanwhile 28% of the users trust the persuasions function if the model stayed at the same level. The next section is the discussion of the results.

### 7.2.3 Discussion

The feature of learner control in open learner models is to provide a platform that allows learner involved in developing the model. Although providing learners with this feature may affect the accuracy of the model especially if learners provide wrong information, this feature actually help learner to be more responsible to their model, and at some point may affect the degree of learner trust in open learner model systems.

Results obtained in this study show that learners can use the edit and persuade function appropriately. Learners edit the knowledge information when they believed the information in their model was inaccurate. The same situation happened in the persuasion where learners tried to persuade the system to change their model when they believed the information to be inaccurate. However, there are learners who edit or tried to persuade the model when they believed the information is accurate. Although the numbers of learners who did this are not many, their action is surprising.

62% of the learners in Group A edit the model when they did not trust the model inferred by the system. Meanwhile 34% of the learners in Group B tried to persuade the system to change the model. Again, this indicates that learners use the feature appropriately.

In terms of relationship between usefulness and trust, both functions edit and persuade shows a significantly positive relationship. Trust found highly correlated with usefulness of the persuasion feature (*correlation*=0.8; $p<.05$). However, comparison between trust in edit ($M$=3.3, $SD$=1.2) and in persuasion ($M$=3.2, $SD$=1.3) revealed no significant differences $t$=0.29, $p>.05$.

Learners seem to trust the persuasion function when the model changed to a level that in line with their belief. The changes may to the higher level or lower level from the old model.

## 7.3 User Trust in Releasing Own Model and Viewing Peer Models

OLM for others to see is one of the features available in OLM as described in Chapter 3. Viewing peer models and releasing own model for others is a useful feature in OLM because learners can compare their models with peer models, and can support collaborative learning. In this chapter, we describe a study to investigate user trust in viewing peers models and releasing owned model to peers. We hypothesized that user trust in peer model. Our key questions are:

- *Do learners trust the peer model?*
- *Do learners trust the named or anonymous peer model?*

### 7.3.1 Participants, Materials, Methods

Participants were 44 MSc. students from the University of Birmingham in Electronic, Electrical and Computer Engineering Department, who participated in the 'Educational Technology' course. Some students had prior exposure to OLMlets during their undergraduate study. Participants were instructed to use tOLMlets and attempt questions on the subject available in the system. Participants were also asked to consider the features available in tOLMlets including the facility to release owned model to peers and views peer models for comparison. In order to enable peers to see the model, users can release the model with names or anonymous, for all or selected peers. Therefore the peer models that are available to them may be with names or anonymous from the friends who release their models to the user. Participants interacted with the system for about 1.5 hours and all interactions were logged by the system. Then they completed the questionnaires at the end of the session. The questionnaires comprised of statements requiring participants to indicate their level of agreement on a 5-point Likert scale (strongly agree, agree, neutral, disagree, strongly disagree), and a free-response area for users to give opinions (Appendix: Questionnaire4).

### 7.3.2 Results

In this section, we present the results from the system logs and responses from the questionnaires.

### 7.3.2.1 Logs Data

Table 7.16 shows the number of users that login into the system and release their models to be viewed by peers. 30 users open their model to be viewed by peers, and 14 users close their model.

Table 7.16: Number of students who closed and open the model

| | **Closed model** | **Open model** |
|---|---|---|
| Number of students | 14 | 30 |

Table 7.17 gives an idea of how the users release their models to the peers. 15 users fully open their model named, and 7 users partially open with the name, and 3 users with a partial-open unidentified model. 5 users release their models in a combination of full or partial open and name or anonymous model.

Table 7.17: Users released their models

| | Partially open | | Fully open | | Mixed open |
|---|---|---|---|---|---|
| | named | anonymous | named | anonymous | |
| Number of students | 7 | 3 | 15 | 0 | 5 |

Table 7.18: Users interactions with peer models

| | **Closed model** | **Open model** |
|---|---|---|
| Compare the model | 31 | 39 |
| Not compare the model | 13 | 5 |

Figure 7.18 shows the number of users interaction with peer models. 39 users open their models and compare the model with peers. Users who open their models to peers do not necessarily see the peer models that are available for them. Conversely, users who close their models are apparently viewing peer models for comparison. 31 users who close their models do not use the comparison function.

#### 7.3.2.2 Questionnaires Results

Our aim in this study is to explore learner trust in releasing their learner model and viewing peer models in OLM. We divide the questionnaire findings into two sub-sections: (i) releasing model to peers, and (ii) viewing and comparing peers models.

**Releasing Model to Peers**

In this section, we present Likert-rated and free-response questionnaire items related to releasing the model to peers, whether users released the model with names or anonymous in a certain condition. We begin with user opinions regarding how they release the model to peers, as shown in Table 7.19. The majority of users prefer to release the model to everybody ($M$=4.0, $SD$=1.0) compared to peers whom they know well ($M$=2.9, $SD$=1.3). This difference is significant, $t$=3.43, $p$<.05. The same results were found in previous studies in which the majority of students have released their model to everybody (Bull et al., 2007).

Table 7.19: Release the model to peers (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
| Model released to everybody | 34 | 39 | 20 | 7 | 0 | **4.0** | 1.0 |
| Model released to peers that known well | 9 | 30 | 25 | 18 | 18 | **2.9** | 1.3 |

73% of the users release the model to everyone in the group and only 39% release the model to the selected people that they know well. 36% disagree to release the model to the known peers.

Table 7.20: Believed and preferences in opening the model (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
| Believed the information was *accurate* and opened it to peers named | 20 | 50 | 25 | 5 | 0 | **3.9** | 0.8 |
| Believed the information was *accurate* and opened it to peers anonymously | 9 | 27 | 36 | 9 | 18 | **3.0** | 1.2 |
| Believed the information was *inaccurate* and opened it to peers named | 9 | 18 | 39 | 14 | 20 | **2.8** | 1.2 |
| Believed the information was *inaccurate* and opened to peers anonymously | 7 | 20 | 32 | 20 | 20 | **2.7** | 1.2 |

Table 7.20 shows that most users open their models to peers when they believed the information in tOLMlets was accurate. 70% release the model with names while 36% release the model anonymously. Some users release the model to peers though they believed the information was inaccurate. However, the percentage who did this is small. Most users remain neutral or disagree in this matter. Similar results were obtained when users trust or distrust their

models (as shown in Table 7.21). The majority open the model to peers with names when they trust the model and most of them remain neutral or disagree to open the model if they did not trust the model.

