Scaffolding for Social Personalised Adaptive E-Learning

By

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Declaration

This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy. I hereby declare that, except where acknowledged, the work presented in this thesis has been composed by myself, and has not been submitted elsewhere for the purpose of obtaining an academic degree.

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Signature:

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Publications

Below, the publications written during the PhD research are listed, and their connection to the current thesis is explained. The work presented (including data generated and data analysis) was carried out by the author. In all of these cases, the contribution by the author has been greater than 80%.

1. **Shi, L.**, Cristea, A. I., Hadzidedic, S. (2014) The Critical Role of Profiles in Social E-Learning Design. In Proceedings of the 15th Annual Conference on Information Technology Education (SIGITE 2014), pages 71-76, Atlanta, Georgia, US, October 15-18, 2014. ACM.
2. **Shi, L.**, Cristea, A. I. (2014) Designing Visualisation and Interaction for Social E-Learning: A Case Study on Topolor 2. In Proceedings of the 9th European Conference on Technology Enhanced Learning (EC-TEL 2014), pages 526-529, Graz, Austria, September 16-19, 2014. LNCS 8719, Springer International Publishing.
3. **Shi, L.** (2014) Defining and Evaluating Learner Experience for Social Adaptive E-Learning. In Proceedings of the 4th Imperial College Computing Student Workshop (ICCSW 2014), pages 74-82, London, UK, September 25-26, 2014. OASICS Vol. 28, Schloss Dagstuhl – Leibniz Center for Informatics.

Papers 1, 2 and 3 present the design and evaluation of Topolor 2 – a social personalised e-learning system. They are the basis of Chapter 6 and Chapter 7.

4. **Shi, L.**, Cristea, A. I., Hadzidedic, S. (2014) Multifaceted Open Social Learner Modelling. In Proceedings of the 13th International Conference on Web-based Learning (ICWL2014), pages 32-42, Tallinn, Estonia, August 14-17, 2014. LNCS 8613, Springer International Publishing.

Paper 4 describes a new learner modelling approach. It is the basis of Chapter 7.

5. **Shi, L.**, Cristea, A. I., Hadzidedic, S., Dervishalidovic, N. (2014) Contextual Gamification of Social Interaction – Towards Increasing Motivation in Social E-Learning. In Proceedings of the 13th International Conference on Web-based Learning (ICWL2014), pages 116-122, Tallinn, Estonia, August 14-17, 2014. LNCS 8613, Springer International Publishing.
6. **Shi, L.**, Cristea, A. I. (2014) Making It Game-Like: Topolor 2 and Gamified Social E-Learning. In Proceedings of the 22nd Conference on User Modeling, Adaptation and Personalization (UMAP 2014), pages 61-64, Aalborg, Denmark, July 7-11, 2014. Springer International Publishing.
7. **Shi, L.**, Al-Qudah, D. A., Qaffas, A., Cristea, A. I. (2013) To Build Light Gamification upon Social Interactions: Requirement Analysis for the Next Version of Topolor. In Proceedings of the 6th York Doctoral Symposium on Computer Science, pages 63-67, York, United Kingdom, October 29, 2013. York Computer Science (YCS).

Papers 5, 6 and 7 present a new gamification approach. They are the basis of Chapter 6.

8. **Shi, L.**, Cristea, A. I., Awan, M., Stewart, C., Hendrix, M. (2013) Towards Understanding Learning Behavior Patterns in Social personalised adaptive Personalized E-Learning Systems. In Proceedings of the 19th Americas Conference on Information Systems (AMCIS 2013), pages 1-10, Chicago, Illinois, USA, August 15-17, 2013. Association for Information Systems.
9. **Shi, L.**, Cristea, A. I. (2013) Investigating the Impact of Social Interactions in Adaptive E-Learning by Learning Behaviour Analysis. In Proceedings of the 6th York Doctoral Symposium on Computer Science, pages 88, York, United Kingdom, October 29, 2013. York Computer Science (YCS).

Papers 8 and 9 investigate learning behaviour patterns within Topolor – a social personalised e-learning system. They are the basis of Chapter 5.

10. **Shi, L.**, Cristea, A. I., Stewart. C. (2014) Students as Customers: Participatory Design for Adaptive Web 3.0. In The Evolution of the Internet in the Business Sector: Web 1.0 to Web 3.0. IGI Global.
11. **Shi, L.**, Cristea, A. I., Foss, J. G. K., Al-Qudah, D. A., Qaffas, A. (2013) A Social Personalized Adaptive E-Learning Environment: A Case Study in Topolor. In IADIS International Journal on WWW/Internet. Vol. 11, No. 3, pages 13-34. ISSN: 1645-7641. IADIS Press.

Papers 10 and 11 summarise a new approach of synthesising social interaction and adaptation in e-learning. They are the basis of Chapter 4.

12. **Shi, L.**, Awan, M., Cristea, A. I. (2013) Evaluation of Social Personalized Adaptive E-Learning Environments: From End User Point of View. In Proceedings of the 3th Imperial College Computing Student Workshop (ICCSW 2013), pages 103-110, London, United Kingdom, September 26-27, 2013. Schloss Dagstuhl - Leibniz Center for Informatics.
13. **Shi, L.**, Awan, M., Cristea, A. I. (2013) Evaluating System Functionality in Social Personalized Adaptive E-Learning Systems. In Proceedings of the 8th European Conference on Technology Enhanced Learning (EC-TEL 2013), pages 633-634, Paphos, Cyprus, September 17-21, 2013. LNCS 8095, Springer Berlin Heidelberg.
14. **Shi, L.**, Al-Qudah, D. A., Qaffas, A., Cristea, A. I. (2013) Social E-Learning in Topolor: a Case Study. In Proceedings of the 7th IADIS Conference e-Learning 2013 (IADIS-EL 2013), pages 57-64, Prague, Czech Republic, July 23-26, 2013. IADIS Press.
15. **Shi, L.**, Stepanyan, K., Al-Qudah, D. A., Cristea, A. I. (2013) Evaluation of Social Interaction Features in Topolor – A Social Personalized Adaptive E-Learning System. In Proceedings of the 13th IEEE International Conference on Advanced Learning Technologies (ICALT 2013), pages 294-295, Beijing, China, July 15-18, 2013. IEEE Computer Society.
16. **Shi, L.**, Gkotsis, G., Stepanyan, K., Al-Qudah, D. A., Cristea, A. I. (2013) Social Personalized Adaptive E-Learning Environment – Topolor:

Implementation and Evaluation. In Proceedings of the 16th International Conference on Artificial Intelligence in Education (AIED 2013), pages 708-711, Memphis, Tennessee, USA, July 9-13, 2013. LNCS 7926, Springer Berlin Heidelberg.

17. **Shi, L.**, Al-Qudah, D. A., Cristea, A. I. (2013) Designing Social Personalized Adaptive E-Learning. In Proceedings of the 18th ACM conference on Innovation and technology in computer science education (ITiCSE 2013), pages 341, Canterbury, UK, July 1-3, 2013. ACM.
18. **Shi, L.**, Al-Qudah, D. A., Qaffas, A., Cristea, A. I. (2013) Topolor: A Social Personalized Adaptive E-Learning System. In Proceedings of the 21st Conference on User Modeling, Adaptation and Personalization (UMAP 2013), pages 338-340, Rome, Italy, June 10-14, 2013. LNCS 7899, Springer Berlin Heidelberg.

Papers 12 – 18 present the design and implementation of Topolor – a social personalised adaptive e-learning system, and the system assessments that evaluate Topolor from various perspectives. They are the basis of Chapter 4.

19. **Shi, L.**, Al-Qudah, D. A., Cristea, A. I. (2012) Exploring Participatory Design for SNS-based AEH Systems. In Proceedings of the 11th IADIS International Conference WWW/INTERNET (ICWI 2012), pages 242-249, Madrid, Spain, October 18-21, 2012. IADIS Press.
20. **Shi, L.**, Al-Qudah, D. A., Cristea, A. I. (2012) Apply the We!Design Methodology in E-learning 2.0 System Design: A Pilot Study. In

Proceedings of the 2th Imperial College Computing Student Workshop (ICCSW 2012), pages 123-128, London, United Kingdom, September 27-28, 2012. OASICS Vol. 28, Schloss Dagstuhl – Leibniz Center for Informatics.

Papers 19 and 20 report the process of gathering end-user's requirements for the design and implementation of a social personalised adaptive e-learning system. They are the basis of Chapter 3.

Abstract

This work aims to alleviate the weaknesses and pitfalls of the strong modern trend of e-learning by capitalising on and taking advantage of theoretical and implementation advances that have been made in the fields of adaptive hypermedia, social computing, games research and motivation theories. Whilst both demand for and supply of e-learning are growing, especially with the rise of MOOCs, the problems that it faces remain to be addressed, notably isolation, de-personalisation and lack of individual navigation. This often leads to poor learning experience. This work explores an innovative method of combining, threading and balancing the amount of adaptation, social interaction, gamification and open learner modelling for e-learning techniques and technologies.

As a starting point, a novel combination of classical adaptation based on user modelling, fine-grained social interaction features and a Facebook-like appearance is explored. This has been shown to be able to ensure a high level of effectiveness, efficiency and satisfaction amongst learners when using the e-learning system. Contextual gamification strategies rooted in Self-Determination Theory (SDT) are then proposed, which have been shown to be able to ensure learners of the system adopt desirable learning behaviours and achieve pre-specified learning goals, thus providing a high level of motivation. Finally, a multifaceted open social learner modelling is proposed. This allows visualising both learners' performance and their contributions to a learning community, provides various modes of comparison, and is integrated and adapted to learning content. Evidence has shown that this can provide a high level of effectiveness, efficiency and satisfaction amongst learners.

Two innovative social personalised adaptive e-learning systems including Topolor and Topolor 2 are devised to enable the proposed approach to be tested in the real world. They have been used as online learning environments for undergraduate and postgraduate students in Western and Eastern Europe as well as Middle Eastern universities, including the University of Warwick, UK, Jordan University, Jordan, and Sarajevo School of Science and Technology, Bosnia and Herzegovina. Students' feedback has shown this approach to be very promising, suggesting further implementation of the systems and follow-up research. The worldwide use of Topolor has also promoted international collaborations.

Keywords: social e-learning, adaptive e-learning, personalisation, gamification, open social learner modelling, learning analytic, participatory design, user-centric evaluation.

Abbreviations

AEH	Adaptive Educational Hypermedia
AEHS	Adaptive Educational Hypermedia System
AH	Adaptive Hypermedia
AHAM	Adaptive Hypermedia Application Model
AHS	Adaptive Hypermedia System
AJAX	Asynchronous JavaScript and XML
ALEF	Adaptive LEarning Framework
AM	Adaptation Model
ARP	Adaptation Rule Parser
ATR	Action TRacker
CM	Concept Model
CSS3	Cascading Style Sheets Level 3
DAG	Directed Acyclic Graph
DM	Domain Model
EC-TEL	European Conference on Technology Enhanced Learning
EDM	Educational Data Mining
FAME	a model-based Framework for Adaptive Multimodal Environments

GAF	Generic Adaptation Framework
GAM	Generic Adaptivity Model
GM	Goal and Constrains Model
HCI	Human-Computer Interaction
HTML5	Hypertext Mark-up Language Version 5
IM	Interaction and connection Model
ITS	Intelligent Tutoring Systems
KDD	Knowledge Discovery in Databases
LAOS	Layered WWW AH Authoring Model and their corresponding Algebraic Operators
LBP	Learner Behaviour Parser
LM	Learner Model
LRS	Learning Record Stores
MM	Module Model
MOOC	Massive Open Online Course
MOT	My Online Teacher Adaptive Hypermedia Authoring System
MOT2.0	My Online Teacher 2.0 Social Web Adaptive Hypermedia Authoring and Delivery System
OB-AHEM	Object-oriented Adaptive Hypermedia Educational Model
OER	Open Educational Resource

OLM	Open Learner Model
OSLM	Open Social Learner Model
PD	Participatory Design
PHP	Hypertext Preprocessor, an open source general-purpose scripting language that is especially suited for web development and can be embedded into HTML
PK	Player Killer, a naming convention taken from games
PM	Presentation Model
Q&A	Question and Answer
RM	Resource Model
SPADEL	Social Personalised ADaptive E-Learning framework
SD	Standard Deviation
SDT	Self-Determination Theory
SLAOS	Social LAOS: Social Layered WWW AH Authoring Model and their corresponding Algebraic Operators: A framework for authoring of Adaptive Hypermedia
SM	Socialisation Model
SNS	Social Networking Sites
SUS	System Usability Scale
TM	Topic Model
UCD	User-Centric Design

UCE User-Centric Evaluation

UI User Interface

UM User Model

UMAP Conference on User Modeling, Adaptation and Personalization

UML Unified Modelling Language

UX User Experience

XAHM XML-based Adaptive Hypermedia Model

Chapter 1

Introduction

1.1 Background and Motivations

The number of Internet users has grown 1080% since 2000, heading to the third billion in 2014, and causing an evolutionary shift in how people can engage with the world [200]. The global e-learning market is projected to exceed US$230 billion by 2020, driven by technologies and mechanisms such as HTML5 and CSS3-based browsers and cloud computing, smart mobile devices, and broadband Internet [201], and by the next generation of content and its creating and distributing systems such as using Open Educational Resources (OER) [195], Learning Record Stores (LRS) [130] and Massive Open Online Courses (MOOCs) [129]. The feverish market growth and compelling value proposition consistently promote academic research, industrial innovations, and commercial investments, as well as governmental endorsement. Education, which seems most unlikely to be influenced by fashions such as the Internet Industry, has already been facing new opportunities and challenges brought by the Internet.

Furthermore, the picture is permanently changing: the Internet of today looks totally different from that of the past, and its thriving user communities have become even stronger driving forces. The new generation students have embraced the Web as a normal part of their lives. They normally come with a very good background in Web 2.0 (as in social [126]) and some Web 3.0 (as in both personalised and social) systems and platforms, where not only are they content consumers, but also prolific producers. They write blogs and tweets, and upload photos, audios and videos to the cloud by billions. They create, comment, share and categorise the content as frequently as they search, read, listen and watch it. Social media tools [85] such as Facebook, Google+, Qzone, Renren, Twitter, YouTube, Youku, Weibo, Tumblr, Pinterest, Instagram and many others have been penetrating people's lifeblood like never before, and shortening the time and space distances, by connecting everything and everybody together. These phenomenan and trends are driving modern e-learning to support highly efficient connections and interactions between learners and content, so as to cater for learners' tastes and thus achieve a richer learner experience.

Social media tools have been incorporated into recreational and educational practices, aiming at offering more dynamic, flexible and accessible content, and promoting active learning for students [119, 152, 187]. A growing number of colleges and universities are using social media tools to communicate with their students, deliver learning content, and provide participation and discussion opportunities in a social and community-based learning paradigm [97, 106, 147]. Indeed, learning is intrinsically a social endeavour [192, 199], and the social facets of learning have been described in a variety of theoretical frameworks that explain how people learn [46, 191, 193]. The social learning theory postulates that learning is a cognitive process, which can occur through observation and imitation in a social context, and can be influenced by intrinsic reinforcement, as a form of internal reward, such as satisfaction and a sense of accomplishment [7, 8]. Whilst attempts have been made to bring social activities into e-learning (e.g., Moodle 2.3 promotes 'social learning' with wikis, Blackboard 10 facilitates 'social learning' with blogs), yet existing e-learning systems stubbornly focus on instructivist [75] and constructivist [45] approaches, allowing interaction with content alone.

The increasing demand for social and community-based e-learning systems that provide massive open online learning resources and support diverse connections and interactions is driving the development of new solutions that can help students access the most appropriate content and interact with the most relevant peers in the best way. This indicates that, apart from the elimination of the barriers of time and space, social e-learning must also personalise the learner experience. It has become clear that the 'one-size-fits-all' approaches are neither effective nor efficient for the diverse learners of today [116, 146]. Social e-learning requires the ability to deliver just-in-time and on-demand learner experiences, tailored to individuals, taking into account their differences such as knowledge, skills, abilities and preferences. However, the biggest encumbrance to personalise learning is that "scientific, data-driven approaches that effectively facilitate personalisation have only recently begun to emerge; learning analytics, for example, is still in the very nascent stage of implementation and adoption within higher education" [81].

Acknowledging the importance of personalisation in teaching and learning can be traced back as far as the *Spring and Autumn* period in the Chinese history.

Confucius (551 – 479 BC, a Chinese teacher, politician and philosopher) asserted already that teaching different learners requires flexible and individualised approaches. Modern psychologists, since the 1950s have also argued that no single teaching approach could best fit all learners, and have suggested the importance of adapting instructional procedures to individual differences [42, 44, 66, 80]. More recently, the research area of adaptive hypermedia (AH) [16] and adaptive e-learning [17] has been prospering and developing for three decades. It has produced a plethora of adaptive e-learning systems to support, verify and evaluate the newly proposed models, system architectures and methodologies that aim at breaking away from the 'one-size-fits-all' mentality [19] and enabling e-learning to adapt to learners' individual needs, and thus to provide an adaptive and personalised learner experience. Note that a social dimension has already been considered to be integrated into adaptive e-learning, to cater for the needs from the social e-learning paradigm [21, 40, 165]. However, research on how to efficiently intertwine social interaction and personalised learning content, and how the novel adaptive social e-learning can influence learner experience, remains elusive.

Successful social e-learning requires tools to assist learners in directing their own learning and having a high level of motivation so as to participate in meaningful interactions [94], similar to popular social software. Motivation is an inner drive, e.g., the desire and goal that activates, energises and directs behaviours [118]. It corresponds to physiological processes that influence directions and persistence of behaviours [118]. In e-learning, motivation plays a significant role – it initiates, guides and maintains efficient goal-oriented behaviours, for effectively achieving learning goals [1]. Social e-learning allows learners to take a self-motivating role of participating in determining their own learning paths; it allows for information discovery, as well as collecting, sharing, and personalisation of information [115], requiring support of a self-determined approach. Among motivation theories applied in learning, Self-Determination Theory (SDT) is an empirical one that focuses on the degree to which individual behaviours are self-determined and self-motivated [144]. It states that an individual becomes increasingly self-determined and self-motivated when three basic innate needs, i.e., autonomy, competence and relatedness, are satisfied [144]. A social e-learning system that satisfies all these three basic innate needs is expected to sustainably increase learners' intrinsic motivation, leading to an efficient self-determined learner experience [64, 177].

Gamification has been the carrier of utilising and understanding the motivation benefits of Self-Determination Theory (SDT) in the context of e-learning. Gamification is the use of gameplay mechanics for non-game applications [134]. It describes an efficient way of utilising game design elements to engage users and motivate their activities, in order to solve problems and promote learning [86]. It has been incorporated into numerous domains such as marketing, work and educational systems, especially social ones, as a way of creating strong connections between users and systems, and driving their interactions to increase popularity [54]. This trend is increasingly catching researchers' attention – to explore theories and practices of gamification in social e-learning, aiming at increasing learner motivation, driving desirable learning behaviours and achieving learning goals [100]. According to their nature, gamification and social e-learning have various mechanics in common, such as achievement, collaboration, discovery, and virality, so that their combination may have a greater impact on e-learning. In fact, researchers have already started exploring this combination, reporting its various influences on the learning process [54, 175].

Whilst both demand for and supply of e-learning are growing, the issues that are facing it remain, such as isolation, information overload and lack of individual narrative, often leading to disengagement and poor learner experience. Towards addressing these issues and thus offering motivating e-learning systems and achieving rich learner experience, this research aims to take advantage and capitalise on theoretical and implementation advances that have been made in various fields such as adaptive learning, social networking, motivation theories and gamification research, in order to alleviate the weaknesses and pitfalls of a strong trend in current society, that of e-learning.

1.2 Research Questions and Objectives

The present work combines and develops various techniques and technologies to answer a research question that can broadly be formulated as the following.

> **R0.** How can we ensure that e-learning systems achieve rich learner experience, in terms of a high level of effectiveness, efficiency, satisfaction, motivation and engagement amongst learners?

There are many ways to explore this question, but here we build on the assumption that it is worth exploring and providing an innovative method of combining, threading and balancing the amount of adaptation, social interaction, gamification and open learner modelling for e-learning. This attempts to look at the global picture by combining the aforementioned subjects arises from the fact that new generations of learners 'live' in social e-systems, with a high level awareness of game paradigms, and an increased need of control. However, few research projects, if any, have made this attempt. From this perspective, the original question (**R0**) is explored further and subdivided into the following three closely related questions, which are the main focus of the thesis.

- **R1.** How can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and engagement amongst learners?
- **R2.** How can we implement gamification techniques and technologies, in order to enhance social e-learning systems, and thus provide a high level of motivation amongst learners?
- **R3.** How can we implement open learner modelling techniques and technologies, in order to enhance e-learning systems, and thus provide a high level of effectiveness, efficiency and satisfaction amongst learners?

Formulating and addressing the following objectives operationalize the process of answering the research questions.

O1. Reviewing the state of art in the fields of adaptive e-learning, social e-learning, gamification and open learner modelling to investigate their influence on the e-learning process.

O2. Exploring and understanding the needs of the learners for a social personalised adaptive e-learning system, aiming at gathering the requirements for the implementation of the research environment.

O3. Based on the hypotheses and conclusions from **O1** and **O2**, developing a social personalised adaptive e-learning system that fosters a social, personalised and adaptive e-learning experience, and evaluating it from the perspectives of learner effectiveness, efficiency, satisfaction and engagement.