Table 7.21: Trust and release the model to peers (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
| Trust the model and release to peers named | 30 | 39 | 23 | 2 | 7 | **3.8** | 1.1 |
| Trust the model and release to peers anonymously | 14 | 34 | 30 | 11 | 11 | **3.3** | 1.2 |
| Did not trust the model and release to peers named | 3 | 28 | 36 | 28 | 15 | **2.7** | 1.1 |
| Did not trust the model and release to peers anonymously | 8 | 23 | 28 | 28 | 13 | **2.9** | 1.1 |

User opinions of why they release their models to everybody or selected peers shown in Table 7.22.

Table 7.22: Opinions on releasing the model to everybody or selected peers

| **Released model to everybody:** |
|---|
| ▪ *I don't care what they think of my model, I want to encourage them to release their models for comparison*<br>▪ *I find no reason to discriminate somebody*<br>▪ *No peers are special so why release model to specific people*<br>▪ *Because it doesn't matter who see my model*<br>▪ *I thought it was the nice thing to do*<br>▪ *I think all learners must have the same opportunities*<br>▪ *I don't care if people I don't know have access to my model* |
| **Released model to peers that known well:** |
| ▪ *Because I know the peers*<br>▪ *They may help me with what I have misconceptions* |

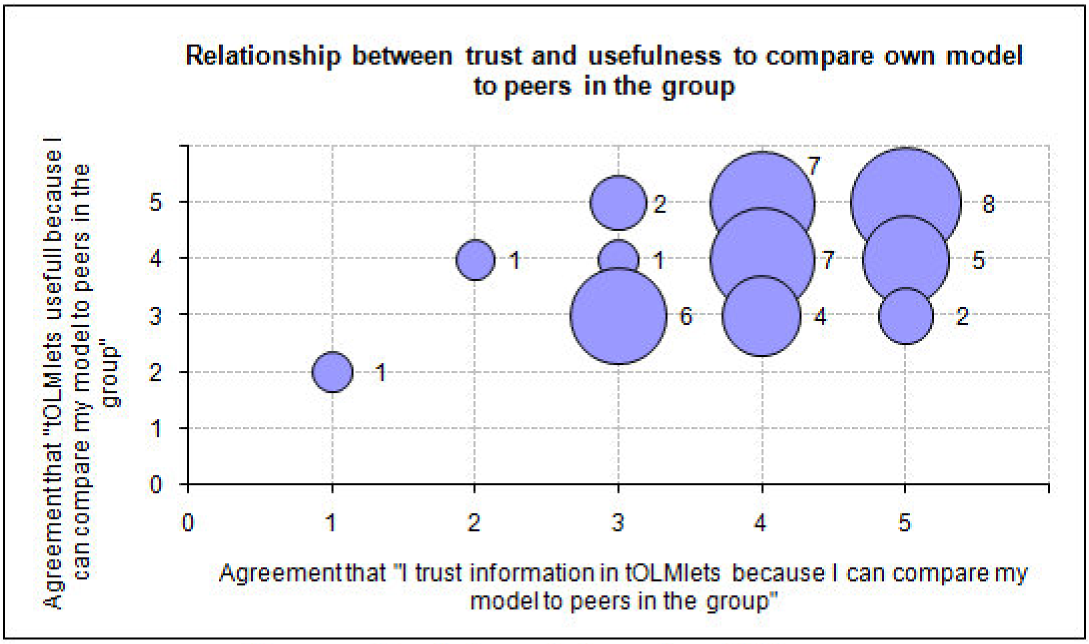
## Viewing and Comparing Peers Model

We present user opinion about the features of comparing their models to peers in Table 7.23. Users find that comparing the model with peers in the group and comparing the model to individual peer model (whether named or anonymous) are useful for their learning. Users also seem to trust all the functions of comparison.

Table 7.23: Features of comparing the model to peers (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 4 | 3 | 2 | 1 | **Mean** | **Median** |
| Comparing model to peers in group is useful | 39 | 32 | 27 | 2 | 0 | **4.1** | 0.9 |
| Comparing model to named peers is useful | 36 | 20 | 36 | 7 | 0 | **3.9** | 1.0 |
| Comparing model to anonymous peers is useful | 36 | 27 | 30 | 5 | 2 | **3.9** | 1.0 |
| Trust tOLMlets because can compare to peers in group | 34 | 39 | 20 | 5 | 2 | **4.0** | 1.0 |
| Trust tOLMlets because can compare to individual named peers | 30 | 39 | 23 | 7 | 2 | **3.9** | 1.0 |
| Trust tOLMlets because can compare to individual anonymous peers | 23 | 41 | 25 | 9 | 2 | **3.7** | 1.0 |

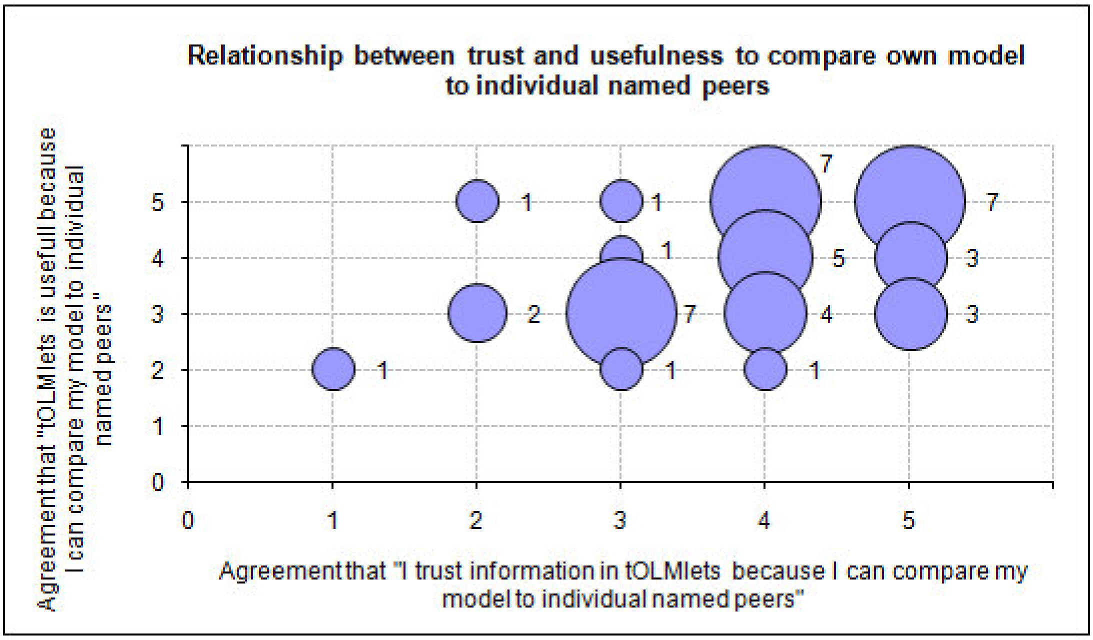
For each type of comparison in this study, we examine the relationship between usefulness and trust built. In Figure 7.7, 27 out of 44 users claim that tOLMlets is useful for comparing the model to the whole group and trust it. There are 6 users who trust to compare their model to peers in the group but are neutral about the usefulness. The relationship between trust and usefulness of comparing models in the group is positive and significantly correlated (*correlation*=0.4; $p$<.05).




Pearson Correlation = 0.4; p-value = 0.00

Figure 7.7: Relationship between trust and usefulness in comparing models in a group.

Figure 7.8 shows the relationship between trust and usefulness in named peer models. 22 users agree about the usefulness of comparing the model to named peers and trust it. Meanwhile, 8 users trust in comparing the model to named peers but disagree or remain neutral in terms of its usefulness. Trust is significantly correlated with the usefulness of comparing the model to the named peer models (*correlation*=0.4; $p$<.05).




Pearson Correlation = 0.4; p-value = 0.00

Figure 7.8: Relationship between trust and usefulness in comparing the model to named peers.

There is a stronger relationship between trust and usefulness of comparing the model to the anonymous peer models with correlation value of 0.5 ($p$<.05) as shown in Figure 7.9. Similar to results in named peer models, 22 users agree about the usefulness of comparing models to anonymous peer model and trust it. 6 users trust in comparing the model to anonymous peers model but disagree or remain neutral about the usefulness. The same number of students agrees with the usefulness but disagrees or remains neutral in trusting it.

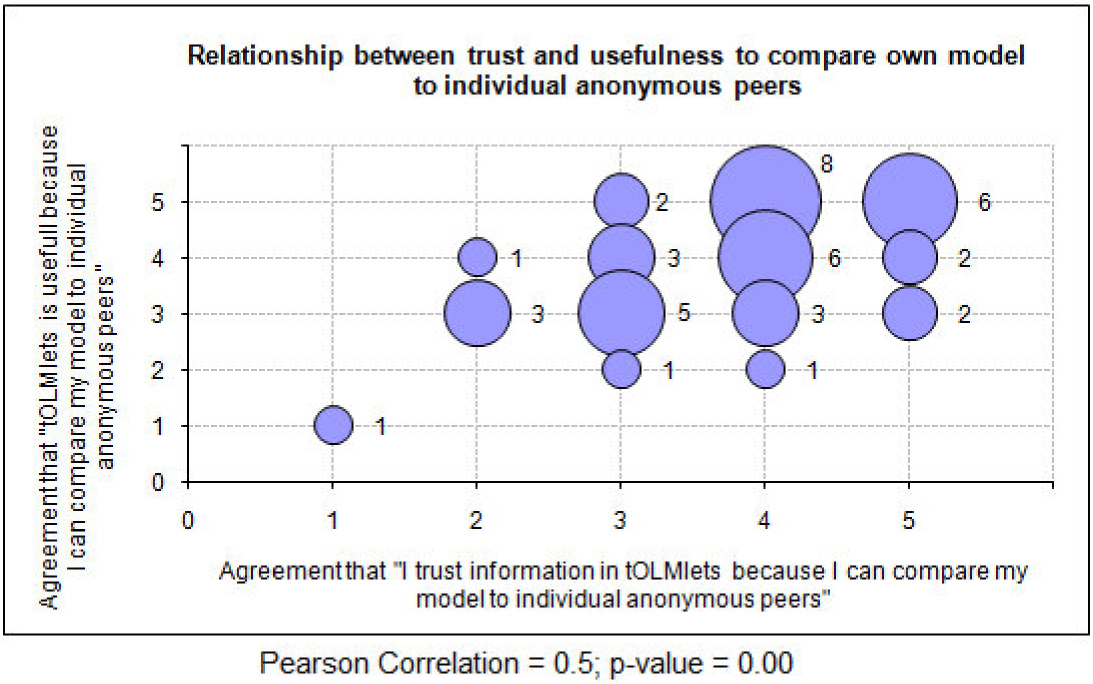



Figure 7.9: Relationship between trust and usefulness in comparing the model to anonymous peers.

We also assess whether users trust peer models that appear with the name or anonymous. The results obtained are shown in Table 7.24. Generally, users trust peer models when it released with the name (*M*=3.8, *SD*=0.9) compared to the one that released anonymously (*M*=3.4, *SD*=1.0). This difference was significant, *t*=2.72, *p*<.0.05.

Table 7.24: Trust in peer models – named and anonymous (in percentage)

| | <str. agree … str. disagree> | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 4 | 3 | 2 | 1 | **Mean** | **SD** |
| Trust peer models when it released with named | 23 | 48 | 20 | 9 | 0 | **3.8** | 0.9 |
| Trust peer models when it released anonymously | 14 | 32 | 36 | 16 | 2 | **3.4** | 1.0 |

Users also provide some comments on why they trust or do not trust in named or anonymous peer models. Table 7.25 shows the opinions in three categories.

Table 7.25: Opinions of why trust the named and anonymous peer models

| |
|---|
| **Named peer models:** |
| ▪ *Hard to explain but people always trust someone who shows his first, but no one who doesn't show his name*<br>▪ *They can try few questions and got high marks*<br>▪ *I trust peer models when released with their names because the models are open to positive criticism based on the understanding* |
| **Anonymous peer models:** |
| ▪ *Anonymous means it's less trustworthy for me*<br>▪ *Don't trust anonymous people as much*<br>▪ *If anonymous, questions raised as to why?*<br>▪ *If someone doesn't put his/her name, it means either he's not satisfied with the results or he is really not good at the entire subject*<br>▪ *Anonymous is more likely to be fake, but there is no reason to do that so it's ok* |
| **Named and anonymous peer models:** |
| ▪ *I trust it equally, named or anonymous*<br>▪ *It doesn't bother me who it is, as I only look at how high the knowledge level is in the skill meter*<br>▪ *The identity doesn't affect the model*<br>▪ *It's doesn't matter to me whether they declare their name or not. I'm more caring about their performance*<br>▪ *It helps me compare my levels with others*<br>▪ *I believe everybody (anonymous or named) is trying to do their best* |

### 7.3.4 Discussion

In this study we found that the majority of users prefer to release their model to everyone in the group. This would be a good sign towards an effective collaboration in learning. Only few users release their model only to people that they know well. In terms of releasing the model to everybody, learners claim that they like to share theirs without worrying about what people say about the model because they want to encourage others to release the model as well. They also assume that all peers are equal, and they should have equal opportunities (in this case the opportunity to see the peers model). Therefore, they emphasised the purpose of releasing the model is for comparison. Users who release their model only to people they know well, is simply because they know the peers and this enables them to get help if they have a problem in the subject (e.g. misconceptions).