O4. Based on the hypotheses and conclusions from **O3**, building novel gamification strategies upon the initial social personalised adaptive e-learning system, and examining the impacts of the new gamification features on learners' motivation.

O5. Based on the hypotheses and conclusions from O3, extending the previous system with new open learner modelling, and examining its influence on learners' effectiveness, efficiency and satisfaction.

In summary, **O1** serves as background knowledge and inspiration to support research questions **R1**, **R2** and **R3**. **O2** and **O3** support research question **R1**. **O4** and **O5** support research questions **R2** and **R3** respectively.

1.3 Methodology

As stated in sections 1.1 and 1.2, this research work ultimately strives to obtain the appropriate balance and granularity of adaptation, social interaction, gamification and open learner modelling techniques and technologies in e-learning. Such balance and granularity need to be able to ensure a rich learner experience, in terms of a high level of effectiveness, efficiency, satisfaction, motivation and engagement amongst learners. A user-centric approach is adopted for the investigation and validation processes, through a continual process of design, development and evaluation.

1) Literature Review

The starting point of the work in this thesis is the enunciation of the umbrella research question defined and developed in the previous section. A systematic literature review [36], which is presented in Chapter 2, was undertaken to investigate current thinking and benefits from previous experiences. The review process began in 2011 and was subsequently updated up to the completion of this thesis. It focused on the areas of adaptive and social e-learning, gamification and open learner modelling techniques and technologies. For each of these areas, the literature review aims to articulate its related definitions, revisit its development process, summarise its pros and cons, and clarify how this research work further develops this area.

2) User-Centric Design

The user-centric design (UCD) [124] method is adopted, aiming to retrieve the learners', i.e., end-users', needs, wants and limitations, and eventually optimise the acceptance and satisfaction of the innovation. Contextual inquiry, prototype testing and usability testing initiate the design process. This allows analysing end-users' cognition, characteristics, preferences, etc., as well as the tasks that techniques and technologies may help them complete. The participatory design (PD) [148] methodology is applied, so that the end-users' opinions can be considered from the early design stages, and thus build more customer-oriented systems [4]. The reason for this is the assumption that if the systems were designed to provide its end-users with exactly what they need, these would achieve a high level of user experience. This could eventually lead users to try other features and content, enabling the system to collect more usage data, which in turn would lead to a more usable system, with greater benefits for its users.

3) Iterative and Incremental Development

The Iterative and Incremental development model [98] is adopted in this work. It is a cyclic process of system development proposed in response to the weaknesses of the Waterfall model [142]. It guides us to develop a system through repeated cycles (iterative) and in smaller portions at a time (incremental). The process flows in iterative loops, so that it is always possible to adapt to the adjustment of requirement and technology. Each of the iterations consists of a well-defined set of objectives, as well as development disciplines, such as design, implementation and evaluation. Each of the successive iterations builds upon the previous iteration, in order to evolve and refine the system. This iterative process allows for taking advantages of what has been learnt during the earlier iteration of development, as well as the earlier version of the system. The iterative process of design, implementation and evaluation of the innovative method of combining, threading and balancing the amount of adaptation, social interaction, gamification and open learner modelling for e-learning, is described in Chapter 3 to Chapter 7.

4) Case Study and Evaluation

Several case studies were conducted to gather feedback from the end-users including learners, tutors and observers, during real-life online learning sessions. Learners are asked to study online courses using the implemented system, while a logging mechanism keeps track of distinct learners’ usage data. After the online learning sessions, they are asked to complete optional and anonymous Likert scale [103] questionnaires. In addition to the questionnaire data, oral feedback from some of the learners, tutors and observers is also collected. Various features of the system are evaluated in terms of effectiveness, efficiency and satisfaction amongst learners. Data mining methods and data visualisation tools are used to analyse logging data, in order to discover learning behaviour patterns, so as to understand more deeply how the innovation influence learner experience and engagement.

1.4 Thesis Outline

In total, this thesis contains eight chapters, organised as follows.

Chapter 1, the current chapter, introduces the goals and methodology of the work conducted for the thesis, including background and motivation, research questions and objectives, a description of how the research was conducted and an outline of the thesis.

Chapter 2 elaborates the related work. Firstly, it introduces the state of the art in adaptive hypermedia and user modelling, including the evolution of the adaptive hypermedia frameworks and systems. Subsequently it reviews social, gamification and open learner modelling techniques and technologies in e-learning, investigates their merits and limitations, and proposes the direction that this research aims to address. Finally, it presents the user-centric evaluation approach adopted to assess the design and implementation of the innovation.

Chapter 3 reports the experiment conducted, which applied the participatory design (PD) methodology, aiming to gather the real-life needs from the learners, i.e., the end-users. For this purpose, it starts with introducing the PD methodology and the We!Design (PD) framework. It then describes the experimental study, emphasising how the We!Design (PD) framework has been applied. Finally, it suggests the initial system requirements, resulting from the experiment, and orders them based on their implementation priority.

Next, Chapter 4 describes the design, implementation and evaluation of the initial social personalised adaptive e-learning system – Topolor, with the aim of addressing the gap that current adaptive e-learning systems have only marginally explored: the integration of social interaction features and adaptation techniques. Based on the background literature study in Chapter 2 and the system requirements suggested in Chapter 3, Topolor is built by integrating classical adaptation, fine-grained social interaction features, and Facebook-like appearance, aiming to foster effective and efficient social personalised adaptive e-learning experience with high satisfaction of learners. The evaluation results indicate positive feedback from the learners, the end-users, and guide the follow-up research, including introducing gamification (Chapter 6) and open learner modelling (Chapter 7).

Chapter 5 reports on the learning behaviour pattern analysis that aims to gain significant new insights into learner behaviours and engagement within Topolor, introduced in Chapter 4. Data mining methods and data visualisation tools are used to analyse the log data. The analysis of action frequencies and sequences aims to identify common and individual behaviour patterns. However, deviations from what is most common are also sought, to grasp a better understanding of learners' participation and engagement within the system, and provide suggestions on further development and improvement of the system.

Chapter 6 shows the second version of the social personalised adaptive e-learning system – Topolor 2, which is developed based on the findings described in Chapter 4 and Chapter 5. It introduces new gamification strategies that are inspired by Self-Determination Theory (STD) and aim to improve the first version of Topolor with gamification mechanisms and gamified social interactions. The newly introduced gamification strategies are expected to promote learners' intrinsic motivation, and thus build an efficient self-determined learner experience.

Chapter 7 presents follow-up research, based on the findings described in Chapter 4 and Chapter 5; it consists of learner data visualisation that could potentially influence effectiveness, efficiency and satisfaction amongst learners. Having learnt from the open learner modelling techniques and technologies introduced in Chapter 2, which visualise learner model to a learner themself, this chapter proposes a new approach that can seamlessly and adaptively integrate open learner modelling with learning content. Thus, its ubiquity and context-awareness can support new adaptation and personalisation methods for social personalised adaptive e-learning. This new approach allows the visualisation of both performance and contribution of learners, reflecting not only their role as a knowledge consumer, but also that of a knowledge producer, a view which is better integrated with the social web era.

Finally, Chapter 8 concludes the thesis through a review of the general research progress, and a discussion of the overall research achievements, contributions and impacts. It also recommends potential directions and areas in which future research could be undertaken.

Chapter 2

Background and Related Work

2.1 Introduction

This chapter aims to address the research objective **O1**: "reviewing the state of art in the fields of adaptive e-learning, social e-learning, gamification and open learner modelling to investigate their influence on the e-learning process", which serves as background knowledge and inspiration to support research questions defined in section 1.2.

Firstly, section 2.2 sketches an overview of adaptive e-learning systems, including various terminologies, theories and techniques of adaptive hypermedia and user modelling, focusing on various architectures of adaptive hypermedia frameworks. Secondly, section 2.3 reviews the use of social techniques in e-learning such as social navigation, and discusses their advantages and limitations. Thirdly, section 2.4 explores gamification techniques in e-learning. It explains the differences between full games and serious games, and provides examples of gamification systems, with special focus on the educational ones. It also introduces motivation theories that could potentially guide the design of gamification. Fourthly, section 2.5 investigates the existing open learner modelling approaches, analyses their merits and limitations, and describes solutions that could potentially address the limitations. Fifthly, section 2.6 presents a user-centric approach that will be used to evaluate the innovation made in this work. Finally, section 2.7 summarises the literature review, the research background and related work.

2.2 Adaptive E-Learning

Adaptive hypermedia (AH) is a 20-year-old field of research at the crossroads of hypermedia and user modelling. In contrast to the traditional approach whereby all users are offered the same content or even directed to the same series of hyperlinks, AH tailors the offering and direction of the hypertext and hypermedia to an individual, by modelling, for example, goals, preferences and knowledge. It updates this model via interaction with the user [18], in order to provide adaptive navigation and content support. The main goal of AH research is to improve the personalisation of hypermedia systems, by making them adaptive and adaptable. A system that adapts to users using implicit inferences based on the interaction with the users is called *adaptive*, whilst systems that adapt to users using explicit user input are called *adaptable*. AH is one of the basic research areas supporting the research in this thesis.

As the most popular branch of the AH research area, *adaptive e-learning* combines *adaptive hypermedia systems* (AHS) and *intelligent tutoring systems* (ITS) [176], with the aim of breaking away from the 'one-size-fits-all' mentality [19], and producing e-learning systems in which the learning content and the order of learning the content are adapted to each learner's needs, such as their knowledge level, learning goal, preferences, stereotypes, cognitive and learning styles [23], in a given context, and thereby providing a personalised learner experience.

Many conceptual frameworks/models have been proposed since the early 2000s, aiming to simplify the process of building adaptive systems. Well-known frameworks include AHAM proposed by De Bra *et al.* [13], XAHM proposed by Cannataro *et al.* [30], LAOS proposed by Cristea and De Mooij [41], the Munich model proposed by Koch and Wirsing [92], GAF proposed by Knutov [89], and so on. Later, some conceptual frameworks with a social dimension were proposed, such as SLAOS [40] and ALEF [174].

AHAM [13] extends the storage layer of the Dexter Model [71], aiming at providing more functionality than just storing information about the hypertext structure. AHAM divides the storage layer into three models: the *domain model* (DM), the *user model* (UM) and the *teaching model*. DM describes the mechanism by which the information is structured and linked with each other. UM records user data including knowledge, interest, preference and goals. The *teaching model* maintains pedagogical rules that indicate how to combine DM and UM in order to perform the actual adaptation.

Similarly to AHAM [13], the Munich Reference Model [92] is also based on the Dexter Model, but includes a *user model* (UM) and an *adaptation model* (AM) as part of the Storage Layer. AM describes adaptation rules which can dynamically provide a user behaviour-triggered runtime session and a rule-based adaptation.

The Munich Reference Model is defined by *unified modelling language* (UML), taking an object-oriented software engineering point of view, and providing an object-oriented formalisation for the adaptive e-learning reference model, which are the main differences from AHAM.

LAOS [41] is built upon AHAM. It introduces a *goal and constraints model* (GM) between DM and UM. *Goals* give a focused presentation, and *constraints* limit the space of the search. GM filters useful concepts from domain(s) and arranges them for the current pedagogical goal, e.g. to construct a course for a group of learners that should last one semester. GM can filter concepts from more than one DM, and a DM can generate multiple GMs.

Later, the GAF framework was proposed, aiming at enhancing adaptation capabilities and including new methodologies and techniques [89]. It introduces ontologies into DM to provide interoperability in different adaptive applications; a *resource model* (RM) to meet the need of open corpus adaptation [21], where learning resources come from search results in dynamic learning object repositories or from a web search engine; a *context model* (CM) to define user and usage context which capture the context of user behaviour and system usage, in order to make adaptive applications more sensitive to adapt in many other ways rather than through a set of predefined rules [91]; and a *group model* to maintain a collaborative profile of the user or stereotyping search results so as to rank and recommend these results.

Besides the frameworks mentioned above, many other layered frameworks (reference models) have also been launched since the early 2000s. XAHM [29] is a data-centric model based on the class diagrams of UML, which integrates a graph-based description of navigational properties and an object-oriented semantic description of the hypermedia, and uses a logical formalism to support run-time adaptation to user behaviours, technologies and external systems. OB-AHEM [128] is a high level model that inherits many advantages from the object-oriented paradigm, which provides the ability to reuse the solutions in navigation, user modelling, definition and application of adaptive rule. GAM [190] provides the state-machine mechanism for an adaptation engine including push modelling and pull modelling in the shape of rules and questions, which can be used in a modular way to allow for more flexible adaptation systems. FAME [55] proposes a model-based architecture for adaptive multimodal systems, which provides adaptation rules for each adaptable component that are encoded in a behavioural matrix, in order to adapt to user actions, system events and systemic changes.

Some of the frameworks were later extended to accommodate some social features. For example, ALEF (Adaptive LEarning Framework) [174] combines different learning activities, such as learning from explanatory texts and additional interactive content, in the form of short quiz questions and exercises, and benefits from all the possibilities that Web 2.0 techniques can currently offer, integrating them with personalised educational resource access. Within ALEF, three principles are proposed to develop a social personalised adaptive e-learning system: 1) the possibility of automatically creating certain parts of domain models as well as collaboratively modifying the domain models by the students; 2) the extensible personalisation and course adaptation based on comprehensive user modelling that simultaneously employs different adaptive techniques; and 3) the ability for the students to collaboratively participate in the learning process, interact and create learning content via different types of annotations that allow for rich interaction with the learning content.

Another framework that takes into consideration a social dimension is SLAOS (Social-LAOS) [61]. It is built on top of the LAOS framework [41], extending it by integrating a social layer, and by blending the authoring and delivering phases (i.e., removing the barrier between tutors, learners and authors, all of whom become authors with different sets of privileges). In such way, learners are able to collaboratively contribute to the learning content authoring process with different privileges, which can be set based on their knowledge level. The new social layer expresses all social activities within an adaptive hypermedia system such as *collaborative authoring* (editing content of other users, describing content using tags, rating, commenting on the content, etc.), *authoring for collaboration* (adding author activities such as defining author groups, subscribing to other authors, etc.), *group-based adaptive authoring* via group-based privileges, and *social annotation* (tagging, rating, and commenting on the content via group-based privileges) [39].

As the SLAOS framework has been the basis for the architecture of the e-learning system implemented in this work, here it is described in more detail. Figure 1 presents the components of the SLAOS framework.

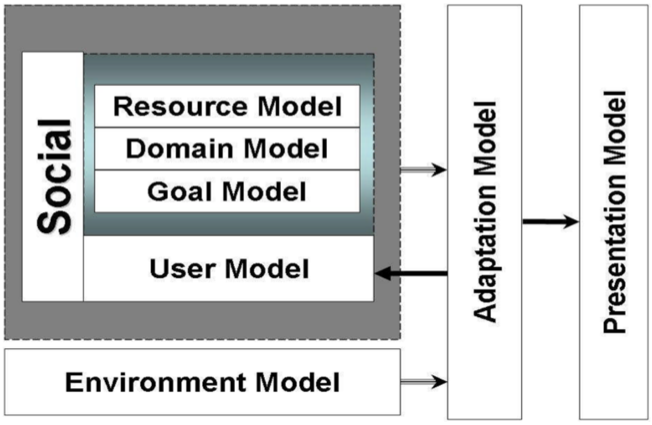

Figure 1 The SLAOS framework [39]

- The **Social Resource Model** stores items that learners are reading at a particular time, in a module. Its metadata, such as rating and feedback, represent a social overlay.
- The **Social Domain Model** represents structured concepts within a domain map, which permits reusability, as one concept can be used in more social domain maps.
- The **Social Goal Model** defines goal and constraints maps, which are a subset of structured concepts within a social domain map, with *goals* and *constraints* given by lesson constructions.
- The **Social User Model** contains both free variables, as well as an overlay over the **Social Goal Model**, recording a status of the user against the concepts, such as '*learnt*' or '*ready-to-learn*', which can be updated according to the user's activities, similar to typical user models in adaptive hypermedia. Additionally, the **Social User Model** also defines other items, such as user groups, user roles, and

user subscribers, to name a few, which cater for the social aspects of the users. Furthermore, links between the users of arbitrary nature within the framework permit various social interactions.

- The **Environment Model** represents physical devices such as desktops, laptops and tablets, to allow adaptation to them.
- The **Adaptation Model** is a set of *adaptation rules* that form the connection between the above models**,** to decide on the presentations (specifications) to be generated in the **Presentation Model**. It also allows for strategies that update the **Social User Model**.
- The **Presentation Model** is an overlay over the conceptual structure, to decide if, where and how a specific concept (or part thereof) will be displayed. It also contains a set of definitions of user interface (UI) components that visualise *navigations*, *layouts* and *content*, which are generated based on the adaptation strategies within the **Adaptation Model**.

These theoretical and technical works have shown that the research focus has shifted from an individual orientation [6] (on the learner and their cognitive process) to a social orientation. In comparison with *adaptive educational hypermedia* (AEH) and adaptive e-learning systems, social-AEH and social personalised adaptive e-learning systems have been pushing the research area of AEH towards fostering diversification of user modelling [10]. The work presented in this thesis continues this progress and builds on the SLAOS framework, but further explores its social dimension, in order to support richer learner experience.

2.3 Social Techniques in E-Learning

Learning is intrinsically a social endeavour [7, 192, 199]. Social facets of learning have been described in a variety of theoretical frameworks about people and their learning [46, 191, 193]. However, moving from a face-to-face experience into a computerised domain, the creation of effective and efficient online social learning remains an unsolved problem. Whilst online exchange via social networking is immensely popular and an important component of day-to-day life, providing solutions that foster creation of effective e-learning spaces is not straightforward. Therefore, in this work, we decide to build our own social personalised adaptive e-learning systems (sections 4.3 and 6.3), in which the social flavour is naturally built and more tightly integrated.

The use of social techniques in e-learning systems has become increasingly popular in the research community. Social techniques can attract learners to interact with one another, and generate trails for peers to follow. Not only can they promote learners to produce learning content by themselves, but they also encourage them to participate in various learning activities within the system [162]. In the social e-learning paradigm, learners achieve learning goals via social interaction, such as tagging, rating and commenting within learning communities, where they share knowledge, skills, abilities and learning resources [168]. In such a system, connectedness and interactivity try to satisfy learners' basic innate needs, including autonomy, competence and relatedness [144], and thus can lead to an increase of engagement and motivation [34].

As a well-known social techniques in e-learning, social navigation has been one of the first attempts to combine social techniques with adaptive e-learning [20, 50]. A more recent approach is the social and adaptive e-learning system MOT2.0 [62], which goes a little further in terms of social features incorporated. It provides features that allow learners to chat, comment, rate and tag parts of the learning content. This allows the system to provide adaptive navigation personalisation techniques, by suggesting content that the learner's peers recommend, as well as suggesting appropriate peers to contact. An interesting technique also used by this system is that of adaptive rights, i.e., rights adapted to the deduced level of the user. However, this system is still at a level of concept proving, and the granularity of its adaptation and social interaction, is still quite coarse (e.g., complete topics are recommended, the peer recommendation is relatively simple, etc.). This work thus has been the basis and initial inspiration for the work presented in this thesis. Here, however, much finer-grained adaptation and recommendations as well as fine-grained social interactions are introduced (see Chapter 4).

Whilst previous systems cater for personal needs within specific learning contexts, they are often limited in their strategies for adapting to social needs or in their social features. Some recent works [72, 174, 196] have outlined the need for creating adaptive and highly interactive integrated learning systems. However, their works suggest only a limited number of mechanisms for enabling social interaction. Therefore, there is a gap for extending and evaluating social interaction tools in adaptive e-learning settings, which is one of the objectives of the work presented in this thesis. Additionally, the familiarity of a user interface is important in the user-system interaction design, as it can shorten users' reaction time, and thus reduce their burden of getting used to the system [104]. However, existing frameworks and systems do not take into account a learner's familiarity with other social interaction tools, encountered either in other e-learning systems, or on social networking websites, such as Facebook and Google+. Therefore the work presented in this thesis intends to investigate the combination of classical adaptation based on user modelling and fine-grained social interactions as well as system appearances that learners are familiar with (see Chapter 4).

2.4 Gamification Techniques in E-Learning

The field of gamification seeks to apply game mechanics and game design techniques, such as incorporating challenges and rewards to encourage more engaged participation [86]. Gamification techniques strive to leverage people's basic desires and needs that revolve around thoughts on competition, status, self-expression, achievement and community collaboration. In academia, gamification has been defined as the practice of utilising game design elements in non-game contexts [49]. Different from a traditional digital game, gamification incorporates game thinking [194] (game-like approach to aesthetics and usability) and game elements [2] (elements from computer games, such as avatars, badges, goal settings, progression bars, countdown, urgent optimism, behavioural momentum, and appointments) in a non-game system, and aims to achieve some goals such as learning and marketing, other than just entertaining players. Gamification differs from serious games [178] that themselves are similar to traditional digital games, but also have defined purposeful goals, such as learning outcomes.

The aim of gamification is to engage desirable behaviours and to achieve the designed goals, or to fulfil an experiencing purpose. For instance, *Nwplyng*[1] rewards users for identifying and sharing what music they are listening to with friends via Facebook and Twitter with badges. *Viggle*[2] rewards users for watching television and sharing their favourite shows with their friends. *FuelGood*[3] gamifies the driving process and motivates users to reduce their carbon footprint by tracking users' driving and offering tips on how to improve gas mileage. *Foursquare*[4] uses badges and leaderboards to encourage users to visit different places and report what places they have visited.