In terms of the user beliefs and their motivations in opening the model to the peers, the majority of users open their model when they believe the model is accurate. More than two-thirds of the users open the model with their names, and less than half of users open their models anonymously. However, at the same time, users still release their models even if they feel the model is not accurate. This may be motivated by the desire to share their models with peers even though they are not sure about the accuracy of the model. In terms of identification of the model, most students release their models to the peers with their names.

In terms of usefulness, users find the functions of comparing their own model to peer models useful in their studies. Users show some level of trust for peer models in the group and in the individual peer models (named and anonymous). In terms of the relationship between usefulness and trust to the model, comparing in a group model shows a positive relationship with a correlation of 0.4 ($p<.05$). The usefulness of comparing the model with anonymous peers correlated with trust in peer models (with *correlation*=0.5; $p<.05$), and with the named peer models (with correlation=0.4; $p<.05$). Based on these results we can conclude that there is a positive relationship between the trust and usefulness of comparing peer models, whether in group or individual names and anonymous.

In terms of whether users trust peer models that appear with the name or anonymous, most of the users trust peer models that are released with the name. Among the responses of why learners trust the named peer model because it can open to discuss for better understanding. Learners less trust the anonymous peer models because it seems that the model is less trustworthy and indicates that the owner is not satisfied with their models. However, there are learners who stated that the identity of the peer model is less important as long as the comparison can be done for the benefit of learning.

# 7.4 Conclusion

The conclusion is based on the key questions for each feature.

## 7.4.1 Externalisation of Learner Models

- *Do learners understand and trust OLM externalisation?*

Learners appeared to understand the content of learner models used in the OLM system, for both simple and structured view. Learners are able to identify the learning benefits they get from using the learner model externalisation in the systems. Understanding the learner model is found to correlate to trust in the externalisation of the learner model. Therefore, we can conclude that learners understand and trust the externalisation of open learner models.

- *Do learners trust simple or more structured view?*

Learners show sufficient trust in both simple and structured view. However, there is a high correlation between trust and criteria assessed in the simple view. Therefore we conclude that learners trust simple and more structured view.

- *Are there any features that makes OLMs view more trustable?*

Accuracy is essential in open learner models. It is not only the underlying model should be accurate but also the way in which the information is presented to the user. In this study, we find that trust the externalisation of the model has a strong relationship with the perceived accuracy of the model presented. This may be the fact that students can see what is inferred by the system, and probably could predict the results of the system evaluation.  Therefore, we can conclude that perceived accuracy of learner models has an impact on learner trust in the externalisation of the learner model.

### 7.4.2 Learner Control over the Learner Model

- *Do learners use and trust the edit function?*

Learners are able to use the edit function appropriately. A higher percentage of learners edited the model they believed inaccurate, and edited the model they do not trust. Trust has a positive relationship with the usefulness of the edit function. Therefore, we conclude that learners use and trust the edit function in OLM.

- *Do learners use and trust the persuade function?*

Similar to the edit function, learners are able to use the persuade function appropriately. A high percentage of learners tried to persuade the model they believed inaccurate, and the model they do not trust. Trust has a positive strong relationship with the usefulness of the persuade function. Therefore, we conclude that learners use and trust the persuade function in OLM.

### 7.4.3 Peer Models

- *Do students trust peers models?*

Learners appear to trust peer models. These include trust in the group and individual peer models (named and anonymous). The usefulness of each peer model in the learning process has contributed to trust in the model itself. Therefore we can say that students trust their peer models.

- *Do student trust the named peers model or anonymous peers model?*

Both peer models with names and anonymous are useful for comparing the model for the purpose of learning. Although some learners stated that identification is less important to compare the model, the majority of the learners have more trust in the peer model that is released with peers' names.

Therefore, we suggest that trust can be built in the OLM when more peer models are released with names in the environment.

In the next chapter, we provide conclusions and limitations of the research. We also provide possible future work.

# Chapter 8

# CONCLUSIONS AND FUTURE WORKS

In this chapter we review the context of the thesis, and integrate the findings in each evaluation in order to provide a series of requirements for OLM designers towards a trustworthy environment. Next, we discuss the limitations of the study and suggestions for future research.

## 8.1 Context

The focus of this thesis is to investigate learners' trust in an open learner model. It is important to provide learners with a trustworthy environment because it can engage them to continue using the system. Issues of trust become more important in an open learner model because the model is available for the learner to inspect and this may increase their perception of how a system evaluates their knowledge and updates the model. Furthermore, designing trustable open learner models may be a critical success factor of the next generation of open learner models (Dimitrova et al., 2007).

In this thesis, we investigated learner trust in two main perspectives: from the perspective of the system as a whole and from the perspective of OLM features. From the perspective of the system as a whole, we investigated the extent to which learners trust and accept the OLM system on their first use, the extent to which learners continue using the OLM optionally after their initial use and the extent to which learner trust and accept the OLM after longer term of use. In the perspective of OLM features, we investigated learner trust in three main common features in OLM environment, namely:(i) complexity of model presentation; (ii) level of learner control over the model; (iii) the facility to view peer models and release one's own model to peers.

## 8.2 Findings

In investigating learner trust in OLM, we established the definition of trust in the learner model. Trust in the learner model is defined as *the individual user's belief in, and acceptance of the system's inferences; their feelings of attachment to their model; and their confidence to act appropriately according to the model inferences* (Ahmad & Bull, 2008).

Most learners have trust the system in their first use of the system. This is especially when learners are uncertain about their knowledge and relies on the system to carry out the evaluation. Although some of the learners have less trust in the system after the first use, they continue to use the system in order to know their level of knowledge which is evaluated by the system.

The relationship between trust and several criteria assessed shows a positive relationship in both studies. Perceived ease of use of the system shows a strong relationship to trust the information in the system in the short term of use. The duration of use of the system is likely to affect the relationship between trust and ease of use of the system. In the short term of use, a strong relationship is also found between trust and understanding of the system's behaviour, in users' interest to see the information presented and liking in using the system. However the longer term of use shows a strong relationship between the perceived accuracy of the learner model with trust.