In the e-learning area, researchers have been investigating the impact of gamification on the learner experience, especially its impact on learners' engagement and motivation. For example, *Comtella* [33] is a small-scale peer-to-peer online community for sharing academic papers and class-related web-resources among students. It has an adaptive reward mechanism to encourage learners to rate contributions, thus ensuring decentralised community moderation.

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[1] nwplyng.com

[2] viggleinc.com

[3] fuelgood.co.uk

[2] viggleinc.com

[4] foursquare.com

[3] fuelgood.co.uk

[5] http://yiiframework.com

[4] foursquare.com

[6] http://getbootstrap.com

[7] https://github.com/aslanshek/topolor

[8] PK (Player killing): in a Player(s) Versus Player(s) (PvP) gaming environment, PK means one player attack another without warning. This can result in a character's death [11].

QizBox [63] provides a learning platform that encourages social engagement from learners. It has a level-based progression mechanism, which is based on five specialisations, in which learners can gain experience points. This mechanism helps to encourage five separate types of behaviours identified in using the system, i.e., social, intelligent, helpful, inquisitive, and hardworking, so as to allow learners to have a sense of freedom and an ability to customise their experience within the system to their own personality. *Classroom Live* [58] is a gamified online tool used in computer science classes for undergraduate students. It takes into consideration various game design elements including points, levels and rewards, aiming at providing enjoyable learner experiences and increasing students' engagement. *WeBWorK* [68] is an online system where students access their homework and submit answers. It allows learners to earn levelling/experience points by correctly answering homework questions; it also provides a progress bar to heighten the sense of accomplishment and notification mechanism to instant feedback of learner achievement. *Schoooools* [175] is a social gamification online learning system that promotes collaboration and socialisation using game mechanics. It provides necessary tools to build the gamified learning process by, e.g., allowing the teacher to personalise and adapt badges, trophies or virtual goods, or the kind of rewards that students can get. These systems inspire the work presented in this thesis, such as the design of gamified social interactions, further described in section 6.3.

However, gamification has been criticised for its overjustification effect, which occurs when an expected external incentive de-motivates learners with already existing high intrinsic motivation [70]. It is believed that people could end up paying more attention to external rewards than internal enjoyment and pleasure obtained from the activity itself [123]. Moreover, evidence suggests that increased extrinsic motivation might reduce learning performance [65]. Therefore, the work presented in this thesis intends to explore a *light gamification* approach that applies motivation theories to promote intrinsic motivation, hosted in a social personalised adaptive e-learning systems, rather than a *full-fledged gamification* approach that may 'over-gamify' the already existing learning community.

Motivation is an inner drive, e.g., desires and goals that activate, energise and direct behaviours. It corresponds to physiological processes, which influence directions and persistence of behaviours [118]. In e-learning, motivation plays an essential role in the success of the learning process. It initiates, guides and maintains efficient goal-oriented behaviours, in order to effectively achieve learning goals [1]. Social e-learning systems allow learners to take a self-motivating role in determining their own learning paths, using social web tools for connecting to each other. They allow for information discovery and sharing, information collection and personalisation [115], yet require special support for this self-determined approach.

Among motivation theories applied in learning, Self-Determination Theory (SDT) is an empirical one that focuses on the degree to which individual behaviours are self-determined and self-motivated [144]. It states that an individual becomes increasingly self-determined and self-motivated when they are satisfied with three basic innate needs, i.e., autonomy, competence and relatedness [144]. A social personalised adaptive e-learning system that can satisfy all these three basic innate needs is expected to sustainably increase learners' intrinsic motivation, leading to an efficient self-determined learner experience [64, 177]. Therefore, in this work, SDT guides the design of the *Contextual Gamification Strategies* (section 6.2), with the aim of satisfying learners' basic innate needs, and thus to increase learners' intrinsic motivation.

2.5 Open Learner Modelling

A learner model often refers to a model of knowledge, or other characteristics of a learner, constructed from direct input or observation of learning activities in, e.g., adaptive e-learning systems, and updated according to the learner's current understanding of the target learning content. An *open learner model* (OLM) has specific provisions for the learner to explicitly view the information in their model, so as to support self-reflection of their own and their peers' learning processes, and explain the reason of getting a particular recommendation [24, 26, 27]. OLM has been implemented using a wide range of modelling approaches, and its various educational benefits are thoroughly discussed in the literature, such as raising learners' awareness of their current knowledge levels and encouraging them to reflect on the learning process [51].

In comparison with OLM, *open social learner modelling* (OSLM) has pushed the research area of adaptive e-learning systems towards fostering diversification of learner modelling, richer visualisation and interaction of learner models [25], and accumulating a large set of theories and techniques to build a variety of e-learning systems with personalised, adaptive and social features. However, previous research and implementations of OSLM, as summarised below, mainly focus on visualising the learning progress and providing social navigation support, based on learner models. Besides their merits, these implementations also have limitations, which our research aims to address, as discussed below.

IntrospectiveViews [76] provides parallel views on models of a learner and their peers. A learner can choose to compare their learning progress (completed, partially completed, pending, following) with either another peer's learning progress or the average progress of the entire learning group. However, the comparisons have limited-level granularity representation of learning content. *QuizMap* [22] has a 4-level hierarchical representation of a tree-map. Each level clusters different information in detail (from an entire class's performance to an individual's performance on a single question). A learner can observe their own performance in comparison with that of the rest of the class. However, *QuizMap* cannot fit larger classes that generate too many cells on the *TreeMap*, causing it to become too crowded (information overload). *ProgressiveZoom* [101] is built upon the Google-Maps paradigm, seeking to address information overload issues, by enabling learners to zoom in or out in a multi-layer fashion. However, it has limited ability to control comparisons between learners.

To address these limitations, the work presented in this thesis intends to seamlessly integrate OSLM at all granularity levels of the learning content (section 7.2), such as at a course level, a topic level and a resource level. This could potentially address the limited-level granularity learning content representations of *IntrospectiveViews*, and the concern of a too crowded user interface or information overload in *QuizMap*. Moreover, the new approach is expected to allow a learner to compare themselves to both individuals and groups (section 7.2), unlike in *ProgressiveZoom*. Table 1 summarises the difference between the existing approach and the new approach.

Table 1 Difference between approaches

Difference		**Introspective Views**	**Quiz Map**	**Progressive Zoom**	**Our approach**
comparison mode	1 to 1	X			X
	1 to n				X
	1 to all	X	X		X
visualisation	progress	X		X	X
	performance		X		X
	contribution				X
	parallel view	X			X
view switching		not available	zoom	zoom	adaptive
main limitation		limited granularity	information overload	no comparison	-

2.6 User-Centric Evaluation

Human-computer interaction (HCI) provides a wide range of definitions and measuring methods for *user experience* (UX) [73]. Parameters used in these methods include subjective data assessed through questionnaire instruments, and objective data assessed through logged usage data. Evaluating adaptive e-learning systems is even more difficult, due to their inherent complexity. Therefore it is necessary to ensure that appropriate evaluation methods and measures are used.

User-centric evaluation (UCE) is one of the best-accepted approaches that identify the determinants of UX issues. It serves empirical system evaluation and uses subjective user feedback on satisfaction and productivity, as well as the quality of work and support [69], aiming to verify the quality of a system, detect problems and support decisions [47]. The nature of UCE makes it a valuable approach to evaluate a system, help researchers and engineers implement more enjoyable UX, and thus eventually lead to a higher adoption of the system [188]. Therefore, this research takes the UCE approach to evaluate the innovation.

To gain insight into the UCE approach, it is crucial to articulate the definition of UX. UX started to attract designers' attention since the early 1990s, when it was first coined and more widely disseminated by Donald Norman. UX is associated with a wide range of meanings [57], from classical usability to fuzzy and dynamic concepts such as emotional, affective, experiential, hedonic and aesthetic variables [99], becoming thus an elusive notion with many different definitions. UX is well discussed in conferences and symposiums, yet there is still no widely shared view of its definition. Different organisations, researchers and designers have made the following definitions – just to name a few.

- Alben [79] defines UX as “all the aspects of how people use an interactive product: the way it feels in their hands, how well they understand how it works, how they feel about it while they are using it, how well it serves their purposes, and how well it fits into the entire context in which they are using it”.
- Hassenzahl and Tractinsky [73] define UX as “a consequence of user’s internal state such as predispositions, expectations, needs, motivation, mood, the characteristics of the designed system such as complexity, purpose, usability, functionality, and the context (or the system) within which the interaction occurs such as social setting, meaningfulness of the activity, voluntariness of use”.
- ISO 9241-210 [52] defines UX as “a person's perceptions and responses that result from the use and/or anticipated use of a product, system or service, including all the users’ emotions, believes, preferences, perceptions, physical and psychological responses, behaviours and accomplishments that occur before, during and after use, influenced by three factors, i.e., system, user and the context of use”.

Since UX includes a lot of dynamic concepts, and there is still no widely shared view of its definition, it is even harder to define criteria against which it could be evaluated [141]. The metrics settings for the UX evaluation could be various, depending on the perspectives of both system aims and user needs. For example, for gaming systems, UX metrics may be concerned more with the fun and enjoyable experience; for banking systems, UX metrics may revolve around the secure and trustworthy experience; for online shopping systems, UX metrics would focus on customers' satisfaction or on the payment process; and for e-learning systems, UX metrics may revolve around learner motivation and engagement or accessing learning materials.

Researchers have been proposing, summarising and classifying UX metrics (or criteria, frameworks) in the literature. The UX metrics proposed by Van Velsen *et al.* [188] consist of *appreciation, user satisfaction, usability, user performance, intention to use, appropriateness of adaptation*, and *comprehensibility*. Morville [120] proposes UX criteria to evaluate if the system is *useful, usable, findable, credible, accessible, desirable* and *valuable*. Wu *et al.*'s UX evaluation framework [198] includes six constructs: *flow, perceived technology acceptance, telepresence, performance gains, technology adoption*, and *exploratory behaviours*.

When evaluating more specific types of systems, the metrics are usually tailored to suite the system type's aims, either by specifying UX metrics, or introducing some other metrics.

In adaptive hypermedia and recommender systems areas, several elaborate user-centric evaluation frameworks have been proposed. For example, Pu *et al.* proposed ResQue [131], which defines a set of metrics that are grouped into four high level layers: *perceived system qualities*, *users' beliefs*, *subjective attitudes*, and *behavioural intentions*. For each metric, ResQue also specifies several questions to ask users. Knijnenburg *et al.*'s framework [88] contains five dimensions to evaluate, including *objective system aspects*, *subjective system aspects*, *user experience*, *interaction*, and *personal and situational characteristics*.

In the e-learning system area, Ardito *et al.* [3] proposed four dimensions for the evaluation, including *presentation*, *hypermediality*, *application proactivity* and *user activity*. For each of them, both *effectiveness* and *efficiency* are considered as the informing principles. Liaw and Huang [102] examined the relationships between *perceived self-efficacy*, *perceived anxiety*, *interactive learning systems*, *perceived satisfaction*, *perceived usefulness* and *perceived self-regulation*, and proposed *perceived satisfaction*, *perceived usefulness* and *interactive learning systems* as predictors for self-regulation in e-learning systems.

These definitions and metrics indicate that, in order to evaluate the innovation implemented in this work, it is crucial to understand the changes that have occurred due to the merging of techniques into the innovation. Taking into account their potential influence on the learning process, it is necessary to characterise *learner experience of social personalised adaptive e-learning* and define the metrics of its evaluation. In this work, *learner experience* (LX) is defined as "a learner's perceptions and responses resulting from the use and/or anticipated use of an e-learning system" – as an emulation of the definition of UX. This is a more extensive approach. It encompasses and goes beyond the traditional research of skills and cognitive process of users and their behaviours when interacting with the e-learning system. The definition of LX guides the system evaluations presented in this thesis, including those described in sections 4.4 and 7.4.

Note 3 of ISO 9241-210 [52] implies that *usability* addresses aspects of UX, i.e., "*usability* criteria can be used to assess aspects of *user experience*". ISO 9241-11 [78] defines *usability* as "the extent to which a product can be used by specified users to achieve specified goals with *effectiveness*, *efficiency* and *satisfaction* in a specified context of use". In line with this, the metrics that have been chosen to evaluate the *learner experience* (LX) of the innovation in this work include learners' *effectiveness*, *efficiency* and *satisfaction* of using an e-learning system (sections 4.4 and 7.4).

ISO 9241-11 [78] defines *effectiveness* as "the accuracy and completeness with which specified users can achieve specified goals in particular environments", *efficiency* as "the resources expended in relation to the accuracy and completeness of goals achieved", and *satisfaction* as "the comfort and acceptability of the work system to its users and other people affected by its use". Evaluation of learners' *effectiveness* and *efficiency* of using an e-learning system is inherently difficult, as there are many definitions of these terms and many different evaluation metrics (e.g., [35, 182, 197]), and no universally accepted method. In this work, we take a direct approach, and thus evaluate (perceived) *effectiveness* by asking learners if the system (or the functionality, or the feature) is useful (fit for purpose), and we evaluate (perceived) *efficiency* by asking learners if the system (or the functionality, or the feature) is easy to use (effort required to use). As for the evaluation of *satisfaction*, we ask learners a set of questions about their feelings, beliefs, attitudes and behavioural intentions (detailed in sections 4.4 and 7.4).

The most common method for evaluating learners' *effectiveness*, *efficiency* and *satisfaction* is with questionnaires, after completing given tasks with a system. In fact, the questionnaire is one of the most frequently used instruments for data collecting in educational research. It can be very useful for measuring appreciation of personalisation, user satisfaction, and general opinions about the system [188]. Therefore, in this work, several questionnaires are designed to evaluate learners' *effectiveness*, *efficiency* and *satisfaction* of using the innovation.

The Likert scale is a summative rating scale introduced by Likert [103]. It has frequent usage in research that employs questionnaires as instruments, because it is much easier to construct Likert scales than other rating scales [84]. When respondents respond to a Likert scale questionnaire, they specify their level of agreement or disagreement on a symmetric agree-disagree scale for a set of Likert questions, so as to capture the range of their feelings for a given statement [28]. In this work, the Likert scale style was applied to closed questions in the questionnaires. In addition, each Likert scale statement was balanced, by introducing a *neutral midpoint* with five ordered response levels, i.e., -2, -1, 0, 1, 2, in order to obviate the problem of acquiescence bias.

Besides questionnaires, observations have also been used for the evaluation of *satisfaction*. Observation is the systematic description of events and behaviours in a system chosen for research [113], entailing careful planning of what to observe and what to record. Data collected through observation represent a first-hand picture of the events and behaviours. Observation can be categorised as *participant observation* and *non-participant observation*. The former allows observers to be actors with a certain amount of power and this will inevitably affect how the observers and other participants see each other. The later needs observers to only watch and record the activities without involvement, which will potentially lower the influence of observers on subjects. In this work, both categories have been adopted, depending on the settings.

Additionally, as usability is often associated with the functionalities of the system, this research evaluates three levels of system granularity, in terms of *effectiveness* (usefulness) and *efficiency* (ease of use), such as the 'system as a whole' level, the 'sub-system functionalities' level and the 'single tasks' level.

At the 'system as a whole' level, the *System Usability Scale* (SUS) – a highly established and well-validated measure – has been used. SUS [14] is a simple, ten-item Likert scale, giving a global view of subjective assessments of system usability. It was developed by Brooke in 1996 as a 'quick and dirty' questionnaire scale of a given product or service. Its merits make it widely accepted and used in both industry and academia: first, SUS is non-proprietary, making it a cost effective tool; second, SUS is technology agnostic, and thus flexible enough to evaluate various products and services, including hardware, software, websites and applications; third, SUS is relatively quick and easy to use by both experimental subjects and researchers; fourth, SUS provides a single score on a scale, which is easy to understand [9]. SUS's ten items (statements) are as follows.

1. I think that I would like to use this system frequently.
2. I found the system unnecessarily complex.
3. I thought the system was easy to use.
4. I think that I would need the support of a technical person to be able to use this system.
5. I found the various functions in this system were well integrated.
6. I thought there was too much inconsistency in this system.
7. I would imagine that most people would learn to use this system very quickly.
8. I found the system very cumbersome to use.
9. I felt very confident using the system.
10. I needed to learn a lot of things before I could get going with this system.

The ten items (statements) in SUS are all scored on a five-point Likert scale of agreement strength - from strongly disagree (1) to strongly agree (5). They are alternately positive and negative, so a better system should have higher scores for question 1, 3, 5, 7 and 9, and lower scores for question 2, 4, 6, 8 and 10. The SUS final score is calculated using Equation 1, where U_i presents the score of the i-th question. It ranges from 0 to 100, where the higher the final score the better the usability. However, normally a good system should have a score between 70 and 80, and an exceptional system should have a score greater than 90 [9].

$$SUS_{SCORE} = 2.5 \times \left[\sum_{n=1, i=2n-1}^{n=5} (U_i - 1) + \sum_{n=1, i=2n}^{n=5} (5 - U_i) \right] \qquad \textbf{(1)}$$

Additionally, in order to evaluate learners' *effectiveness* and *efficiency* at the levels of 'sub-system functionalities' and 'single tasks', we have developed an instrument called the *system functionality scale* (SFS). Each item (statement) in SFS asks about one of the system functionalities/features/tasks in terms of its *usefulness* (for *effectiveness*) and *ease of use* (for *efficiency*), on a five-point Likert scale ranging from -2 (very useless/hard to use) to 2 (very useful/easy to use). The SFS questionnaire is designed in a table format, as shown (partially) in Table 2, and has been used in the evaluation process detailed in sections 4.4 and 7.4.

Table 2 A sample of questions in a system functionality questionnaire

	Features	**Usefulness**					**Ease of Use**				
…	…	-2	-1	0	1	2	-2	-1	0	1	2
13	Checking my performance	-2	-1	0	1	2	-2	-1	0	1	2
14	Checking my contribution	-2	-1	0	1	2	-2	-1	0	1	2
…	…	-2	-1	0	1	2	-2	-1	0	1	2

After collecting data using the abovementioned questionnaire survey instruments, data analysis procedures are carried out. Data analysis must firstly ensure the reliability and validity of the questionnaire ([137], p.438), and then descriptive statistics are used to summarise and interpret the data.

Reliability is defined by Nunnally [125] as "the extent to which measurements are repeatable and that any random influence which tends to make measurements different from occasion to occasion is a source of measurement error" (p. 206). Reliability is a measure of the accuracy and consistency of a measurement instrument. Developing reliable measures aims at minimising the influence of chance or other variables unrelated to the intent of the measure. Without a reliable instrument, the information obtained would be ambiguous, inconsistent or useless, so it is crucial to select and develop highly reliable data gathering procedures [117]. There are several ways to measure reliability.

- *Inter-rater reliability* is used to assess the degree to which different judges or raters agree in their assessment decisions. It is especially useful when judgments can be considered relative subjective, as human observers will not necessarily interpret answers the same way.
- *Test-retest reliability* is used to assess the consistency of a measure from one time to another. It is estimated by performing the same instrument with the same respondents at different time. It assumes that there will be no change in the metrics being measured, so the closer the results the greater the test-retest reliability of the instrument.
- *Alternate-form reliability* is used to assess the consistency of the results of two tests constructed in the same way from the same content domain. It

carries out two different forms of the same test (with initial and re-worded questions) to the same individuals, which overcomes the 'practice effect' – typical test-retest reliability.

- *Internal consistency reliability* is used to assess the consistency of results across items with a test. It defines the consistency of the results delivered in the instrument, ensuring that various items measuring the different metrics deliver consistent scores.

The use of the above ways to measure reliability depends on the nature of the data (nominal, ordinal, interval/ratio). To assess artwork as opposed to math problems, *inter-rater reliability* is more appropriate to use. To assess reliability of knowledge questions, *test-retest reliability* is more appropriate to use. To assess reliability of critical thinking, *alternate-form reliability* is more appropriate to use. To assess reliability of questions measured on an interval/ratio scale, *internal consistency* is more appropriate to use [132].

In this work, data reliability has been measured using *Cronbach's Alpha* [42], a measure of internal consistency, as Likert scales have been adopted. *Cronbach's Alpha* was first named by Lee Cronbach in 1951 [42]. It is a general version of the *Kuder-Richardson coefficient* of equivalence [96], as *Cronbach's Alpha* applies to any set of items regardless of the response scale, whilst *Kuder-Richardson coefficient* applies only to dichotomous items [42]. There are two versions of *Cronbach's Alpha*: *normal Cronbach's Alpha* is used when items on a scale are summed to produce a single score for that scale; *standardised Cronbach's Alpha* is used when items on a scale are standardised before being summed. The general formula for calculating a *Cronbach's Alpha* value is as in Equation (2), where n refers to the number of scale items on the test, s^2_i refers to the variance of i items, and s^2_{sum} refers to the variance of the sum of all items. The *standardised Cronbach's Alpha* value can be calculated by Equation (3), where n is the number of variables, and $\bar{r}$ is the average correlation among all pairs of variables.

$$\alpha = \frac{n}{n-1} \times (1 - \frac{\sum s^2{}_i}{s^2{}_{sum}}) \qquad (2)$$

$$\alpha_{standardised} = \frac{n\bar{r}}{1+(n-1)\bar{r}} \qquad (3)$$

The theoretical value of the *Cronbach's Alpha* varies from 0 to 1. There is no lower limit to the coefficient, but the closer *Cronbach's Alpha* is to 1.0, the greater the internal consistency of the item in the scale. With George and Mallery providing the following rules of thumb (as shown in Table 3) [60], a *Cronbach's Alpha* of 0.8 seems to be a reasonable goal [67]. Therefore, in this work, *Cronbach's Alpha* 0.8 has been used as the baseline value to examine the data reliability in the evaluation processes (sections 4.4, 6.4 and 7.4).

Table 3 Rule of thumb for describing internal consistency [60]

Cronbach's Alpha	**Internal Consistency**
$\alpha \geq 0.9$	Excellent (High-Stakes testing)
$0.7 \leq \alpha < 0.9$	Good (Low-Stakes testing)

$0.6 \le \alpha < 0.7$	Acceptable
$0.5 \le \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

Validity is the degree to which a measure succeeds in describing or quantifying what it is purported to measure. It is one of the main concerns with research. "Any research can be affected by different kinds of factors which, while extraneous to the concerns of the research, can invalidate the findings" ([151]). There are two main categorises of validities: *internal validity* and *external validity*. *Internal validity* refers to the extent to which a causal conclusion based on a research is warranted. *External validity* refers to the extent to which the findings can be generalised to other situations and populations [5]. In this work, the focus is on the validity of the measurement technique, i.e., internal validity, which has the following main types of validity [15].

- *Face validity* is the degree to which the measurement appears 'on its face' to measure the intended metric of interest. Although it is a very weak kind of evidence, because a test seems to be measuring a particular metric is no guarantee that it is, it can be important because it may affect people's attitudes towards a test [32].
- *Content validity* is the degree to which a measure represents all facts of a given contrast of interest. It requires the use of recognised subject matter experts to evaluate if items of an instrument reflect the knowledge actually required for a given domain [111].

- *Criterion validity* is the degree to which the measures are demonstrably related to concrete criteria in the 'real' world. It has two sub-types – Concurrent Validity and Predictive Validity [149].
    - *Concurrent validity* is the degree to which the measure is related to another more established measure.
    - *Predictive validity* is the degree to which the measure can predict future or independent past events.
- *Construct validity* is the degree to which a test measures what it claims, or purports, to be measuring. It is often divided into Convergent Validity and Discriminant Validity [43].
    - *Convergent validity* refers to the degree to which two measures of metrics that theoretically should be related, are in fact related.
    - *Discriminant validity* tests if measurements that should be unrelated are in fact unrelated.

In this work, several experts approved the *face validity*, after the initial design of the instrument. This panel of experts included professors, research fellows and PhD researchers in the field of human-computer interaction, adaptive hypermedia and technology-enhanced learning. They also assessed *content validity*, prior to the instrument being used in the experiments with the end-users. *Criterion validity* was assessed with various questionnaires; e.g., highly established questionnaires, such as the System Usability Scale (SUS) [14]. *Construct validity* was also determined by correlating the results with each designed questionnaire.

Descriptive statistics have been used in this work (sections 3.6, 4.4, 5.3, 6.4 and 7.4) to summarise the quantitative data in a manageable form and to convey the important aspects of the distribution of the data. Four features of the data distribution were described: *mean* and *median* were used to measure the central tendency of the data; *range* and *standard deviation* (SD) were used to measure the statistical dispersion of the data. They were presented in the form of tables and/or graphs (see sections 4.4.3, 6.4.3 and 7.4.3).

2.7 Conclusions

This chapter has presented the research background and related work in the social personalised adaptive e-learning research area. It has examined previous research that has attempted to support rich learner experience, from both theoretical and technical perspectives. It has discussed what the merits of each of the presented prior researches are, how the research direction is progressing, how this research area can continue to improve, and how to evaluate the innovation. In particular, this chapter has described the basis of the research vision in this thesis, by introducing related theories, techniques and methodologies, including adaptive (educational) hypermedia and user modelling, social interaction and gamification in e-learning, open learner modelling, and user-centric evaluation methodologies.

In conclusion, the study presented in this chapter has addressed the research objective **O1**: "reviewing the state of art in the fields of adaptive e-learning, social e-learning, gamification and open learner modelling to investigate their influence on the e-learning process". By addressing this research objective, this chapter describes the background knowledge and inspiration that generated the research questions defined in section 1.2.

Chapter 3

User-Centric Requirement Analysis

3.1 Introduction

This chapter aims to address the research objective **O2**: "exploring and understanding the needs of the learners for a social personalised adaptive e-learning system, aiming at gathering the requirements for the implementation of the research environment". The process of addressing this research objective, together with the outcome from the work that will be presented in Chapter 4 and Chapter 5 – the next two chapters – supports answering research question **R1**: "how can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and engagement amongst learners?"

In the conventional research process in the adaptive e-learning area, researchers normally take a researcher-centric (or designer-centric) approach, while the learners are usually involved only in the evaluation stage [108, 122, 150]. For instance, the researchers firstly build an adaptive e-learning system based on hypotheses and the new features desired, and then conduct experiments to collect learners' usage data and/or distributed questionnaires, in order to evaluate the system's usefulness, ease of use, ease of learning, satisfaction, privacy and data sharing, and so on. However, the researcher-centric approach has limited ability to cater for the learners' real needs [110], because researchers' knowledge about the adaptation process does not necessarily guarantee that they know about the end-users' expectations from the system. Not only are more time and effort needed in the initial design process, but the researchers (or designers) may also face costly redesigns, if they want to improve the system in the follow-up research (or design) iterations.

Therefore, the adoption of user-centric design (UCD) [124], participatory design (PD) [148] and the analysis of phenomena characterising the human-computer interaction (HCI) [173] process should be considered even since the early design stages, in order to build more usable systems [184]. If the system were designed to provide its end-users with exactly what they need, it would provide a better user experience, as well as encourage users to try new features and content, so that greater benefits for the learner are achieved earlier in the process.

In order to gather the real-life needs from the learners, the end-users, in the early design stage, the participatory design (PD) methodology has been adopted. This chapter firstly introduces the PD methodology and the We!Design (PD) framework, and then illustrates an experimental study that has been conducted applying the We!Design framework, aiming at extracting an ordered list of initial system implementation requirements, and gathering issues and initial preferences for the follow-up research.

3.2 Participatory Design and We!Design

As one of the most important User-Centric Design (UCD) approaches, Participatory Design (PD) places greater emphasis on allowing users to make decisions [189]. March [112] states that “new and unexpected interactions with the immaterial have expanded the design territory to include people as designers”. Rather than the traditional view that users are not necessary to participate in the design process before the requirement gathering phase, PD requires designers and end-users to equally work together to set design goals and plan prototypes, and engages users as active members of the design process [121]. Researchers and system designers who endorse PD approaches believe that users are capable (with necessary knowledge and skills) and should play a more active role during the design process [180]. PD offers end-users opportunities to participate during the design process so as to increase the probability of a usable design. It provides a chance for system designers to work with end-users so as to better understand end-users’ real needs. It supplies a tool that helps to identify issues and solutions [133].

The research on learners as co-designers of educational systems has been increasingly appealing to researchers. Könings *et al.* [93] assert PD can be “adapted for use in education as a promising approach to better account for students’ perspectives in the instructional design process in different school subjects”. Seale [150] claims that participatory methods have “the potential to both empower students and increase the possibility that teachers will respond to student voices”. Many PD approaches introduce learners as co-designers in the design process, and bring together design techniques of needs assessment, evaluation, brainstorming, prototyping, consensus building, and so on. However, most of the existing PD methodologies have strict requirements, and most of them are focused on learning content design only [180]. Learners are the core participants in an e-learning process, so it is essential for the system designers to take into consideration the learners' opinions. Involving learners in the design process brings benefits not only for applications, but also for the learners themselves, because it can help exchange knowledge between students and designers [138].

As one of the PD methodologies, the We!Design framework is student-centric and can be easily applied in real educational contexts [180]. It brings some merits compared to other PD methodologies:

- It conducts cooperation between students and designers in a short time;
- It supports a content-independent learning process, including note-taking and assessment; and
- It exploits the potential of highly computer-literate students who are driven to collaborate in order to produce a description of needs, task sequences and user interface prototypes [180].

For these reasons, the We!Design framework was selected in this work for the requirement analysis.

The We!Design framework contains two phases, as shown in Figure 2.

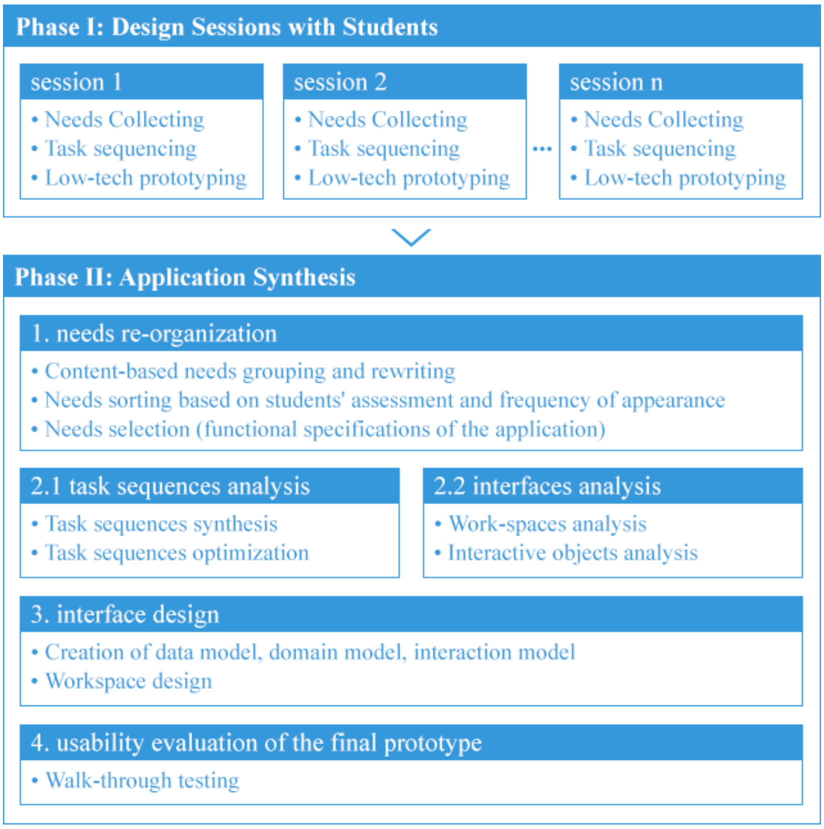

Figure 2 The We!Design framework [180]

In Phase I, several parallel design sessions are conducted with small groups of students under the supervision of coordinators, aiming to propose a low-tech prototype and a requirements list. The size of session groups is kept small, in order to minimise conflict possibility between the students, reduce time cost, and establish a friendly and informal atmosphere. Each session consists of three stages: *needs collecting*, *tasks sequencing* and *prototype designing*. In the first stage, *needs collecting*, students build a set of needs based on their experience of using a similar system and their expectations from a new system. In the second stage, *tasks sequencing*, students design task sequences to satisfy the previously built set of needs. In the third stage, *prototype designing*, students design a low-tech prototype application to complete the designed task sequences.

During Phase II, the system designers analyse the requirements proposed in Phase I and synthesise them into a single application, with an ordered requirements list. Initially, the designers organise, group and rewrite the collected needs to avoid overlapping. Next, these needs are ordered based on the number of sessions that they are proposed and their importance assessed by the students. Finally, the designers compile the diverse task sequences of each final need into one task sequence, analyse the prototypes designed by the students, and eventually synthesise the final prototype application. In the next section, we will present the detailed process of applying the We!Design framework, together with the actual data collected from the performed case study.

3.3 Experiment Setup

In this small-scale experimental study, two coordinators and six undergraduates participated. One coordinator was a computer science Ph.D. student from the University of Nottingham, UK; the other one was a computer science Ph.D. student from the University of Warwick, UK. The six undergraduate students were from the ‘Politehnica’ University of Bucharest, Romania. They were fourth year computer science students, studying a course entitled ‘Semantic Web’.

A short seminar was delivered at the beginning of the case study to introduce the experimental process, explain the case study's goals, and recall the required background knowledge, such as how to design a system and what an adaptive e-learning system is. Firstly, one coordinator presented the concept of AH and adaptive e-learning, followed by some case studies of adaptive e-learning systems, including AHA! [12], MOT 2.0 [62] and LearnFit [56]. Then, the coordinator introduced the concept of social networking sites (SNS) to the students. All the students were, as expected, familiar with SNS, such as Facebook, Google+ and YouTube, etc. They were also familiar with UML and UML-based design.

Thereafter the students could take upon themselves the main roles of discussing and presenting, while the coordinators were in charge of time controlling and summarising. The seminar focused on the features of adaptive e-learning systems and SNS, and aimed to acquaint the students with both domains, and encourage them to think deeply about these two kinds of system, so they could integrate both, to design new social personalised adaptive e-learning systems.

3.4 Phase I: Design Session with Students

Two parallel design sessions were conducted. Each of them was run with three students, and lasted for about two hours and a half. The two coordinators supported these sessions, without interfering, unless they considered it necessary to bring the students back on track. One coordinator was a human computer interaction (HCI) expert, whose role was that of ensuring that students consider issues related to the usability of the system. The other coordinator was an e-learning system expert, whose task was to be preventing the students from loosing track of the system design goals. Furthermore, the coordinators were also in charge of guiding and facilitating the students to go through the session, and providing support without interfering in the process of decision-making.

For facilitating the work, students in a group sat together. In front of the students there was a table with pens and a php board for the students to record their ideas on, and eventually draw their joined initial user interface of the prototype. The two design sessions were recorded by a video camera, so the coordinators could focus on guiding the case study and solve current issues, instead of taking notes for further research.

The whole process in this phase was grouped according to the three stages described in section 3.2. Before the start of the three design stages, the coordinators explained the study's objectives and the system design goals to the students.

3.4.1 Stage 1: Needs Collecting

During this stage, the students were asked to extract a set of needs that were currently not met, according to their previous e-learning experiences. The expectation was that these needs could be addressed by using a social personalised adaptive e-learning system. The students contributed to the needs collection by brainstorming and discussing ideas. Initially, the students considered the main features that they expected to be provided by such an e-learning system, as well as briefly discussed problems that they encountered when using such systems previously. All the students had opportunities to present their own ideas. Taking suggestions in turn was supported. Additionally, while one student was presenting, the others were encouraged to ask questions and provide suggestions and comments. Afterwards, the students summarised all the ideas into an initial *need list*, and then continually elaborated, categorised and evaluated these needs. As a result of this process, ninety-seven 'raw' needs were proposed and ordered into a requirement list, according to their perceived importance.

3.4.2 Stage 2: Task Sequencing

In this stage, *personas* and *scenarios* were used, as a lightweight method to capture the system requirements. *Personas* contain the users' background information and specific relation to using the system [38]. The students created two *personas*, in order to outline the real characteristics of the system's end-users, as below.

> *Anna is a freshman student, studying a course of 'Web Programming', which introduces fundamental knowledge of HTML, CSS and JavaScript. She does not have much programming knowledge before joining this course, but she likes asking expert students for help.*

> *Brian is a sophomore student, studying a course of 'Java Programming Language'. He participated in the course of 'Web Programming' last year, and achieved higher scores than most of the other students in the*

final examination. He prefers to analyse examples, and then design his own program to check whether he has learnt the constructs from the examples. He likes to share and discuss with other students.

Personas were used as the base for creating scenarios, with settings and a sequence of actions and events [31]. Some *scenarios* created by the students are listed below.

Anna is doing a piece of coursework by using the developing tools provided by the e-learning system. She is asked to design a webpage, which contains a news timeline. Each news item has a title, a time when the news is published, and several tags about the news. She developed one news item, and then 'copy/paste'-ed the code to create another nine news items in the news timeline. Later, she decided to change the colour of the tags, so she had to 'copy/paste' again. She is wondering if there is an easier way of doing so. She finds Brain is on the 'expert Web coder' list provided by the e-learning system, so she decides to ask him.

Brain is following the 'Java Programming Language' course by using the e-learning system. He submitted a quiz just now, and got the feedback on the result immediately. One of the questions that he answered incorrectly was 'if a class can extend two or more classes'. Next to the quiz result was a link to a webpage containing the topic about 'the multiple inheritance of Java'. Brain clicked on the link and then the webpage showed. He read the content and some comments made by other students, and then started to discuss with them about how a class could reuse the *properties and methods of more than one other class. Finally, he had an idea, which was to implement more than one interface.*

Brain is now debugging his Java program by using the programming tool provided by the system, in order to try the idea of implementing more than one interface. He receives a message from Anna, asking for help. He saves his work, and asks what Anna needs. After Anna describes her 'copy/paste' problem, Brain shares a note he took before, which describes how to control HTML element styles using CSS properties.

To conclude, in this second stage, *personas* and *scenarios* were used to describe the interaction between the *persona* and the potential application, to fulfil the proposed needs, and enable rapid communication about usage possibilities, which should satisfy the needs proposed in Stage 1: Needs Collecting.

3.4.3 Stage 3: Prototype Designing

This stage was a refinement process, asking the students to convert the needs collected in Stage 1: Needs Collecting, and the task sequences designed in Stage 2: Task Sequencing, to concrete requirements, so as to design a low-tech prototype application. Firstly, as previously mentioned, the students finalised the task sequences and visualised the scenarios on large shared white paper. They created the necessary notes to present the basic ideas of the interaction process and user interface. For instance, the students drew a dropdown list that could be used as a menu to switch between different views of the concept structure. Secondly, the students re-evaluated each component of the initially co-designed user interface, and proposed new components and/or re-organised existing components, to make sure each task sequence could be completed smoothly. Finally, a stereotypical end-user role-play was conducted to evaluate the usability of the designed prototype.

3.5 Phase II: Application Synthesis

In Stage 2: Task Sequencing, the principal designers gathered and analysed the product designed in the first phase, in order to synthesise a single application [180]. The requirements were firstly grouped into thirty-five final ones, by removing duplicates. Then these requirements were categorised into four categories, which represented the main areas for which features could be built in a system (according to the designer), and which are as follows.

- **Learning**: this category included requirements such as the use of multiple types of files, including photos, videos, slides, etc.; allowing for multiple files was considered of high importance by students; other (optional) requirements of lesser importance were, e.g., taking tests after learning a topic; getting assessment and feedback from teachers.
- **Social Networking**: this category included important requirements, such as creating groups that are registered for the same topic; and, in decreasing order of priority, discussing the topic with other students.

- **Adaptation**: this category involved requirements such as recommending other topics according to the current learning topic; recommending topics according to student's knowledge level and other students' rating.
- **Usability**: this category listed requirements such as visibility of the system status; instructions and tips; graphical user interfaces.

The results of these phases are described in section 3.7 – Suggestions on System Requirements. However, before this data-mashing phase, more information was gathered from the students, as follows in section 3.6.

3.6 Additional Quantitative and Qualitative Feedback

In order to extract more information about the application design, the students who participated in the design sessions were all invited to answer a questionnaire with twenty-eight questions (Appendix A). The questionnaire asked the students to evaluate the e-learning systems that they had used in the past, and to elicit their extra expectations for features of a new social personalised adaptive e-learning system. As the students had already been through the introductory material and design sessions, their answers were more informed, and they were able to be more specific in the evaluation of past systems, as well as be quite concrete in their expectations of new required features, based on the priorities that the students themselves had set and the previously extracted requirements.

3.6.1 Student's Previous Experience with E-learning Systems

There were several reasons for students to use e-learning systems in the past, as shown in Figure 3. The most important reason they gave was to 'Save Time and Effort'. This corresponded to their answers in the open-ended questions part of the questionnaire, where the students also stated that 'Availability 24/7, everything is organised in one place' as being some of the features of e-learning systems that they liked the most. Out of this clear preference, one of the requirements would be to provide a simple, constantly available 'one stop-shop', where all the material and functionality is present, and thus not increase the learning burden.

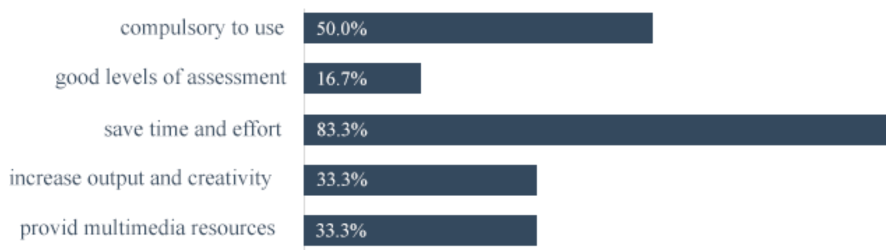

Figure 3 Reasons for using e-learning systems

From the point of view of social websites used, the questionnaire results also indicated that all the students had experience with collecting learning resources from Wikipedia, as shown in Figure 4. Wikipedia is indeed the largest (even if not most accurate or reliable or stable) general reference on the Web, offering around 32 million articles by June 2014 [202]. According to the questionnaire results, YouTube was mentioned as the second most popular social networking website for the students to collect learning resources from, while the third one was LinkedIn.

In the case study, students also mentioned the requirements of access and search for open learning resources from outside of the system. Therefore access open learning resources, such as Wikipedia, should be in the requirement list. From here we also started gathering information about the type of systems users were familiar with, in order to be able to provide a familiar look and feel [173].