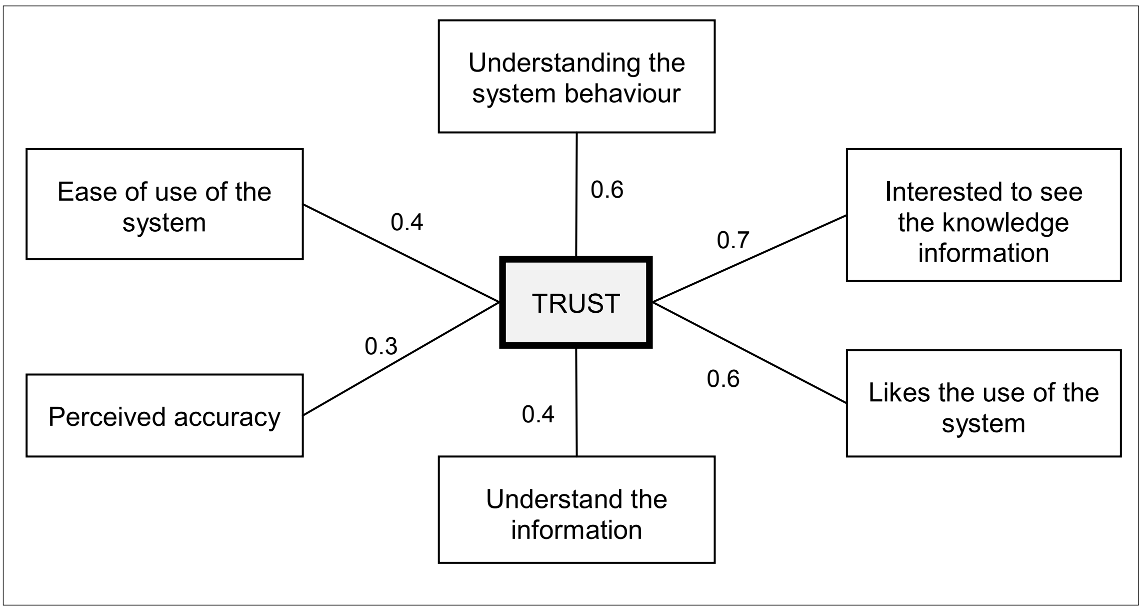



Figure 8.1: Main significant correlations coefficients in laboratory study

We found that there is a significant correlation between trust and the six criteria (refer Table 6.10) in the laboratory study (Figure 8.1), but not in the deployed study. This may be due to the small number of participants in the deployed study. Figure 8.2 shows the correlations between trust and OLM features.

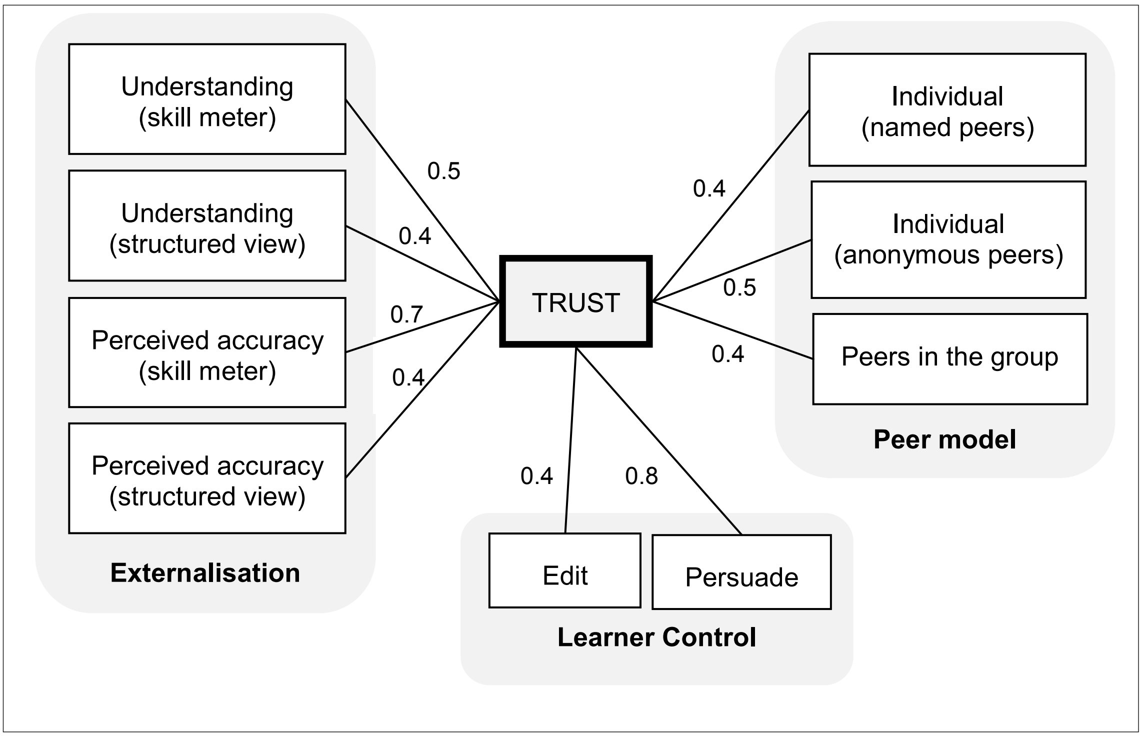



Figure 8.2: Main significant correlations coefficients in OLM features

In terms of externalisation of the learner model, learners seem to understand both the simple and structured view. The understanding of the learner model is found to correlate with trust in the externalisation of the learner model. Learners show a sufficient trust in both the simple and structured view. However the simple view is found to have a higher correlation between understanding and trust as compared to the structured view. In addition, trust in externalisation of the model is also found to have a strong relationship with the accuracy of the model presented especially when using the simple view as shown in Figure 8.2. This is not a surprise because accuracy of the model presented is one of crucial aspects in an open learner models environment. Our evidence shows that both simple and structured view contributes to trust in OLM system. Therefore, we propose that the use of various externalisations of the learner model not only complement each other in presenting a model (e.g Perez-Marin, 2007; VanLabeke et al., 2007) or as an alternative view in the system (e.g Mabbot t& Bull, 2006; Johnson & Bull, 2009; Xu & Bull, 2010), but it also contributes to trust in the open learner models system.

In terms of control over the model, learners seem to be able to utilize the functions provided. More learners are found to be using the function of edit and persuade when they believe the model is not accurate or when they do not trust the model. This result is contra with the initial result where learners edit the model when they believe the model is accurate. It is likely that learners in the recent study have more understanding on when to use the features and this also indicate that they trust the features, with the condition that they not cheat themselves especially when using the edit function. Learners are found to have more trust in the persuade function when the final model after persuasion is equivalent to what they believe. These include whether the new model after persuasion is lower or higher than their old model. In this study we also found that there is a significant positive relationship between trust and the edit and persuasion function a depicted in Figure 8.

In terms of the facility of peer models, more learners released their own model that they consider accurate to everybody in the group. One reason is because they consider that comparing the model with others is useful in learning. Therefore learners trust the named or anonymous peer model. Learners show trust in the group and individual peer model. Although some learners stated that identification is less important as compared to the model, the majority of the learners have more trust in the peer model that is released with peers' name. Therefore we suggest that trust can be built in the OLM when more peers models are released with names in the environment.

In summary, our proposed requirements are:

- Learners have trust in a simple and structured view of OLM. Therefore providing multiple externalisations consisting of simple and structured views may increase learner trust in the system.
- Learners have trust in both edit and persuade function in OLM. Therefore providing the function that allows users to contribute to their learner model may increase learner trust in the system. However, if the full control feature like edit is to be considered in the system, the designer may be can limit them to certain amount.
- Learners trust the system because they can compare the model with others. The comparison maybe in group or individual. Therefore the feature of comparing the knowledge may increase learners' trust in the system.

- Learners trust more in the model that released with name. Learners also prefer to open their model to everybody with name. The model with known identity help learners in learning especially to find peers that can help them in learning outside the system. Therefore, identifiable model can encourage learner trust in the system.

## 8.3 Limitations and Future Work

This thesis has several limitations that can be improved in future work.

Most of the evaluations done in this thesis are based on experimental studies especially on the common features in the open learner models environment. As trust is developed over time, the results may be different if it is done in the real setting. Therefore, future works may investigate learner trust in open learner models in the real setting.

This thesis is focused on comparing the model to peers, however the comparison with an expert is lacking in this study. Therefore future work may investigate learner trust in comparison with instructor expectation.

In summary, this thesis has considered the issues of learner trust in open learner model, criteria that may effect trust in the open learner models and open learner models features that are common in the environment

# List of References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# Appendix: List of Publications


Ahmad, N. & Bull, S. (2008). Do Students Trust their Open Learner Models?, in W. Neijdl, J. Kay, P. Pu & E. Herder (eds), Adaptive Hypermedia and Adaptive Web-Based Systems, Springer-Verlag, Berlin Heidelberg, 255-258

Kerly, A. Ahmad, N. & Bull, S. (2008). Investigating Learner Trust in Open Learner Models using a 'Wizard of Oz' Approach, in B.P. Woolf, E. Aimeur, R. Nkambou & S. Lajoie (eds), Intelligent Tutoring Systems: 9th International Conference, Springer-Verlag, Berlin Heidelberg, 722-724.

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Ahmad, N., Iahad, N. & Bull, S. (2008). The Potential to Facilitate Self-Directed Learning in Malaysian Public Higher Education Institutes using an Open Learner Model, Proceedings of International Conference on University Learning and Teaching: INCULT, Malaysia.

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Ahmad, N. & Bull, S. (2009). Learner Trust in Learner Model Externalisations, in V. Dimitrova, R. Mizoguchi, B. du Boulay & A. Graesser (eds), Artificial Intelligence in Education 2009, IOS Press, Amsterdam, 617-619.

Ahmad, N., Britland, M., Bull, S. & Mabbott, A. (2010). A Role for Open Learner Models in Formative Assessment: Support from Studies with Editable Learner Models, Proceedings of Workshop on Technology-Enhanced Formative Assessment, EC-TEL 2010.

# Appendix: Questionnaire1

**OLMlets Questionnaire**

This questionnaire is designed to get feedback on OLMlets. Please answer honestly based on your experience while using the application. **Data will be stored anonymously.**

**Instruction:** Tick (√) at the appropriate box.

Background/General

1. Student ID number: ________________

**Instruction:** Rate the following statements by placing a tick (√) in the appropriate box.

| | | strongly agree 5 | 4 | 3 | 2 | strongly disagree 1 |
|---|---|---|---|---|---|---|
| A | I am good at self-assessment | | | | | |
| B | OLMlets helped me identify my: | | | | | |
| | - knowledge (things I did not know I knew) | | | | | |
| | - misconceptions | | | | | |
| | - difficulties | | | | | |
| | - what to learn next | | | | | |
| C | OLMlets is easy to use | | | | | |
| D | I understood the information given by OLMlets | | | | | |
| E | I know what will happen the next time I use OLMlets because I understand how it behaves | | | | | |
| F | OLMlets accurately evaluates my current knowledge | | | | | |
| G | When I am uncertain about my knowledge, I believe OLMlets | | | | | |
| H | When OLMlets shows a high level of my knowledge, I believe OLMlets | | | | | |
| I | When OLMlets shows a higher level of my knowledge than I expected, I believe OLMlets | | | | | |
| J | When OLMlets shows a low level of my knowledge, I believe OLMlets | | | | | |
| K | When OLMlets shows a lower level of my knowledge than I expected, I believe OLMlets | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| L | I believed my knowledge information in OLMlets was correct and | | | | | |
| | - I opened it to my peers | | | | | |
| | - I opened it to my instructor | | | | | |
| M | I believed my knowledge information in OLMlets was incorrect and | | | | | |
| | - I opened it to my peers | | | | | |
| | - I opened it to my instructor | | | | | |
| N | OLMlets suits my style of learning | | | | | |
| O | I like using OLMlets | | | | | |
| P | I am interested to see my knowledge information in OLMlets | | | | | |
| Q | I trust the information about my understanding in OLMlets | | | | | |
| R | I trust OLMlets because it shows me how much I know | | | | | |
| S | I trust OLMlets because it shows me my misconceptions | | | | | |
| T | I trust the information because I can compare it to peers | | | | | |
| U | I trust the information because I can compare it to lecturer expectations | | | | | |
| V | I trust the information because it is a simple overview | | | | | |

Please add any general comments regarding your use of OLMlets:

**Please tick (√) as appropriate**

☐ My data MAY be used anonymously for research

☐ My data MAY NOT be used for research

Kindly sent this questionnaires to n[redacted]

- THANK YOU –

## FlexiOLM Questionnaire

This questionnaire is designed to get feedback on FlexiOLM. Please answer honestly based on your experience while using the application. **Data will be stored anonymously.**