Figure 4 SNS websites for collecting learning resources

After finding out about the students' experience with e-learning systems and SNS, we further asked about specific features, if they should or not be included in the system, as shown in section 3.6.2 below.

3.6.2 Preferences for the New E-learning System Features

In Figure 6, 67% of the students prefer courses to be published by both teachers and students; while the other 33% think that the courses can only be published by teachers. Besides, more students (83%) prefer topics to be recommended according to students' ratings rather than the count of visits. Figure 5 shows that half of the students prefer that learning paths are kept static from creation, while the other half of the students consider that learning paths should be adapted to the learning context. Furthermore, the same percentages of students agree that learning paths can be both designed by teachers and calculated by data collected from other students' behaviour. Figure 7 shows that 17% of the students prefer asynchronous interaction with others in the system (such as comments), while the other 83% of the students prefer synchronous interaction (such as a chat window). Figure 7 also shows that 33% of the students hope to have all social interaction tools when they begin to use the system, while the other 67% of the students prefer to obtain more social interaction tools when they move up to a higher user-level.

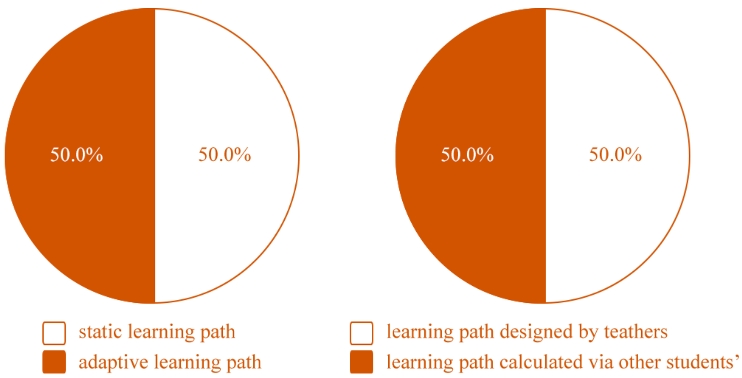

Figure 5 Preferences for learning material

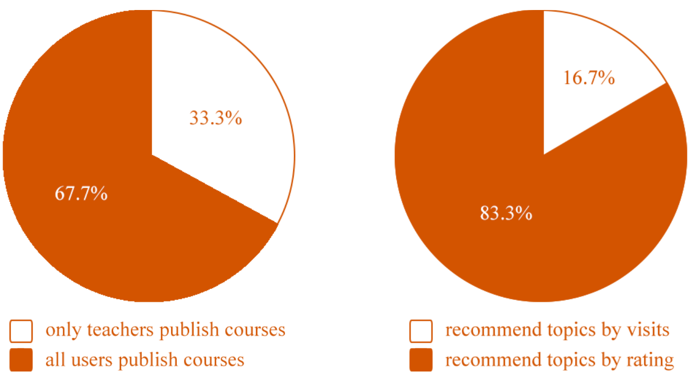

Figure 6 Preferences for learning path

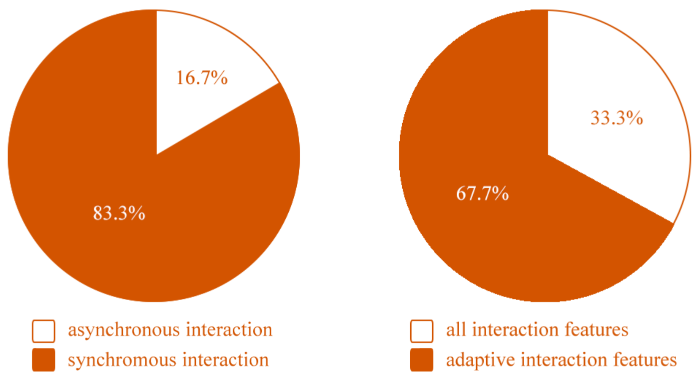

Figure 7 Preferences for interaction

3.6.3 Suggestions on Designing a New E-learning System

In addition to the closed questions as described above, the questionnaire also contained several open-ended questions, which were aimed at eliciting suggestions from students on designing the new social personalised adaptive e-learning system. This allowed students to provide unrestrained wide-range responses, which could reveal originally unanticipated findings in the questionnaire [136].

The suggestions of the students are summarised in the list below.

- Exercise tools are essential, especially for practice courses such as programming language courses. It would be better to learn by using the knowledge rather than just reading some chapters.
- Students should also be able to create their own learning paths in the courses that they were interested in, while other students could provide suggestions or use these learning paths for their own study.

- The recommendation of learning materials for a particular student should be based on their performance during learning, mixed with results from the tests/practice.
- The system should provide an interface to access online libraries for reference while students are learning related topics, and make it possible for the students to save these references inside the system.
- The user interface should be as simple as possible, concentrating all needed resources in one place (a 'one stop-shop': either physically – with all material in one place, or on one server, or virtually – as in a portal to all the needed information).
- The system should be easy to use, so it shouldn't interfere with students' learning, but instead provide some help and tips when needed.
- The system should introduce some learning aid for students to improve their learning efficiency.

3.7 Suggestions on System Requirements

Finally, the designer merged the results from Phase II: Application Synthesis and the responses from the questionnaire into a list of system requirements. Table 4 shows the resulting list of requirements for a social personalised adaptive e-learning system. Note that, in this work, the implementation focuses mainly on the Social Networking requirements, i.e., they have a high priority of implementation.

Table 4 System requirements

	Requirement	#[1]
Learning	Use multiple types of files; e.g. PDFs, photos, videos, slides.	5 (q)
	Take tests after learning a topic.	4 (q)
	Get assessment and feedback from teachers.	5 (q)
	View learning progress in percentage.	5
	Tag and flag up topics in the learning path.	1
	Access open learning resource, e.g. Wikipedia.	6
	Search learning resource within and outside of the system.	6
	Use interactive learning content, e.g. debugging tools.	q
	Contribute to learning content by creating and uploading files.	3
	Choose to view the whole or partial learning path.	1
Social Networking	Create groups that are registered for the same topic.	3
	Discuss the current learning topic with other students.	6
	Set access rights for learning materials.	q
	Set access rights for groups.	q
	Ask and answer questions of other students.	5
	Create groups that share common learning interests.	4
	Use feedback & questions forum at the end of each lesson.	5
	Share and/or recommend learning materials.	2
	Use communication tools to chat and leave messages.	4 (q)
	Write comments/notions wherever and whenever wanted.	5
	View history discussion when selecting a particular topic.	1
	Design and publish courses for others to use.	q
Adaptation	Recommend other topics according to current learning topic.	5 (q)
	Recommend topics according to student's knowledge level.	4 (q)
	Recommend topics by referring to other students' rating.	2 (q)
	Adapt learning path according to learning progress.	2 (q)
	Adapt learning tools according to student's user-level.	1
	Adapt social interaction tools according to students user-level.	q
	Recommend other students according to the current topic.	q
	Recommend other groups according to student's interests.	q
Usability	View system status.	2
	Use graphical user interfaces.	4
	Get instructions and tips.	3 (q)
	Select full screen option.	1
	Set themes, layout, etc.	2

#: The number of times the requirement appeared in the students' suggestions, (q: from questionnaire results).

The above-suggested requirements have been guiding the system implementations in this work. The following chapters and sections refer to them and Table 4 when appropriate. Some of the requirements have been implemented in the first version of the social personalised adaptive e-learning system, as detailed in section 4.3; some of them in the second version system, as detailed in section 6.3.

3.8 Discussions

In Stage 1: Needs Collecting, the coordinators must be very clear in which situation they needed to intervene and to what extent. In the needs collection stage, especially at the beginning, the students were always impatient to start exploring solutions to satisfy the proposed needs, rather than focusing on collecting needs, so the coordinators had to stop them in time. In Stage 2: Task Sequencing, *personas* and *scenarios* were used to capture the requirements of the system. One of the best practices is to identify *primary personas*, ‘the individual who is the main focus of the design’ [38]. To be primary, a *persona* is ‘someone who must be satisfied but who cannot be satisfied with an interface designed for any other persona. An interface always exists for a *primary persona*.’ [37] With regard to *scenarios*, storyboards or customer journeys were used to test the validity of design and assumptions. The students had to be encouraged to design an appropriate level of detail. In Stage 3: Prototype Designing, some solutions might be found to be flawed to some extent, either by the students or the coordinators. In such a case, the risk was that students might be unwilling to fix flaws or they might need extra time. The coordinators had to encourage them to get the solution as well as control the time, because even if the work was incomplete, the highlighted issues could still inspire the designers.

In Phase II: Application Synthesis, the designers arranged the requirements proposed by the students, the descriptions of content-based requirements. It is always possible for the designers to misunderstand the original meaning intended by the students. Hence it is necessary to show the reorganised requirements to the students, and ask them to check whether the requirement list is consistent with their original ideas. Finally, the students were asked to confirm the resulting requirement list, to ensure its closeness to their original desires.

Overall, the students willingly contributed to generating the requirements for the system design according to their intended learning outcomes, previous knowledge and e-learning experience. They were satisfied with both the experiment and the knowledge they acquired during the experiment. Some of them mentioned that they really enjoyed this type of design process and learnt what was a Participatory Design. From the system designer's perspective, the requirement list obtained represents a generic level of detail into the requirements definition, which was collected as natural language statements describing what services the system was expected to provide. Besides, these requirements created a common vision between the students and the system designers, to make sure the system that would be developed was what the students really needed.

Facebook is the biggest social networking website in the world. It has 802 million daily active users and 609 million mobile daily active users on average in March 2014 [203]. However, most people use Facebook for entertainment [179] rather than learning, which is why the questionnaire result shows that only 16.7% of the students chose that they have ever collected learning resource from Facebook.

Another interesting result is that half of the students chose ‘Compulsory to Use’ as a reason to use an e-learning system. This might be because the systems are hard to use, or the students are not confident to use such systems. Therefore it is necessary to evaluate and analyse existing e-learning systems, in order to find out how to improve them, or how to design a better new system. The opinions of the systems’ end-users, the students, are very important, and many aspects (e.g., system usability, accuracy of recommendation, intended learning outcomes, learning context) of the systems need to be taken into consideration. Therefore the evaluation should be conducted by using a multi-dimensional approach [127].

The main difference of this experimental study from the original We!Design framework was that all the students who participated in the design sessions were asked to answer a questionnaire, more information could be collected about the system design requirements. Although the coordinators were trying to avoid transferring their own opinions in the design session, it remains possible that they could still have influenced the students. In contrast to the design sessions, the questionnaires have uniform questions, but no middleman bias, and the research instrument does not interrupt the students. Besides, the structured questionnaires enable the responses to be standardised, hence easier to analyse. The questionnaires were delivered after the application synthesis phase, because on the one hand, as the designers had already analysed the requirement proposed by the students, they would be able to ask pointed questions to further understand students' opinions, and on the other hand, since the students had already gone through the design session, they might like to have more chance of proposing extra expectations as well as helping the system designers to understand the priorities of the previously extracted requirements.

One issue to raise here is that although the software engineering knowledge of the computer science undergraduate students could help shorten the design duration, as the author of the We!Design framework stated [180], this might also have limited their ability to create a domain-independent e-learning system. For instance, they mentioned the importance of tools for practice courses such as those of programming languages, but they did not consider multimedia delivery as highly important, when for instance, for art and social science subjects, the quality of multimedia transmission and presentation might be very important.

3.9 Conclusions

This chapter has described the experimental study performed to gather issues and initial preferences for the overall research. The We!Design framework has been applied in this work, in order to investigate needs of the learners, the end-users, of a social personalised adaptive e-learning system. The main outcome of this chapter is that a list of initial system implementation requirements has been extracted, based on which the initial social personalised adaptive e-learning system has been developed, detailed in Chapter 4.

Additionally, this chapter has also explored how to better apply Participatory Design (PD) methodology in the early stage of system development. The We!Design framework has been further developed with some advice for better conducting such experiments. The main difference from the original We!Design framework is the combination of the additional questionnaire survey, which provides more information about the system requirements from an end-user point of view, and avoids middleman bias produced by experiment coordinators.

In conclusion, the study presented in this chapter has addressed the research objective **O2**: “exploring and understanding the needs of the learners for a social personalised adaptive e-learning system, aiming at gathering the requirements for the implementation of the research environment”. The process of addressing this research objective, and the results – section 3.7 Suggestions on System Requirements – have contributed to answering the research question **R1**: “how can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and engagement amongst learners?” These suggested system requirements are further implemented in the initial social personalised adaptive e-learning system (Chapter 4), in order to answer the research question **R1**.

Chapter 4

Initial Social Personalised Adaptive E-Learning

4.1 Introduction

The main objective of the work presented in this chapter is to answer the research question **R1**: "how can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and engagement amongst learners?" In particular, this chapter focuses on the students' perception of *effectiveness*, *efficiency* and *satisfaction*. The students' perception of *engagement* is explored and presented in Chapter 5.

As stated in Chapter 1 and Chapter 2, adaptive e-learning systems typically focus on providing adaptive learning resources, including learning path and topics, which adapt to the learner's knowledge level, learning goals, preferences, and so on. The rapidly emerging and growing social networking sites offer a new opportunity to improve adaptive e-learning experience by introducing a social dimension, and by connecting learners within e-learning systems [40]. Making connections and providing communication tools has been shown to engage learners in creating an effective learning environment and enriching learning experiences. However, the review of the previous work (see section 2.2) indicates that current adaptive e-learning systems have only marginally explored the integration of social interaction features and adaptation techniques [39].

This chapter, therefore, intends to address this gap by designing, implementing and evaluating a social personalised adaptive e-learning system that was developed to foster effective and efficient social and adaptive e-learning experiences. In particular, this chapter describes an initial social personalised adaptive e-learning system that provides:

1) '*classical' adaptation based on user modelling*,
2) *fine-grained social interaction features*, and
3) *a Facebook-like appearance*.

The 'classical' adaptation builds the basis of the system that the fine-grained social interaction features are integrated into. The Facebook-like appearance aims to make the system more familiar to learners, subsequently providing a high level of perceived *effectiveness*, *efficiency* and *satisfaction* in using the system.

The remainder of this chapter is structured as follows. Firstly, section 4.2 presents the overall architecture of the system, emphasising the models that support adaptations and social interactions, as well as the relationships between these models. Section 4.3 presents the implementation of the initial social personalised adaptive e-learning system – an application of the proposed architecture, focusing on various features provided by the system. Section 4.4 reports a case study that evaluates the system in a real-life online learning session, focusing on the system's various social interaction features, and discusses the evaluation results. Finally, section 4.5 concludes this chapter with the summary of discoveries and suggests further improvement and further evaluation.

4.2 Architecture

Based on the study of prior and related work (sections 2.2 and 2.3), and the elicited system requirements (section 3.7), the architecture of the initial social personalised adaptive e-learning system has been designed. As shown in Figure 8, it adopts a classical layered structure (inspired by the Dexter model [71], and the more recent SLAOS model [39]), extended with a clear and well-defined *social flavour*: a *Storage Layer*, a persistence infrastructure for physical entities; and a *Runtime Layer*, parsing adaptation strategies to present adaptations and social interactions, and tracking learner behaviours.

In the system architecture, models are represented in the *Storage Layer*, and can be accessed via the four basic functions of persistent storage, CRUD (create, read, update and delete) [74]. The *Adaptation Model* (**AM**) and *Presentation Model* (**PM**) are similar to typical *adaptation models* and *presentation models* in adaptive hypermedia. The other models present in the architecture are loosely based on the LAOS [41] and SLAOS [39] frameworks. Whilst at a conceptual level, the similarity is stronger to previous frameworks, for the actual implementation, it was often useful to break models into smaller ones, which interact with each other. Hence, models represented by the architecture often contain sub-models. They and their interactions are described in the following.

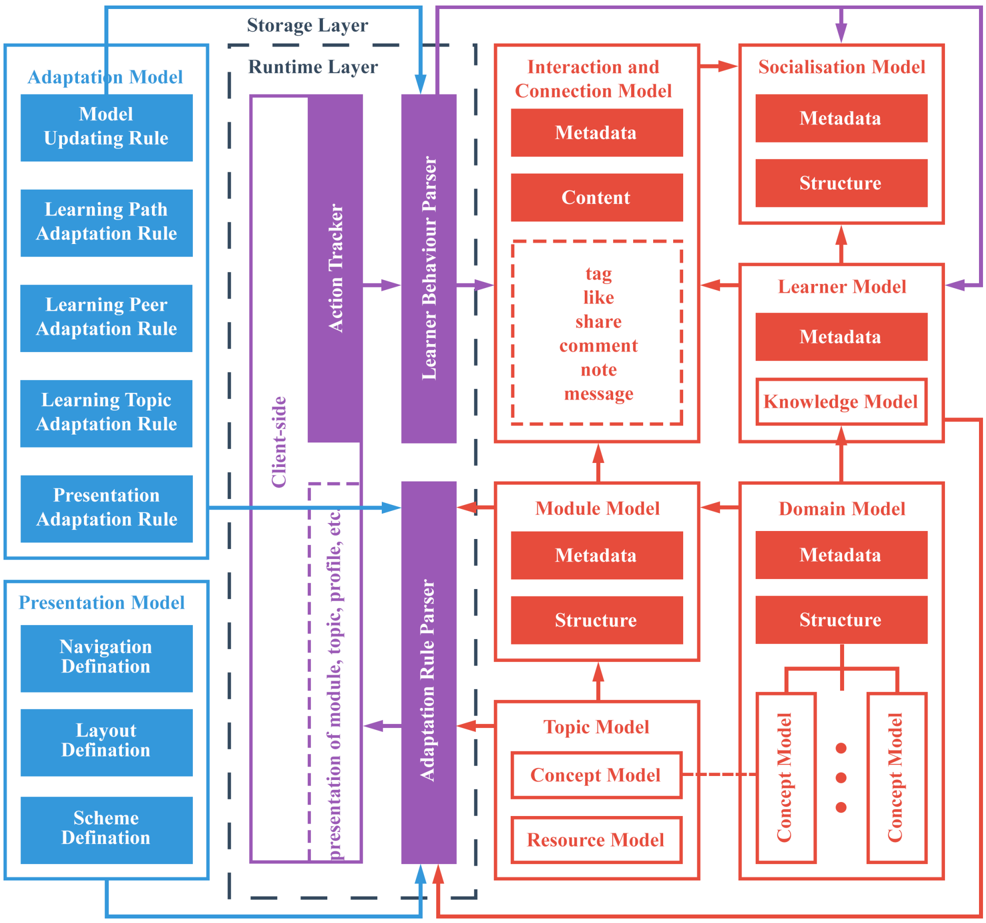

Figure 8 System architecture

- The *Concept Model* (**CM**) defines the knowledge cell with the minimum granularity that contains the basic information about this concept, such as its title, tags and description.

- The *Domain Model* (**DM**) is a knowledge network defining a domain map, which consists of a set of **CM**s and concept relationships (structure). This inherits the classical **DM** defined in the LAOS [41] framework.
- The *Resource Model* (**RM**) represents concrete learning content, which can be a text, an image, an audio, a video, etc.
- The *Topic Model* (**TM**) wraps around and basically contains a **CM**, as well as one or several **RM**(s), so it is called a 'wrapper model'.
- The *Module Model* (**MM**) is an overlay over the **DM** – and defines goal and constraints maps, which are a subset of structured concepts within a domain map, with *goals* and *constraints* given by module (course) constructions. Similarly to the domain maps, goal and constraints maps can, and in practice, often do contain hierarchical structures. This is similar to the *Goal and Constrains Model* (**GM**) in the LAOS framework [41]. Here a **MM** is a self-contained module, which contains structured **TM**s.
- The *Knowledge Model* (**KM**) is an overlay over the **DM** and **CM** – a subset of structured *concepts*, mapping the learners to the concepts, such as '*learnt*' or '*ready-to-learn*' a concept, which can be updated according to the learner's activities, similar to typical user models in adaptive hypermedia.
- *Learner Model* (**LM**) represents a learner's cognitive preferences and knowledge space. Whilst the former are recorded in its *metadata*, the latter is recorded in a **KM**. It is also called a 'wrapper model', as an **LM** wraps around and basically contains a **KM**

- The *Interaction and Connection Model* (**IM**) is an 'abstract model', which can be 'instantiated' as a 'message model', a 'tag model', a 'like model', a 'share model', a 'comment model' or a 'note model' (a 'comment' can be seen by others, whilst a 'note' can only be seen by its author) and so on. It represents one of the pre-defined *social interactions*, such as messaging, tagging, liking, sharing, commenting and noting, performed by a *learner* (with characteristics stored in an **LM**) to another *learner* (with characteristics stored in another **LM**), or to a *topic* (with metadata stored in a **TM**, which belongs to an **MM**). While interacting with each other, *social connections* are built and maintained by the *Socialisation Model* (**SM**).
- The *Socialisation Model* (**SM**) is a social network that maintains social relations between learners. These relations could be either built when learners interact with one another, such as sending or replying to a message, or built when they interact with the same content, such as registering on the same module, or commenting on the same topic. As an **SM** is derived from *Interaction and Connection Models* (**IMs**) and *Learner Models* (**LM**), it is called a 'derived model'. By doing so, the connected learners could be grouped into a learning community, so as to better support adaptive (expert) peer recommendations and social interactions.