**Instruction:** Tick (√) at the appropriate box.

Background/General

1. Student ID number: ________________

**Instruction:** Rate the following statements by placing a tick (√) in the appropriate box.

| | | strongly agree 5 | 4 | 3 | 2 | strongly disagree 1 |
|---|---|---|---|---|---|---|
| A | I am good at self-assessment | | | | | |
| B | FlexiOLM helped me identify my: | | | | | |
| | - knowledge (things I did not know I knew) | | | | | |
| | - misconceptions | | | | | |
| | - difficulties | | | | | |
| | - what to learn next | | | | | |
| C | FlexiOLM is easy to use | | | | | |
| D | I understood the information given by FlexiOLM | | | | | |
| E | I know what will happen the next time I use FlexiOLM because I understand how it behaves | | | | | |
| F | FlexiOLM accurately evaluates my current knowledge | | | | | |
| G | When I am uncertain about my knowledge, I believe FlexiOLM | | | | | |
| H | When FlexiOLM shows a high level of my knowledge, I believe FlexiOLM | | | | | |
| I | When FlexiOLM shows a higher level of my knowledge than I expected, I believe FlexiOLM | | | | | |
| J | When FlexiOLM shows a low level of my knowledge, I believe FlexiOLM | | | | | |
| K | When FlexiOLM shows a lower level of my knowledge than I expected, I believe FlexiOLM | | | | | |
| L | I believed my knowledge information in FlexiOLM was correct and | | | | | |
| | - I edited the information | | | | | |
| | - I tried to persuade FlexiOLM to change the information | | | | | |

M I believed my knowledge information in FlexiOLM was incorrect and
- I edited the information
- I tried to persuade FlexiOLM to change the information

N FlexiOLM suits my style of learning

O I like using FlexiOLM

P I am interested to see my knowledge information in FlexiOLM

Q I trust FlexiOLM because it shows me how much I know

R I trust FlexiOLM because it shows me my misconceptions

S I trust the information about my understanding in FlexiOLM

T I trust the information because I can edit it

U I trust the information because I can try to persuade FlexiOLM to change it

V I trust the information because it is detailed

Please add any general comments regarding your use of FlexiOLM:

**Please tick (√) as appropriate**

☐ My data MAY be used anonymously for research

☐ My data MAY NOT be used anonymously for research

Kindly sent this questionnaires to

- THANK YOU -

# Appendix: Questionnaire2

**tOLMlets Questionnaire**

**Student ID:** ________________________

Please rate the following statements by placing a tick (√) in the appropriate box.

strongly agree ⟷ strongly disagree

| | | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|
| 1 | I am good at self-assessment | | | | | |
| 2 | The information in my learner model is accurate | | | | | |
| 3 | The information in my learner model is accurate in *skill meters* | | | | | |
| | The information in my learner model is accurate in *structured* | | | | | |
| 4 | I understood the information given by *skill meter* view | | | | | |
| | I understood the information given by *structured* view | | | | | |
| 5 | The *skill meter* view helped me identify my knowledge | | | | | |
| | The *skill meter* view helped me identify areas of difficulty | | | | | |
| | The *skill meter* view helped me identify my misconceptions | | | | | |
| | The *skill meter* view helped me identify what to study next | | | | | |
| 6 | The *structured* view helped me identify my knowledge | | | | | |
| | The *structured* view helped me identify areas of difficulty | | | | | |
| | The *structured* view helped me identify my misconceptions | | | | | |
| | The *structured* view helped me identify what to study next | | | | | |
| 7 | The following features are useful: | | | | | |
| | - I can see how much of the subject I know | | | | | |
| | - I can see my misconceptions | | | | | |
| | - I can compare my model to the group as a whole | | | | | |
| | - I can compare my model to individual anonymous peers | | | | | |
| | - I can compare my model to individual named peers | | | | | |
| | - I can try to persuade my model to change the information | | | | | |
| 8 | tOLMlets is easy to use | | | | | |
| 9 | I know what will happen the next time I use tOLMlets because I understand how it behaves | | | | | |
| 10 | I trust the information in tOLMlets | | | | | |
| 11 | I trust the information in tOLMlets about my understanding using *skill meter* | | | | | |
| | I trust the information in tOLMlets about my understanding using *structured* | | | | | |

12 When I am uncertain about my knowledge, I believe tOLMlets

13 When tOLMlets shows a *high* level of knowledge, I believe tOLMlets
When tOLMlets shows a *low* level of knowledge, I believe tOLMlets

14 When tOLMlets shows a *higher* level of knowledge than I expected, I believe OLMlets
When tOLMlets shows a *lower* level of knowledge than I expected, I believe OLMlets

15 I would keep using tOLMlets if the information was *higher* than I expected
I would keep using tOLMlets if the information was *lower* than I expected

16 I am interested to see my knowledge information in tOLMlets

17 If my tOLMlets information is lower than I expected, I
- search for new information (e.g. in the library, using google)
- answer more tOLMlets questions to better understand the topics
- answer more tOLMlets questions to get the right answers (but not necessarily to understand the topics)
- talk to my friends about my/our difficulties
- find somebody to help/discuss difficulties using the peer models
- other (please state): ____________________________________________

18 I like using tOLMlets in my learning

Please provide definition of trust in OLM.

# Appendix: Questionnaire3

**tOLMlets Questionnaire – Edit**

**Student ID:** ________________________

Please rate the following statements by placing a tick (√) in the appropriate box.

strongly agree ⟷ strongly disagree

| No. | Statement | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|
| 1 | I am good at self-assessment | | | | | |
| 2 | The information in my learner model is accurate | | | | | |
| 3 | The information in my learner model is accurate in *skill meters* | | | | | |
| | The information in my learner model is accurate in *structured* | | | | | |
| 4 | I understood the information given by *skill meter* view | | | | | |
| | I understood the information given by *structured* view | | | | | |
| 5 | The *skill meter* view helped me identify my knowledge | | | | | |
| | The *skill meter* view helped me identify areas of difficulty | | | | | |
| | The *skill meter* view helped me identify my misconceptions | | | | | |
| | The *skill meter* view helped me identify what to study next | | | | | |
| 6 | The *structured* view helped me identify my knowledge | | | | | |
| | The *structured* view helped me identify areas of difficulty | | | | | |
| | The *structured* view helped me identify my misconceptions | | | | | |
| | The *structured* view helped me identify what to study next | | | | | |
| 7 | tOLMlets is easy to use | | | | | |
| 8 | I know what will happen the next time I use tOLMlets because I understand how it behaves | | | | | |
| 9 | I trust the information in tOLMlets | | | | | |
| 10 | I trust the information in tOLMlets about my understanding using *skill meter* | | | | | |
| | I trust the information in tOLMlets about my understanding using *structured* | | | | | |
| 11 | I am interested to see my knowledge information in tOLMlets | | | | | |
| 12 | I believed my knowledge information in tOLMlets was *accurate* and<br>- I edited the information | | | | | |
| 13 | I believed my knowledge information in tOLMlets was *inaccurate* and | | | | | |

- I edited the information

14 I trust the information in tOLMlets because :
- I edited the information

15 I trust my model and
- I edited the information

16 I did not trust my model and
- I edited the information

17 If my tOLMlets information is lower than I expected, I
- search for new information (e.g. in the library, using google)
- answer more tOLMlets questions to better understand the topics
- answer more tOLMlets questions to get the right answers (but not necessarily to understand the topics)
- talk to my friends about my/our difficulties
- find somebody to help/discuss difficulties using the peer models
- other (please state): ____________________________________________________

18 I like using tOLMlets in my learning

## tOLMlets Questionnaire – Persuade

**Student ID:** ________________________

Please rate the following statements by placing a tick (√) in the appropriate box.

strongly agree ⟷ strongly disagree

| | | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|
| 1 | I am good at self-assessment | | | | | |
| 2 | The information in my learner model is accurate | | | | | |
| 3 | The information in my learner model is accurate in *skill meters* | | | | | |
| | The information in my learner model is accurate in *structured* | | | | | |
| 4 | I understood the information given by *skill meter* view | | | | | |
| | I understood the information given by *structured* view | | | | | |
| 5 | The *skill meter* view helped me identify my knowledge | | | | | |
| | The *skill meter* view helped me identify areas of difficulty | | | | | |
| | The *skill meter* view helped me identify my misconceptions | | | | | |
| | The *skill meter* view helped me identify what to study next | | | | | |
| 6 | The *structured* view helped me identify my knowledge | | | | | |
| | The *structured* view helped me identify areas of difficulty | | | | | |
| | The *structured* view helped me identify my misconceptions | | | | | |
| | The *structured* view helped me identify what to study next | | | | | |
| 7 | tOLMlets is easy to use | | | | | |
| 8 | I know what will happen the next time I use tOLMlets because I understand how it behaves | | | | | |
| 9 | I trust the information in tOLMlets | | | | | |
| 10 | I trust the information in tOLMlets about my understanding using *skill meter* | | | | | |
| | I trust the information in tOLMlets about my understanding using *structured* | | | | | |
| 11 | I am interested to see my knowledge information in tOLMlets | | | | | |
| 12 | I believed my knowledge information in tOLMlets was | | | | | |

*accurate* and
- I tried to persuade tOLMlets to change my model

13 I believed my knowledge information in tOLMlets was *inaccurate* and
- I tried to persuade tOLMlets to change my model

14 I trust the information in tOLMlets because :
- I can try to persuade tOLMlets to change my model

15 I trust my model and
- I persuaded the information

16 I did not trust my model and
- I persuaded the information

17 I trust the 'persuasion' function when I used it if
- it changed my model to higher level (in line with my belief)
- it changed my model to lower level (in line with my belief)
- it changed my model to higher level (*not* in line with my belief)
- it changed my model to lower level (*not* in line with my belief)
- my model stayed at the same level

18 If my tOLMlets information is lower than I expected, I
- search for new information (e.g. in the library, using google)
- answer more tOLMlets questions to better understand the topics
- answer more tOLMlets questions to get the right answers(but not necessarily to understand the topics)
- talk to my friends about my/our difficulties
- find somebody to help/discuss difficulties using the peer models
- other (please state): ____________________________________________

19 I like using tOLMlets in my learning

# Appendix: Questionnaire4

**tOLMlets Questionnaire – Peer Models**

**Student ID:** ________________________

Please rate the following statements by placing a tick (√) in the appropriate box.

strongly agree ↔ strongly disagree

| | | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|
| 1 | I am good at self-assessment | | | | | |
| 2 | The information in my learner model is accurate | | | | | |
| 3 | The information in my learner model is accurate in *skill meters* | | | | | |
| | The information in my learner model is accurate in *structured* | | | | | |
| 4 | I understood the information given by *skill meter* view | | | | | |
| | I understood the information given by *structured* view | | | | | |
| 5 | The *skill meter* view helped me identify my knowledge | | | | | |
| | The *skill meter* view helped me identify areas of difficulty | | | | | |
| | The *skill meter* view helped me identify my misconceptions | | | | | |
| | The *skill meter* view helped me identify my misconceptions | | | | | |
| 6 | The *structured* view helped me identify my knowledge | | | | | |
| | The *structured* view helped me identify areas of difficulty | | | | | |
| | The *structured* view helped me identify my misconceptions | | | | | |
| | The *structured* view helped me identify what to study next | | | | | |
| 7 | The following features are useful: | | | | | |
| | - I can see how much of the subject I know | | | | | |
| | - I can see my misconceptions | | | | | |
| | - I can compare my model to the group as a whole | | | | | |
| | - I can compare my model to individual anonymous peers | | | | | |
| | - I can compare my model to individual named peers | | | | | |
| 8 | tOLMlets is easy to use | | | | | |
| 9 | I know what will happen the next time I use tOLMlets because I understand how it behaves | | | | | |
| 10 | I trust the information in tOLMlets | | | | | |
| 11 | I trust the information in tOLMlets about my understanding using *skill meter* | | | | | |
| | I trust the information in tOLMlets about my understanding using *structured* | | | | | |
| 12 | When I am uncertain about my knowledge, I believe | | | | | |

tOLMlets

13 When tOLMlets shows a *high* level of knowledge, I believe tOLMlets

When tOLMlets shows a *low* level of knowledge, I believe tOLMlets

14 When tOLMlets shows a *higher* level of knowledge than I expected, I believe tOLMlets

When tOLMlets shows a *lower* level of knowledge than I expected, I believe tOLMlets

15 I would keep using tOLMlets if the information was *higher* than I expected

I would keep using tOLMlets if the information was *lower* than I expected

16 I am interested to see my knowledge information in tOLMlets

17 I believed my knowledge information in tOLMlets was *accurate* and
- I opened it to peers named
- I opened it to peers anonymously
- I opened it to instructors named
- I opened it to instructors anonymously

18 I believed my knowledge information in tOLMlets was *inaccurate* and
- I opened it to peers named
- I opened it to peers anonymously
- I opened it to instructors named
- I opened it to instructors anonymously

19 I trust the information in tOLMlets because :
- it shows me how much I know
- it shows me my misconceptions
- I can compare my model to individual anonymous peers
- I can compare my model to individual named peers
- I can compare my model to peers in the group
- I can try to persuade tOLMlets to change my model

20 I trust my model and
- I opened it to peers named
- I opened it to peers anonymously
- I opened it to instructors named
- I opened it to instructors anonymously

21 I did not trust my model and
- I opened it to peers named
- I opened it to peers anonymously
- I opened it to instructors named
- I opened it to instructors anonymously

22 I trust other users' models when they are:

- released with their names ☐☐☐☐☐
- released anonymously ☐☐☐☐☐

Please explain your answer: ______________________________________________

23 I released my model only to people that I know well ☐☐☐☐☐

I released my model to everybody in the group ☐☐☐☐☐

24 I like using OLMlets in my learning ☐☐☐☐☐