Additional to the above models contained in the *Storage Layer*, this system architecture also includes an *Adaptation Rule Parser* (**ARP**), an *Action Tracker* (**ATR**) and a *Learner Behaviour Parser* (**LBP**), which are in the *Runtime Layer*, detailed as the following.

- The *Adaptation Rule Parser* (**ARP**) combines and analyses the *adaptation rules* provided by the **AM,** in order to support adaptive and/or adaptable client-side presentations, e.g., a webpage that presents a module, a topic, or a profile, etc. In particular, it determines whether to present certain learning content, learning paths and expert peers, and how to present them in terms of personalised *navigations*, *layouts* and *schemes*.
- The *Action Tracker* (**ATR**) is embedded in each of the client-side presentations, e.g., a webpage that presents a module, a topic, or a profile, etc., generalised by **ARP**. It is explicitly and non-intrusively tracks learner actions, and sends them (raw logging data) to **LBP** for further process.
- The *Learner Behaviour Parser* (**LBP**) collects and analyses the raw logging data sent by the **ATR,** to interpret learner actions into meaningful learner behaviours that contains information about learners' intentions, feeling, behaviour patterns, etc., and then triggers the updating function in the related **IM**, **SM**, and **LM** in the *Storage Layer*, for persistent storage.

4.3 Implementation

This section presents an application of the architecture proposed in section 4.2 and the requirement suggestions presented in section 3.7, towards answering the research question **R1** on "how can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and engagement amongst learners?"

The application, the new social personalised adaptive e-learning system, is called Topolor, inspired by the word *topology* – the mathematical study of shapes and topological spaces, because the new system provides various connections between knowledge and learners, fostering a hybrid network that combines a *knowledge network* and a *social network*. It is built on Yii[5] and Bootstrap[6], and hosted on Github[7] for open source sharing and version control. Since launched in November 2012, it has been used as a real-life online learning system for postgraduate level students in the Department of Computer Science, at the University of Warwick, UK; for undergraduate level students in the Department of Computer Science, at the University of Jordan, Jordan; and for undergraduate level students in the College of Computer Science, University of Taibah, Saudi Arabia.

Topolor has been implemented to meet the system requirements suggested by the students, as described in Table 4, section 3.7. An extended set of system requirements and other follow-up suggestions from experiments have been later on implemented in the next version of Topolor (sections 6.3 and 7.3). This section introduces Topolor' three main 'sub-systems': the Dashboard, the Module Centre and the Q&A Centre, whilst full features are shown in Appendix I.

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[5] http://yiiframework.com

[6] http://getbootstrap.com

[7] https://github.com/aslanshek/topolor

4.3.1 Dashboard

As shown in Figure 9, The *Dashboard* provides a chronological list of the learning statuses posted by individual learners. It also provides access a set of interaction tools that encourage informal communication and collaboration such as commenting on, sharing and favouring of learning statuses. These features have been implemented based on system requirements suggested by the learners, as described in Table 4, section 3.7, specifically, the Social Networking requirements: “ask and answer questions of other students”, “use communication tools to chat & leave messages”, and “write comments/notes wherever & whenever wanted”.

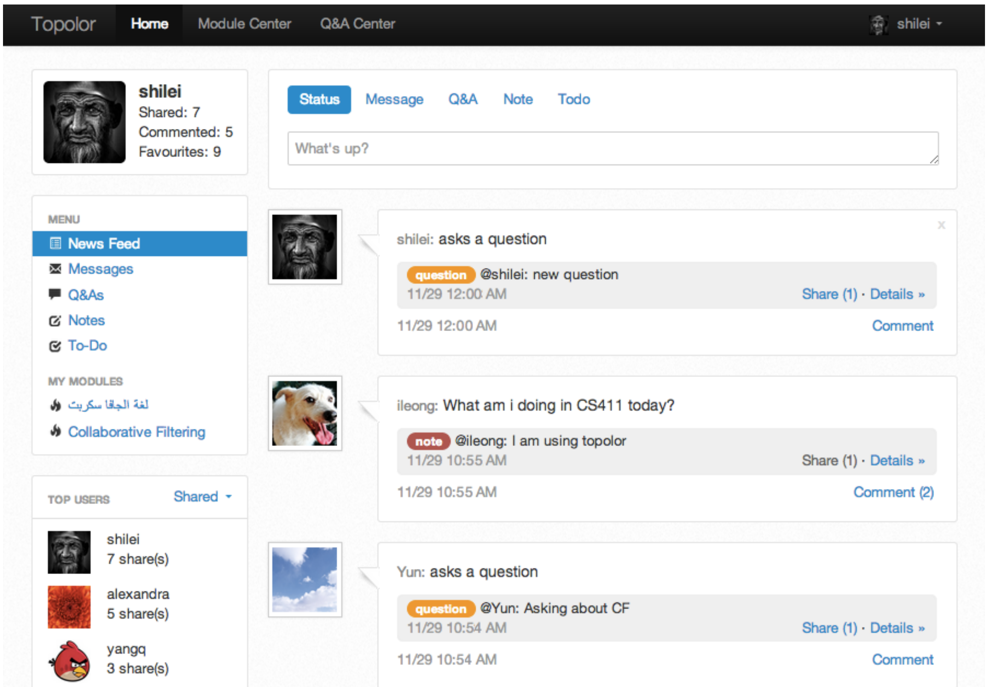


Figure 9 Topolor UI – Dashboard

4.3.2 Module Centre

The *Module Centre* offers a warehouse of online modules, as well as provides adaptive learning topic recommendations, learning peer recommendations and interaction tools that encourage personalised social learning, such as sending messages to recommended peers. Besides, learners can take either tests for whole modules, or quizzes for single learning topics. Figure 10 shows the index page of the *Module Centre*, where learners can have an overall view of their learning status, such as the module structure, topics they have learnt, quizzes they have done, and which next topic for them to learn is (learning path recommendation).

Figure 11 shows topic recommendation based on tags. When clicking on a tag, a *popover* pops-up with a list of topics ordered by the number of common tags. These features have been implemented based on the system requirements suggested by the learners, as described in Table 4, section 3.7, specifically, the Learning requirement: “choose to view the whole or partial learning path”, the Social Networking requirement: “create groups that share common learning interests”, and the Adaptation requirement: “recommend other topics according to current learning topic”.

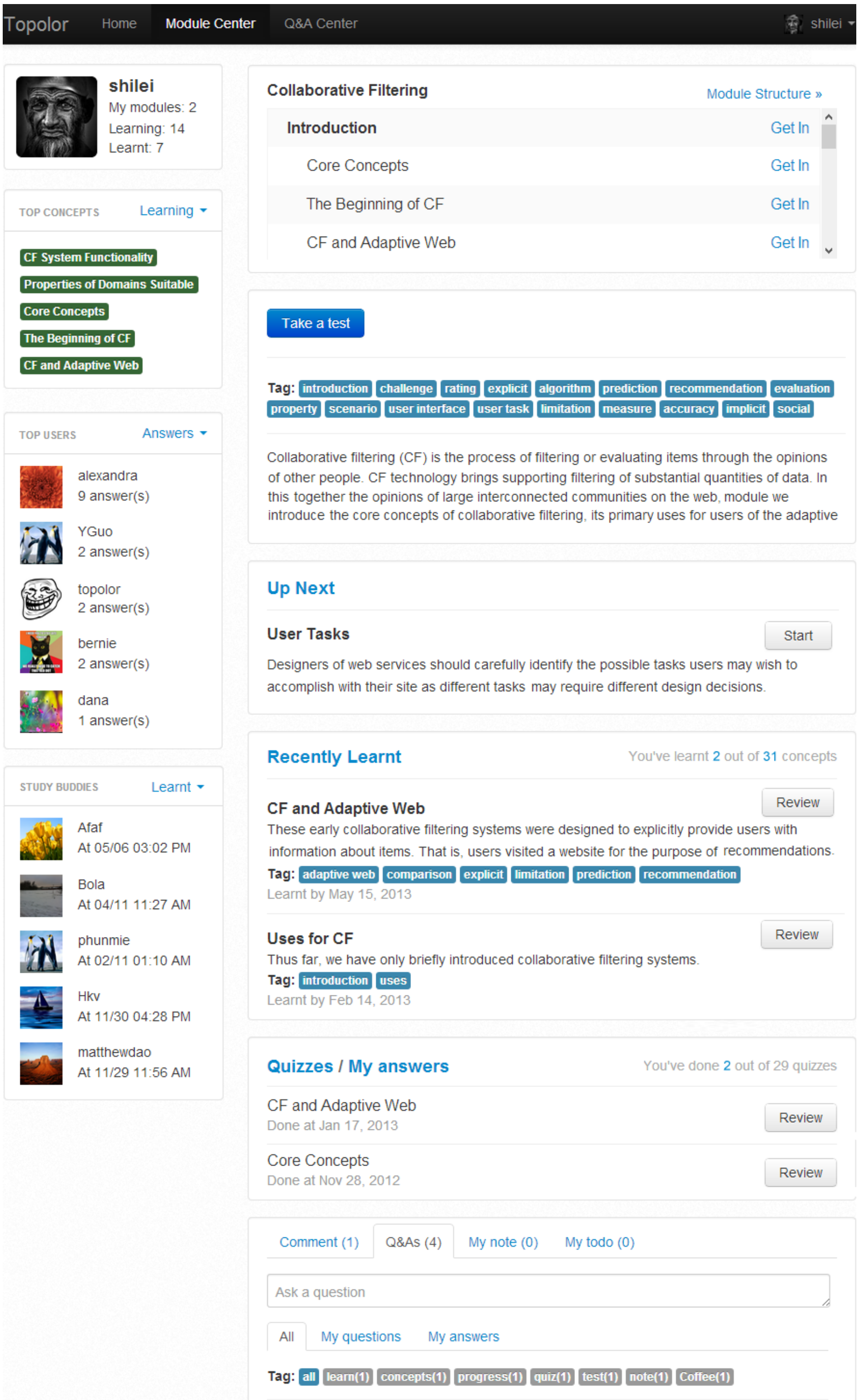


Figure 10 Topolor UI – Module Centre – Index

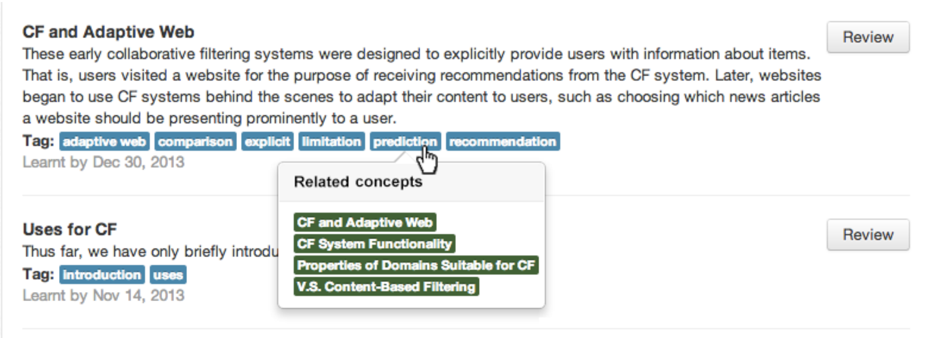


Figure 11 Topolor UI – topic recommendation based on tags

When clicking on a topic title in the module structure or a recommendation list, the learner will be directed to the topic page, as shown in Figure 12. The topic page provides the title, tags and description of the topic. It also recommends related topics to learn, and expert learning peers to contact. The learner can claim that they have learnt this topic (adaptability), taken an quiz (a quiz page is shown in Figure 13), gone to the 'previous' or 'next' topic (learning path recommendation), and commented, asked a question, taken a note, or created a to-do on the topic. These features have been implemented based on the system requirement suggested by the learners, as described in Table 4, section 3.7, specifically, the Learning requirement: "take tests after learning a topic", the Social networking requirements: "discuss the current learning topic with other students", "ask and answer questions of other students", "use feedback & questions forum at the end of each lesson", "share and/or recommend learning materials", "use communication tools to chat and leave messages", "write comments/notions wherever and whenever wanted", "view history discussion when selecting a particular topic", "recommend other topics according to current learning topic", and the Adaptation requirement: "adapt learning path according to learning progress".

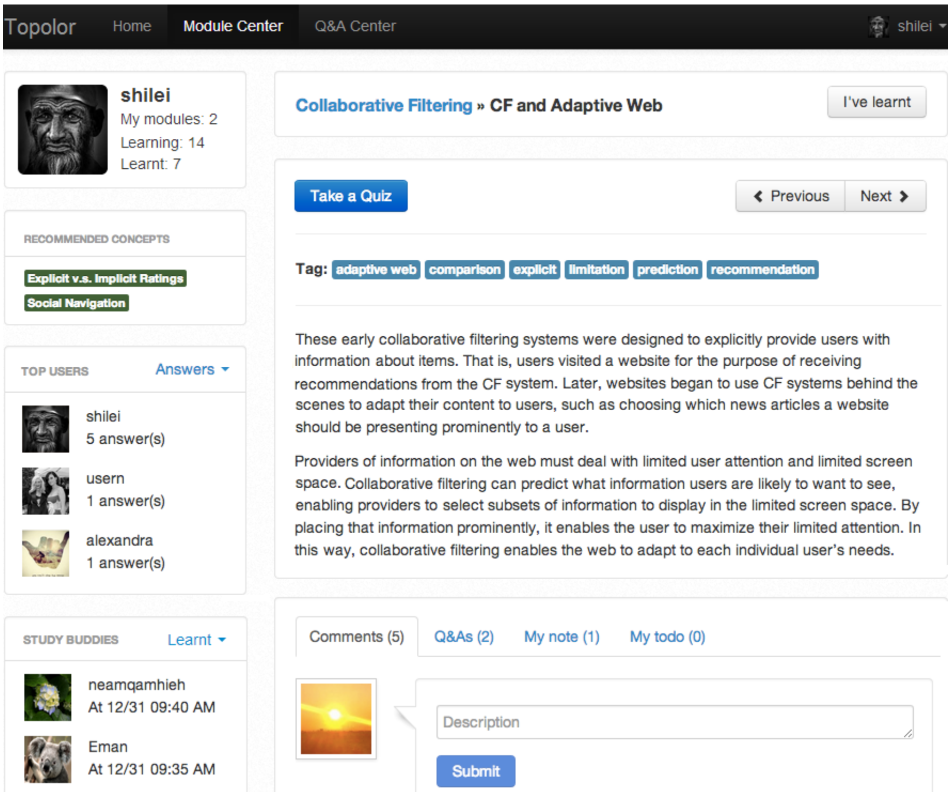


Figure 12 Topolor UI – Module Centre – Topic page

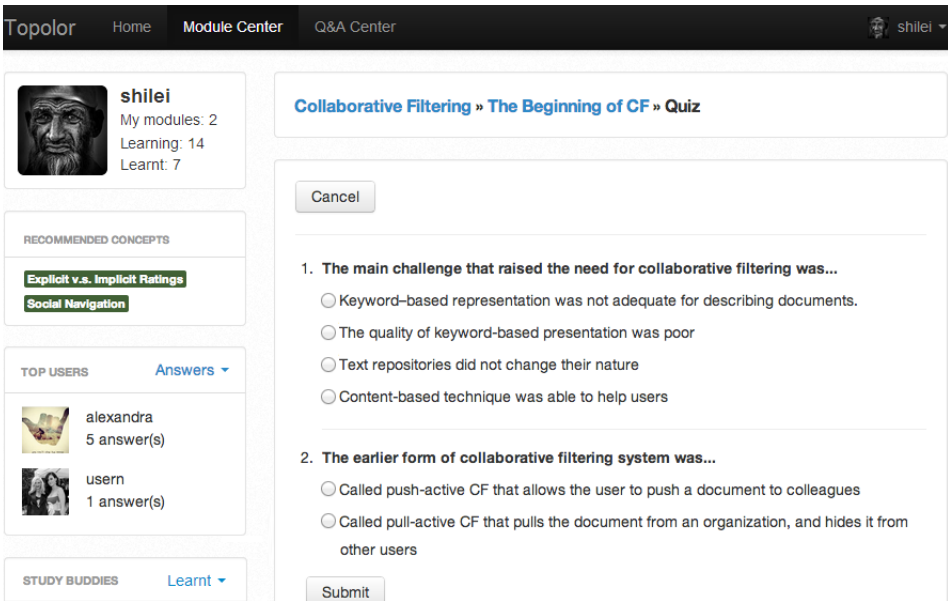


Figure 13 Topolor UI – Module Centre – Quiz

4.3.3 Q&A Centre

As shown in Figure 14 and Figure 15, the Q&A Centre has different ways of listing and ordering questions. It provides adaptable question and topic recommendation, i.e., the learner can select the order of the questions, as well as the way of showing the relationship between learners, topic, question and tags. These features have been implemented based on the system requirement suggested by the learners, as described in Table 4, section 3.7, specifically, the Social Networking requirements: "create groups that are registered for the same topic", "ask and answer questions of other students", and "use feedback & questions forum at the end of each lesson".

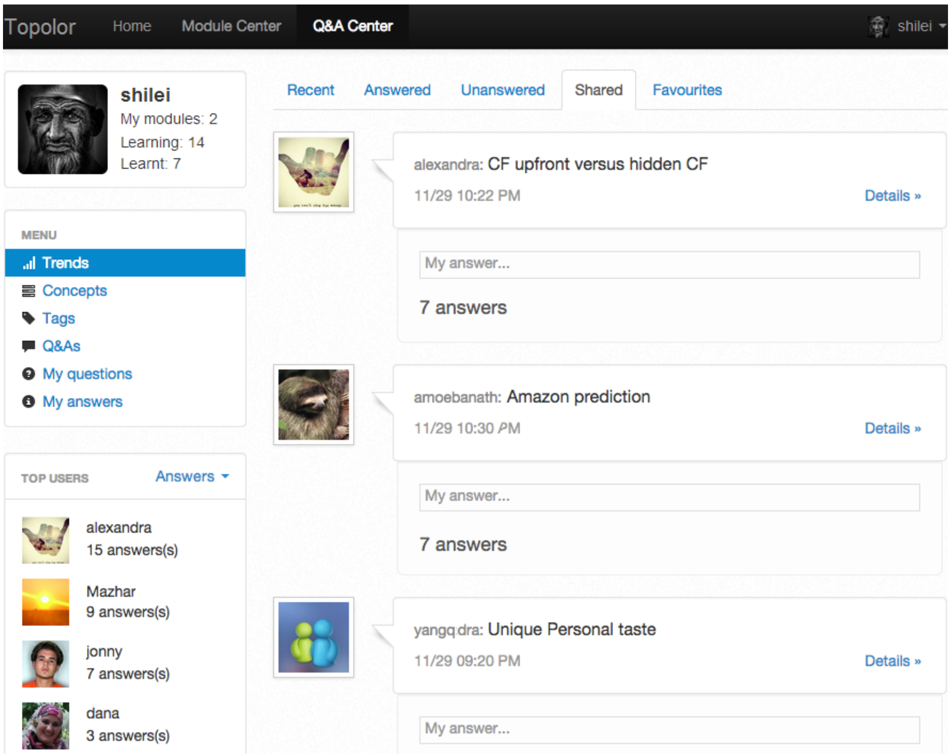


Figure 14 Topolor UI – Q&A Centre

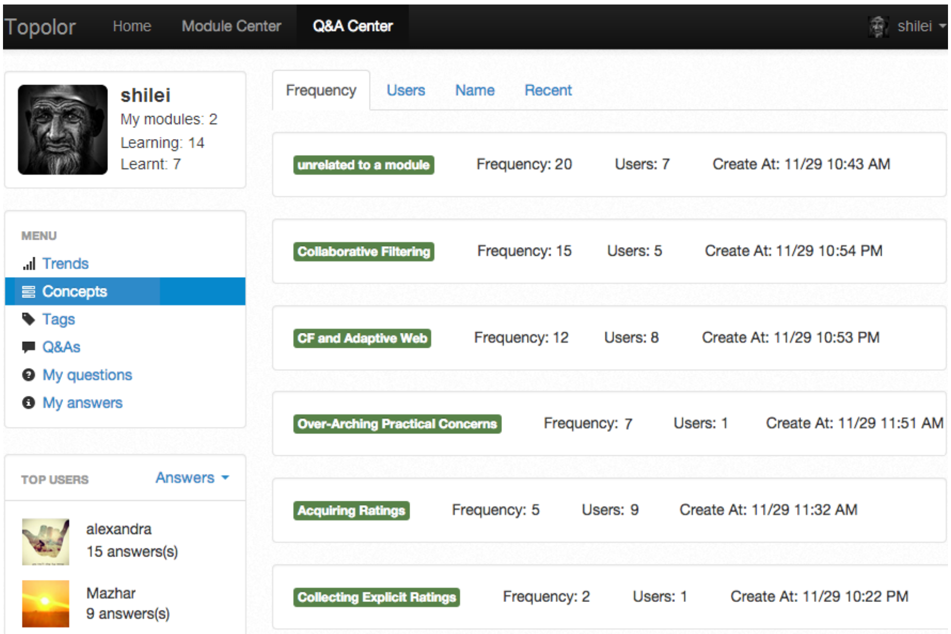


Figure 15 Topolor UI – Q&A Centre (2)

4.3.4 Requirement Revision

Table 5 below revisits the requirements (suggested in Table 4, section 3.7) that have been implemented in the first version of Topolor, as well as comment upon the level of implementation. Some of the requirements have been implemented in the second version of Topolor, detailed in section 6.3.

Table 5 System requirements – revisited

	Requirement	Comment
Learning	Use multiple types of files; e.g. PDFs, photos, videos, slides.	
	Take tests after learning a topic.	Implemented.

	Requirement	**Comment**
	Get assessment and feedback from teachers.	This is possible via interaction toolsets and comments on the learning pages.
	View learning progress in percentage.	Implemented.
	Tag and flag up topics in the learning path.	Open and closed topics in the learning path are flagged up, according to the Learner Model.
	Access open learning resource, e.g. Wikipedia.	
	Search learning resource within and outside of the system.	
	Use interactive learning content, e.g. debugging tools.	
	Contribute to learning content by creating and uploading files.	
	Choose to view the whole or partial learning path.	Implemented.
Social Networking	Create groups that are registered for the same topic.	Implemented.
	Discuss the current learning topic with other students.	Implemented.
	Set access rights for learning materials.	
	Set access rights for groups.	
	Ask and answer questions of other students.	Implemented.
	Create groups that share common learning interests.	Implemented.
	Use feedback & questions forum at the end of each lesson.	Implemented.
	Share and/or recommend learning materials.	Implemented.
	Use communication tools to chat and leave messages.	Implemented.
	Write comments/notions wherever and whenever wanted.	Implemented.

	Requirement	**Comment**
	View history discussion when selecting a particular topic.	Implemented.
	Design and publish courses for others to use.	Whist whole courses cannot be published by the students, contributions can.
Adaptation	Recommend other topics according to current learning topic.	Implemented.
	Recommend topics according to student's knowledge level.	Implemented.
	Recommend topics by referring to other students' rating.	
	Adapt learning path according to learning progress.	Implemented.
	Adapt learning tools according to student's user-level.	
	Adapt social interaction tools according to students user-level.	
	Recommend other students according to the current topic.	Implemented.
	Recommend other groups according to student's interests.	Implemented.
Usability	View system status.	
	Use graphical user interfaces.	
	Get instructions and tips.	
	Select full screen option.	
	Set themes, layout, etc.	

4.4 Evaluation

A case study has been conducted to evaluate the initial social personalised adaptive e-learning system from a learner (end-user) point of view, in terms of learners' *effectiveness* (usefulness), *efficiency* (ease of use) and *satisfaction*. This section presents the specific hypotheses for the system evaluation, and the questionnaires designed to test the hypotheses, aiming to answer the research question **R1** – "*How can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and engagement amongst learners?*" In particular, this section focuses on the perspectives of perceived *effectiveness*, *efficiency* and *satisfaction* from the point of view of the student users.

4.4.1 Hypotheses

The main motivation for the implementation of Topolor is the assumption that the combination of 1) *classical adaptation based on user modelling*, 2) *fine-grained social interaction features* and 3) *a Facebook-like appearance*, can ensure a high level of *effectiveness, efficiency and satisfaction as perceived by learners*. Therefore, this evaluation aims to test the following hypotheses.

1) Effectiveness and Efficiency

As discussed in section 2.6, in this work we evaluate *effectiveness* by asking learners if the system (or the functionality, or the feature) is useful (fit for purpose), and we evaluate *efficiency* by asking learners if the system (or the functionality, or the feature) is easy to use (effort required to use), in three levels of granularities of *effectiveness* (usefulness) and *efficiency* (ease of use) including the levels of 'system as a whole', 'sub-system functionalities' and 'single tasks'.

At the 'system as a whole' level, the *System Usability Scale* (SUS) questionnaire (Appendix D) has been used. The hypothesis regarding learners' *effectiveness* and *efficiency* at 'the system as a whole' level has been defined as follows.

H1.1 Learners perceive high *effectiveness* (usefulness) and *efficiency* (ease of use) of using the system as a whole.

The SUS score that is greater than 70 would support this hypothesis (**H1.1**), whilst the corresponding *null* hypothesis for **H1.1** would be supported if the SUS score is less than 70.

At the 'sub-system functionalities' level, the following ten main 'sub-system functionalities' have been evaluated:

1. **Overall-Sub** represents the overall view of each subsystem.
2. **Status (post)** supports students to publish and share their learning status and comment on each other's status.
3. **Messaging** aims at helping in making the intra-system communication more efficient.
4. **Q&A (questioning and answering)** helps students learn and manage the queries related to learning topics.

5. **Note** records students' personal thought related to learning topics. It can also be shared with other learners.
6. **To-do** helps students arrange their own learning plans and remind them to finish their tasks.
7. **Module** includes activities such as arranging topics within a module, reviewing topics learnt, and accessing a recommended topic.
8. **Topic** represents the functionalities that support topic-learning activities such as accessing the previous and next learning topic according to the recommended learning path, discussing with others who are learning the same topic, and commenting on the topic.
9. **Testing** includes taking quizzes for a learning topic and taking tests for a module (a set of organised learning topics). It also assesses the process of reviewing quizzes/tests, and getting access the learning topics related to the questions in a quiz/test.
10. **Statistics** is about the numbers of, e.g., how many topics a learner has learnt, how many questions a learner has asked/answered, how many status (post) a learner has commented on and shared, and so on.

All the above ten functionalities have been evaluated from two perspectives, i.e., *perceived usefulness* (for effectiveness) and *perceived ease of use* (for efficiency), on a five-point Likert scale ranging from -2 (very useless/hard to use) to 2 (very useful/easy to use). The Sub-System Functionality Scale (SFS) questionnaire (Appendix E) has been used to collect the data.

The hypothesis regarding learners' *effectiveness* and *efficiency* of using these ten sub-system functionalities has been defined as follows.

H1.2 Learners perceive high *effectiveness* (usefulness) and *efficiency* (ease of use) of using these ten sub-system functionalities.

This hypothesis (**H1.2**) would be supported if the mean values and median values of both *perceived usefulness* and *perceived ease of use* for all these ten sub-system functionalities are positive, i.e., greater than the neutral value, i.e., 0, whilst the corresponding *null* hypothesis for **H1.2** would be supported if one or more above values were negative or zero i.e. not greater than the neutral value.

To evaluate learners' *effectiveness* and *efficiency* at the 'single tasks' level, this case study has identified and tested each atomic tasks (i.e., CRUD – create, read, update and delete) that could be performed by learners. However, due to the space limitation, here the focus is on the following three social interaction tools provided by the system.

- The **status creation tool** (Figure 16): sharing learning statuses. Learners can favourite and comment on each other's posted learning statuses.
- The **messaging tool** (Figure 17): sending and receiving private messages.
- The **Q&A tool** (Figure 18): asking and answering questions. Learners can also use the **Q&A tool** for discussions.

Figure 16 Social interaction toolset – the status creation tool

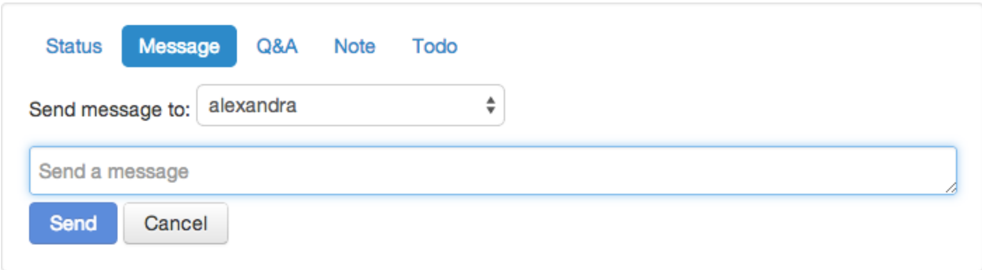


Figure 17 Social interaction toolset – the messaging tool

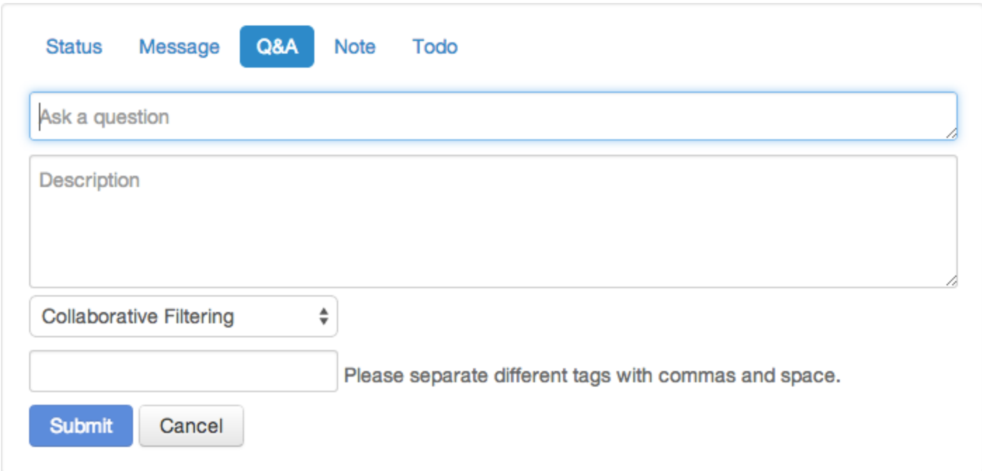


Figure 18 Social interaction toolset – the Q&A tool

Table 6 shows the full list of the 18 tasks related to the social interaction toolset.

Table 6 Tasks performed by the student

Status	**Message**	**Q&A: Question**	**Q&A: Answer**
Create (1)	Send (7)	Create (9)	Create (12)
Edit (2)	Replay (8)	Edit (10)	Edit (13)
Remove (3)		Remove (11)	Remove (14)
Comment on (4)		Share (15)	
Favourite (5)		Favourite (16)	
Share (6)		Add Tag (17)	
		Edit Tag (18)	

All the above tasks have been evaluated from two perspectives, i.e., *perceived usefulness* and *perceived ease of use*, on a five-point Likert scale ranging from -2 (very useless/hard to use) to 2 (very useful/easy to use).

The hypothesis regarding learners' *effectiveness* and *efficiency* at the 'single tasks' level has been defined as follows.

H1.3 Learners perceive the single tasks with high usability.

This hypothesis (**H1.3**) would be supported if the mean values and median values of both *perceived usefulness* and *perceived ease of use* for all these 18 tasks are positive, i.e., greater than the neutral value 0; whilst the corresponding *null* hypothesis for **H1.3** would be supported if one or more above values were negative or zero i.e. not greater than the neutral value.

2) Satisfaction

User satisfaction is "the opinion of the user about a specific computer application, which they use." [53]. The most common method for assessing user satisfaction is with questionnaire surveys, after completing given tasks with a system. The hypotheses regarding *learners' perceived satisfaction* for this case study have been defined as follows.

H1.4 Learners perceive the system helpful with learning more topics.

H1.5 Learners perceive the system helpful with learning more profoundly.

H1.6 Learners perceive the system helpful with identifying weak points.

H1.7 Learners perceive the system helpful with planning their classwork.

H1.8 Learners perceive that the system increased their learning interests.

H1.9 Learners perceive that the system increased their learning confidence.

H1.10 Learners perceive that the system increased their learning outcome.

H1.11 Learners perceive the system easy to use.

H1.12 Learners perceive the system easy to learn how to use.

H1.13 Learners perceive the system easy to remember how to use.

To test these hypotheses, a questionnaire has been developed with the following statements:

S1. Topolor helped me to learn more topics. (For **H1.4**)

S2. Topolor helped me to learn more profoundly. (For **H1.5**)

S3. Topolor helped me to identify my weak points. (For **H1.6**)

S4. Topolor helped me to plan my classwork. (For **H1.7**)

S5. Topolor increased my learning interests. (For **H1.8**)

S6. Topolor increased my learning confidence. (For **H1.9**)

S7. Topolor increased my learning outcome. (For **H1.10**)

S8. It was easy to use Topolor. (For **H1.11**)

S9. It was easy to learn how to use Topolor. (For **H1.12**)

S10. It was easy to remember how to use Topolor. (For **H1.13**)

These statements are based on a five-point Likert scale ranging from -2 (strongly disagree) to 2 (strongly agree). The positive mean values and median values of the questionnaire results (**S1**-**S10**) would support these hypotheses (**H1.4-H1.13**), whilst the corresponding *null* hypotheses for **H1.4-H1.13** would be supported if the results of **S1**-**S10** were negative or zero i.e. not greater than the neutral value.

4.4.2 Experimental Setup

The case study was carried out in November 2012, with the help of twenty-one students from the Department of Computer Science at the University of Warwick, who were registered for a fourth year MSc level module called 'Dynamic Web-Based Systems'. The students were asked to learn an online course on 'collaborative filtering' using the system. Before accessing the online module, a 'to-do list' (Appendix H) was handed out to the students, to make sure they have a reminder of all actions at their disposal. The order of doing actions, and if to undertake or repeat any actions, was up to them.

After the online learning session, all the students were asked to answer the optional questionnaires. Out of the twenty-one students who participated in the online learning session, ten of them returned the optional questionnaire. The analysis presented in this section is based on these ten questionnaires.

4.4.3 Results

1) Effectiveness and Efficiency

1.1) At the 'System as a Whole' Level

Table 7 presents the results from the SUS questionnaires. The SUS score for Topolor is 75.75 out of 100 (σ=12.36). *Cronbach's Alpha* of the SUS scores is 0.85 (>0.8), meaning the results of SUS questionnaires were at a 'good' level of reliability [67]. Therefore, the hypothesis related to leaners' *effectiveness* and *efficiency* at the 'system as a whole' level, i.e., **H1.1**, has been supported.

Table 7 Scores of System Usability Scale (SUS)

#	Statement	Mean	Median	Range	SD
1	I think that I would like to use this system frequently.	4.10	1	1	0.57
2	I found the system unnecessarily complex.	2.10	-1	3	0.88
3	I thought the system was easy to use.	4.40	1	2	0.70

#	Statement	Mean	Median	Range	SD
4	I think that I would need the support of a technical person to be able to use this system.	2.00	-1	3	1.15
5	I found the various functions in this system were well integrated.	3.78	1	1	0.44
6	I thought there was too much inconsistency in this system.	1.90	-1	2	0.74
7	I would imagine that most people would learn to use this system very quickly.	3.80	1	1	0.42
8	I found the system very cumbersome to use.	1.60	-1	1	0.52
9	I felt very confident using the system.	4.30	1	2	0.67
10	I needed to learn a lot of things before I could get going with this system.	2.10	-1	3	0.88

1.2) At the 'Sub-System Functionalities' Level

Table 8 presents the scores of each of the considered sub-system functionalities. The *means* for *usefulness* range between 0.85 and 1.4, and those for *ease of use* range between 0.95 and 1.44. The *medians* for *usefulness* range between 0.58 and 2, and those for *ease of use* range between 0.48 and 2.0. The *standard deviations* (SD) for *usefulness* range between 0.12 and 0.51, and those for *ease of use* range between 0.17 and 0.6. Both *Cronbach's Alphas* of the results of *usefulness* and *ease of use* are 0.97 (>0.9), indicating an 'excellent' level of reliability [67]. As all the means and medians for both usefulness and ease of use are greater than 0 (the neutral response), the hypothesis related to leaners' *effectiveness* and *efficiency* at the 'sub-system functionalities' level, i.e., **H1.2**, has been supported.

Table 8 Scores of sub-system functionality scale

Feature	*Usefulness*				*Ease of use*			
	Mean	**Median**	**Range**	**SD**	**Mean**	**Median**	**Range**	**SD**
Overall-Sub	1.24	1.31	2	0.57	1.58	1.59	1	0.38
Status	1.69	1.82	1	0.36	1.26	1.24	1	0.59
Messaging	0.98	1.00	1	0.12	1.87	2.00	1	0.31
Q&A	1.82	2.00	1	0.27	1.22	1.93	1	0.53
Note	0.58	0.58	1	0.42	1.22	0.48	1	0.37
To-do	0.68	0.72	1	0.20	1.33	0.51	1	0.17
Module	1.23	1.34	2	0.51	.78	0.91	2	0.60
Topic	0.69	0.79	1	0.39	.63	0.80	1	0.39
Testing	1.74	1.68	1	0.23	.89	1.68	2	0.45
Statistics	1.30	1.25	2	0.52	1.11	0.50	1	0.40

1.3) At the 'Single Tasks' Level

Table 9 shows the scores of each of the single task scales. As for *usefulness*, the *means* of the summative results range between 0.70 and 1.60, and the *medians* range between 0.5 and 2. The *standard deviations* (SD) of the overall results are between 0.53 and 0.99. All the reported values of a *mean* are much larger than 0 (the neutral response), suggesting students' attitudes to be generally positive. In terms of *ease of use* the *means* of the overall results range between 0.80 and 1.70, and *medians* range between 1 and 2. The *standard deviations* (SD) of the overall results are between 0.48 and 1.14. As all the *means* are greater than 0, we infer that most of the students found the social interaction toolset to be relatively *easy to use*.

Cronbach's Alpha of *usefulness* is 0.934 (>0.8), and *Cronbach's Alpha* of *ease of use* is 0.948 (>0.9), indicating an 'excellent' level of reliability of the results [67]. Therefore, the hypothesis related to leaners' *effectiveness* and *efficiency* at the 'single tasks' level, i.e., **H1.3**, has been supported.

Table 9 Scores of single tasks scale (social interaction toolset)

Feature	***Usefulness***				***Ease of use***			
	Mean	**Median**	**Range**	**SD**	**Mean**	**Median**	**Range**	**SD**
Task (1)	1.22	1.00	2	0.67	1.67	2.00	1	0.50
Task (2)	1.20	1.00	2	0.63	0.90	1.00	3	0.99
Task (3)	1.30	1.00	2	0.67	1.30	1.50	2	0.82
Task (4)	1.50	1.50	1	0.53	1.50	2.00	2	0.85
Task (5)	0.70	0.50	2	0.82	0.90	1.00	3	0.99
Task (6)	0.90	1.00	3	0.99	1.20	1.00	2	0.79
Task (7)	1.30	1.00	2	0.67	0.90	1.00	2	0.88
Task (8)	1.50	1.50	1	0.53	1.10	1.00	2	0.74
Task (9)	1.50	1.50	1	0.53	1.60	2.00	1	0.52
Task (10)	1.40	1.50	2	0.70	0.80	1.00	3	1.14
Task (11)	1.10	1.00	2	0.88	1.10	1.00	2	0.88
Task (12)	1.60	2.00	1	0.52	1.70	2.00	1	0.48
Task (13)	1.40	1.50	2	0.70	1.10	1.00	2	0.74
Task (14)	1.30	1.50	2	0.82	1.20	1.00	2	0.79
Task (15)	1.30	1.50	2	0.82	1.50	2.00	2	0.71
Task (16)	1.30	1.00	2	0.67	1.50	1.50	1	0.53
Task (17)	1.10	1.00	2	0.74	1.00	1.00	3	1.05
Task (18)	0.80	1.00	3	0.92	1.10	1.00	2	0.74

2) Satisfaction

The questionnaire (Appendix B) results corresponding to learners' perceived *satisfaction* is shown in Table 10. The *means* range between 0.60 and 1.60, the *medians* range between 0.5 and 2, and the *standard deviations* (**SD**) of the overall results are between 0.52 and 0.82. All the *means* and *medians* are greater than 0 (the neutral response). Additionally, *Cronbach's Alpha* of the scores is 0.811 (>0.8), indicating a 'good' level of reliability [67]. Therefore, all the hypotheses related to learners' perceived *satisfaction*, i.e., **H1.4-H1.13**, have been supported.

Table 10 Scores of learner perceived satisfaction scales for Topolor

#	Statement	Mean	Median	Range	SD
1	Topolor helped me to learn more topics.	0.70	0.5	2	0.82
2	Topolor helped me to learn more profoundly.	0.70	1	2	0.67
3	Topolor helped me to identify my weak points.	0.60	1	1	0.52
4	Topolor helped me to plan my classwork.	1.40	1	1	0.52
5	Topolor increased my learning interests.	1.60	2	1	0.52
6	Topolor increased my learning confidence.	1.50	1.5	1	0.53
7	Topolor increased my learning outcome.	0.90	1	1	0.32
8	It was easy to use Topolor.	0.80	1	2	0.63
9	It was easy to learn how to use Topolor.	0.90	1	2	0.57
10	It was easy to remember how to use Topolor.	1.40	1	1	0.52

4.4.4 Discussions

The case study was conducted in a real-life online learning session, to assess Topolor from a learner (end-user) point of view, in terms of learners' perceived *effectiveness*, *efficiency* and *satisfaction* in using the system. These three perspectives were assessed at three levels of functionality granularity: 'system as a whole', 'sub-system functionalities' and 'single tasks' levels.

- At the 'system as a whole' level, the *System Usability Scale* (SUS) – a highly established and well-validated measure – has been used.
- At the 'sub-system functionalities' level, a questionnaire with ten five-point Likert scale statements was used – each statement presenting an identified functionality.
- At the 'single tasks' level, a questionnaire with eighteen five-point Likert scale statements was used – each statement presenting an identified task.

All have been evaluated from the perspectives of *effectiveness* (perceived usefulness) and *efficiency* (perceived ease of use) from a students' point of view. Besides, learner *satisfaction* of using the system was evaluated using a 'learner satisfaction questionnaire' survey instrument, which consists of ten five-point Likert scale statements.

The overall results of the case study have indicated positive impacts of the combination of *classical adaptation based on user modelling*, *fine-grained social* *interactions* and *a Facebook-like appearance* on learners' perceived *effectiveness*, *efficiency* and *satisfaction* in using the system.

The high score of SUS suggests a high overall usability of Topolor; as a 'highly established' measure, it also demonstrates the *criterion validity*, by comparison with other questionnaire results. The high average agreement on the *usefulness* and *ease of use* of the design of social features shows learners' high-perceived *effectiveness* and *efficacy* in using the functionalities provided by the system. The high mean values in the learner satisfaction questionnaires indicate that Topolor can have a positive influence on the overall learner experience – especially, the high score of the statement "Topolor increased my learning interests" supports the idea that the social interface and interaction can trigger learners' interests. Besides, all *Cronbach's Alpha* values are greater than 0.8, indicating the case study results have high reliability. The separately acquired oral feedback from students was that they would have wanted to have more lessons delivered via this e-learning system. Decisive in this, we believe, was the fact that a lot of the social features had a look and feel familiar to them that was similar to the popular Facebook system. Such familiarity is essential to consider in designing such systems.

The results have also suggested further improvement of the initial social personalised adaptive e-learning system. Several features need improvement, and are thus further upgraded in the follow-up version of Topolor, as further explained in Chapter 6.

Moreover, during the online learning session of this case study, Topolor's data logging mechanism kept track of distinct user actions, e.g., clicking on a button. Each of the actions was stored in the database with a timestamp. The next chapter, i.e., Chapter 5, presents the analysis on the log data.

In addition to the questionnaire data collected from the students, we have, as said, also received some qualitative feedback from both students and the lecturer of the module, in the format of interviews and observations. The general feedback was consistent with the results of the questionnaire. However, the responses included some specific suggestions for further improving some of social interaction features.

Overall, the results from the questionnaire indicate that the social interaction features are perceived to be *useful* and *easy to use*. 15 (out of 18) social interaction features have been rated by the students as useful; and 14 (out of 18) as easy to use (i.e., mean > 0). The qualitative feedback also indicated that the system is easy to use – for instance, one comment described the system as "similar to known social networking sites (e.g. Facebook); fast and responsive". Another respondent said: "One of the best aspects of Topolor is the ability to interact with others during the process of learning". In the following, we proceed to a detailed discussion of the individual social interaction tools, namely *status*, *messaging* and *Q&A*.

1) Status

The questionnaire results indicate that the task (4), *commenting on a status,* was rated as the third most useful feature (mean = 1.5), and its *ease of use* was ranked as the fourth highest (mean = 1.5) among all the social interaction features. This result is further supported by the qualitative feedback. For example, one of the respondents explicitly mentioned that commenting on each other's *statuses* was one of their favourite features for interacting with other students. Commenting on a learning status has made the system more appealing to the students, as they haven't experienced such a feature in other e-learning systems. This therefore combined studying with social networking. Furthermore, the students felt that commenting on a learning status made the learner experience richer in terms of exchanging ideas and knowledge, without worrying about the formality of introducing themselves to each other and eliminating the social phobia that some students may experience.

On the other hand, task (5) 'favourite'-ing a *status* had the lowest rating (mean = 0.7) on *usefulness*. One of the aims of this feature is so that learning statuses with a large number of 'favourite'-s can be recommended to other students, since the content of the status might be useful. It could be also used in other education scenarios, such as suggesting ways of solving questions, and suggesting learning materials. The possible reason for this being the lowest rated feature could be that the students might not have known what the use of 'favourite'-ing a status was, or felt that the feature did not provide them with any personal benefit. We assume that it would be necessary to develop a mechanism for providing basic information on less familiar features such as 'favourite'-ing. Additionally, the fact that the 'favourite' option in Topolor is available within a range of features (such as questions/answers) might also affect the future patterns of use. Furthermore, one possible reason for the second lowest rating on task (5) 'favourite'-ing *a status* for its *ease of use* (mean = 0.9), could be that labels for 'favourite'-ing/'unfavourite'-ing statuses became visible only when the status message was being hovered over. The suggested improvement would be to keep the labels and the number of times the statuses have been 'favourite'-ed always visible.

2) Messaging

The rating for task (7), *sending a message* was, whilst high, the second lowest (mean = 0.9) with regards to its *ease of use*. One possible reason for this is that the system currently only notifies the user of new messages when the user is currently viewing the messaging page. Therefore, if the students had not visited the messaging page, they might not have known when and how to start messaging. Additionally, whilst most of the webpages in Topolor provide at least one tool for sending messages to other students, (such as the avatar list of the recommended learning peers that provided a messaging box when the user clicked on a peer), there are still other webpages that did not provide such tools, potentially affecting the results about the *ease of use* of sending messages. However, since messaging is such a vital tool within social media, we consider messaging to be a 'must have' features in Topolor, enabling students to exchange their ideas privately. It also complements the feel and look of Topolor as a social e-learning system.

3) Asking and Answering Questions

The questionnaire results indicated that task (l2) *answering a question* was rated as the most useful feature (mean = 1.6) as well as the easiest feature to use (mean =

1.7), among all the social interaction features. A similar result was found from the qualitative feedback, where the way of asking and answering questions was explicitly mentioned as favourable. Furthermore, (9) *asking a question* was rated very high on the *usefulness* (mean = 1.5) and *ease of use* (mean = 1.5) scales too. Therefore, we can report with confidence that the students were very satisfied with the features of asking and answering questions.

Nevertheless, the *usefulness* of task (18) *editing the tags of a question* was rated as the second lowest (mean=0.8), and the *usefulness* of task (17) *adding tags to a question* was rated as the fourth lowest (mean=1.1). One of the original intentions of providing such features was to enable students to label questions for their own reference; hence they will be able to more easily find the specific questions asked before. It seems, however, that *tagging on questions* was not considered as useful as other features of Topolor. We can conjecture that when a student asked a question within the scope of the course, the relation between the question and the learning content would have been automatically established, so that tagging the question would not have brought additional benefits. Students would need to post questions beyond scope of the course would be necessary to further comment on this feature.

Amongst the *ease of use* of the feature for asking/answering questions, task (10) *editing a question* was rated the lowest (mean=0.8). To provide attractive user experiences, we used AJAX calls to implement this feature. For example, when a student clicked on the title or the description of a question, it would activate the

HTML ‘textarea’; and when the ‘textarea’ ‘focusout’-s, it would be replaced by the updated HTML text. No explicit buttons were provided to trigger editing. This might have not attracted student attention to the existence of this functionality. Although the style of the mouse cursor changes when hovering over the title or the description of a question, this hint might not have been a clear enough indication to the students about the provided editing functionality. Moreover, *editing a question* may require engagement with the system over a longer period of time, so the evaluation of this feature can only be finalised after long term use of the system.

4.5 Conclusions

Adaptive e-learning systems allow for personalisation of the learning process. Social interactions enable learners to create, publish and share content, facilitating interaction and collaboration. Integrating social interactions into adaptive e-learning systems offers new ways for learner engagement and extended user modelling. This chapter has presented the process of design, implementation and evaluation an initial social personalised adaptive e-learning system that combines *classical adaptation based on user modelling*, *fine-grained social interactions* and a *Facebook-like appearance*.

The architecture of the initial social personalised adaptive e-learning system has been designed for providing an implementation-dependent view of building the initial social personalised adaptive e-learning system. It takes into consideration the system requirement suggested in section 3.7, as well as taking advantage of classical adaptive hypermedia models such as LAOS [41] and SLAOS [61]. An application of the system architecture has been implemented, called Topolor. The implementation has been presented from the perspectives of the techniques used, the functionalities supported and the main user interfaces.

The evaluation of Topolor's various features (*classical adaptation based on user modelling*, *fine-grained social interactions* and a *Facebook-like appearance*) has been conducted in real-life online learning sessions. Both qualitative and quantitative data have been collected and analysed. The high scores of the questionnaire results and their high reliability have illustrated a high level of perceived *effectiveness*, *efficiency* and *satisfaction* amongst learners, indicating that this approach is promising. The additional qualitative feedback from the course instructor and the learners after the course has also shown positive attitudes, which is consistent with the qualitative feedback. This result has also suggested further improvements of the system, such as the status sharing tool, the messaging tool, and the asking and answering tool.

In conclusion, the study presented in this chapter has partially addressed the research objective **O3**: "based on the hypotheses and conclusions from **O1** and **O2** (as defined in section 1.2), developing a social personalised adaptive e-learning system that fosters social, personalised and adaptive e-learning experience, and evaluating it from the perspectives of learner effectiveness, efficiency, satisfaction and engagement". In particular, this chapter has focused on the perspectives of perceived *effectiveness*, *efficiency* and *satisfaction* (the perspective of *engagement* are further addressed in Chapter 5). The process of addressing this research objective has partially contributed to answering the research question **R1**: "how can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of **effectiveness, efficiency, satisfaction (the focus of this chapter)**, and engagement (the focus of Chapter 5) amongst learners?" The answer so far is "the combination of classical adaptation based on user modelling, fine-grained social interaction features, and a Facebook-like appearance, can ensure e-learning systems provide a high level of **effectiveness, efficiency, satisfaction** amongst learners".

Chapter 5

Investigating Learning Behaviour Patterns

5.1 Introduction

The main objective of the work presented in this chapter is to further answer the research question **R1**: "how can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and engagement amongst learners?" In particular, this chapter focuses on the learners' perceived *engagement* perspective. The perspectives of learners' perceived *effectiveness*, *efficiency* and *satisfaction* have been presented in Chapter 4. This chapter also aims to gather insight to provide suggestions on further development and improvements to the system.

Data logging can record the actions performed by users when interacting with a system. They can serve as the basis for both quantitative analysis and qualitative analysis of these interactions, as both are meant to allow gain of significant new insights into user behaviour and performance [188]. Data logging is a very efficient way of collecting data, since large amounts of behaviour data can be collected unobtrusively and ubiquitously. Moreover, the log data is objective, since there is no external effect, which may alter normal user behaviour, during the data collecting process. This chapter aims to get better insight into types of learning behaviours of users of the e-learning system, i.e., Topolor, resorting both to data mining methods and visualisation tools.

Data mining or knowledge discovery in databases (KDD) is a process of analysing and extracting knowledge from data contained within a database [139]. Researchers have started exploring various KDD methods to improve e-learning systems [83, 87, 107] starting from 2006, when the first few publications on educational data mining (EDM) appeared [48]. Evidently, EDM has great potential and it is particularly useful for the improvement of e-learning systems, but most researchers focused on the development of data mining algorithms rather than on the empirical analyses of e-learning systems [77]. Typical patterns of accessing an adaptive e-learning system and the interaction information contained in these patterns can be stored in a database, which logs when and how learners are interacting with the system. In this context, EDM is able to recognise regularities in learner trails as learning behaviour patterns. The structured descriptions of these regularities, as the output of EDM, can be used for explaining the original data and to make predictions.

One of the key questions in EDM is how to determine which learning data need to be analysed and what learning behaviour patterns can be captured [59]. Data visualisation techniques are rather useful to highlight useful information and support decision-making. Statistics and visualisation are the two most widely used techniques to analyse learners' online course activities and usage information [140]. Data mining and data visualisation are used together to discover relevant patterns, also providing tools that aid the analysis of these patterns and ultimately allow having a clearer understanding of learning behaviours [153, 183].

This chapter presents the combination of data mining methods and data visualisation tools developed to gain insight into the log data collected when students are using an e-learning system. In particular, we sought to discover learning behaviour patterns in Topolor, the social personalised adaptive e-learning system, introduced in Chapter 4. By analysing these patterns, we gathered insight to provide suggestions on further development and improvements to the system. The novel contributions of this part of the research are: 1) conducting an empirical investigative study using data mining methods and visualisation tools to understand learning behaviour data and explore learning behaviour patterns in a social personalised adaptive e-learning system; and 2) identifying possible directions to improve user modelling and social interactions of the system.

The remainder of this chapter introduces Topolor's learning behaviour tracking mechanisms, and elaborates on the analysis of the experimental results using data mining methods and visualisation tools. The insights obtained are discussed, and follow-up work is outlined.

5.2 Data Collection

A data logging mechanism has been implemented in the initial social personalised adaptive e-learning system Topolor. It can be switched *on* for experimental purposes or *off* for normal use. When switched *on*, Topolor tracks every single action performed by users. These are recorded in a database, each together with a timestamp. The log data tuple is <*user_id*, *controller*, *action*, *type*, *request*, *create_at*>. As an example, on possible value would be as <*12*, "*concept*", "*view*", "*GET*", "*id=20*", "*2012-11-29 10:20:30*">. It means that at 10:20:30 on November 29th 2012, the learner (id=12) accessed a topic page, containing lecture material on the learning concept with id 20. Note that the privacy of the student is kept, there is no way to identify who 'learner 12' is in reality – the data is anonymous.

A first batch of data collection was carried out during the real-life online learning session described in section 4.4. Out of the 21 students involved, 4 had performed less than 10 actions, and 1 student had performed only the social interaction actions. After the exclusion of these 5 students, the remaining 16 students' actions, adding to a total sum of 2175 actions (with an average of 136 actions and a standard deviation of 71 actions per student) were analysed.

5.3 Data Analysis

After the data collection procedure, learners' actions extracted from the log data were analysed. The log data contain all the information about learner-system interaction during the experimental online learning sessions. In this work, the log data analysis aims at discovering the following types of learning behaviour patterns:

- **Action frequency** represents the frequency with which an individual learner or a group of learners performed a type of actions;
- **Action sequence** is a chronologically ordered set of actions, which would be useful to observe a list of action sequences.

These two patterns are expected to help understand the learners' *participation* and *engagement* within the system, as well as the likeness and *perceived ease of use* of the targeted interaction features. Various data visualisation tools have been used for representing relevant aspects extracted from the action frequency and sequence, notably 100% stacked column charts, marked scatter charts and directed acyclic graphs (DAG).

In total, 41 different types of raw actions were identified from the log data, as shown in Table 11. To simplify the visualisation, observation and analysis, the actions were annotated following an expert-designed higher-level categorisation, dividing actions into: a) **assessment**, b) **auxiliary**, c) **social interaction**, d) **navigation**, and e) **reading**, as shown in Figure 19 and Table 11. The variety of actions performed by students suggests their curiosity in exploring various features of Topolor; the high proportion of social interactions indicates high engagement in using this social e-learning system.

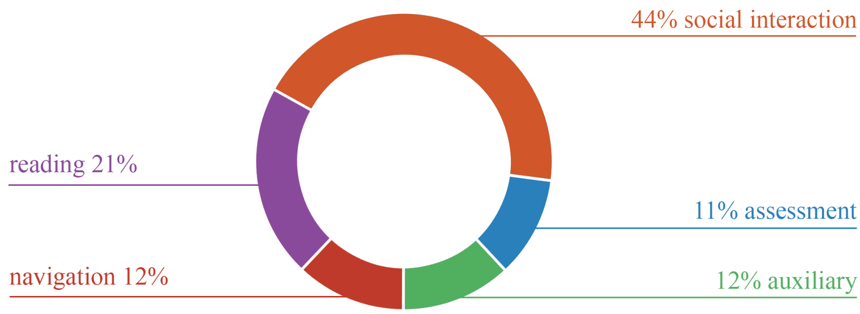


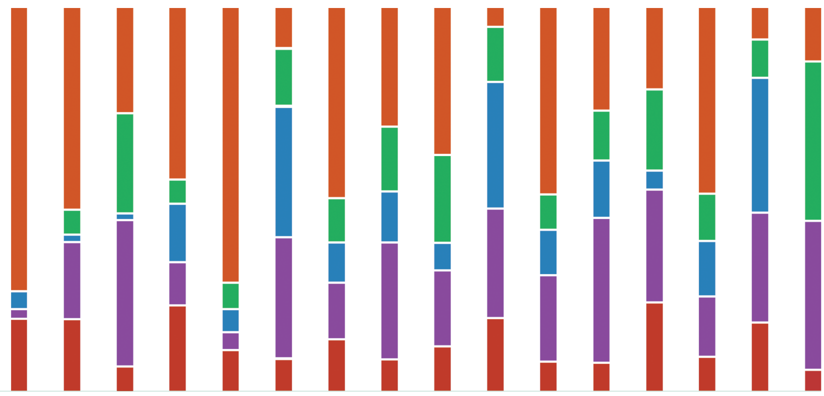
Figure 19 The proportions and categorisations of learner actions

Table 11 Actions tracked and logged

Category	**Raw Action**
Assessment	Create a quiz, submit a quiz, review a quiz;
Auxiliary	Create / view / update / delete a note, filter notes, view note list; Create / view / update / delete a to-do, filter to-dos, view to-do list; Claim "I've learnt the topic";
Social Interaction	Create / view / update / delete a question, filter questions, view question list; Create / update / delete an answer to a question; Create / view / update / delete a learning status, view status list; Comment on / favourite / share a learning status; Send a message, view message list; Comment on / favourite a topic;
Navigation	View the module list; View the topic list, filter topics;
Reading	View a topic page.

5.3.1 Action Frequency

The *100% stacked column chart* shown in Figure 20 was used for displaying, for each student, the proportion of times each type of action was performed. In the plot, each stacked column corresponds to one student and represents a two-hour session. The coloured blocks represent the specific categorised actions taken by the student. As can be seen from the figure, the most frequent actions were of **social interaction** (i.e., question & answer, message, favourite, share, comment, etc.), followed by **reading** actions (i.e., viewing a topic page). This was to be expected, as the students were to focus on learning topics (**reading** actions) – as the core objective of using an e-learning system, and interacting (**social interaction** actions) with each other when learning online courses. All the students did **navigation** actions, because they were recommended relevant topics and they could also find interesting topics using filtering tools and switch between different topics. Not all the students performed **assessment** actions (e.g., submitting a quiz), and the same holds true for the **auxiliary** actions (i.e., creating a note and a 'to-do'). This might be because they were considered minor features.



student no.	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15	#16
social	123	92	57	80	219	13	46	64	24	3	90	41	10	79	5	5
auxiliary	0	10	52	10	19	18	10	34	14	9	15	19	10	19	6	16
assessment	6	2	2	26	16	42	9	26	4	21	20	22	2	23	22	0
reading	3	34	76	19	12	39	13	62	12	18	39	57	14	25	18	15
navigation	31	32	12	39	31	10	12	16	7	12	13	11	11	14	11	2
total	163	170	199	174	297	122	90	202	61	63	177	150	47	160	62	38

Figure 20 Action frequency of each student

Another interesting observation from Figure 20 is the difference between each student's *participation* and *engagement*. During the same 2 hours session, the action frequencies of different students were very different, from the maximum 297 actions to the minimum 38 actions. We examined the correlation of the number of total actions and the proportion of the 5 categories of actions, but there was no significant correlation between them. Nevertheless, we did find some (positive and negative) correlations between the proportions of the categorised actions. For instance, as shown in Figure 21, the proportions of **auxiliary** actions and **reading** actions were positively correlated (the strongest positive correlation that we found). We assume the reason was that if the students viewed more topic pages (**reading** action), they would have more chance to, e.g., claim 'I've learnt the topic' (**auxiliary** action). The negative correlation that we found included those between **auxiliary** actions and **social interaction** actions, **auxiliary** actions and **navigation** actions, etc. However, the negative correlations were relatively weak.

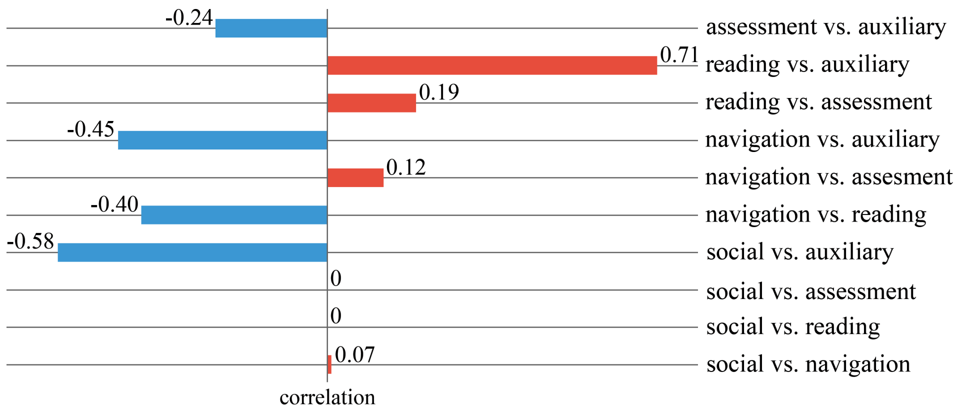


Figure 21 Correlation of action proportion

5.3.2 Action Sequence

The *marked scatter chart*, as shown in Figure 22, was used to represent and compare *action switches* and *action sequences* of different students. The *X-axis* presents the chronological order in which the actions were performed, and the *Y-axis* presents the categorisation of actions. We drew all the actions performed by a student in a row to be composed of an *action sequence*, where each plot represented a single action. We then vertically listed all the *action sequences* in one chart for observation and comparison, in order to find *action sequence* patterns of the students. In Figure 22, we randomly present 4 students' *action sequences*, and for each sequence, we only present the first 180 actions performed by the students.

The overall observation of Figure 22 reveals some common patterns from different students. For instance, all of the students started with performing **social interaction** actions; students switched quite often between **social interaction** and **navigation** as well as **assessment** and **reading**; the performances of **auxiliary** actions varied between different students; there were a lot of exploratory actions in some periods and the rich feature set provided by Topolor was fully exploited. However, different patterns also emerge between different students. For example, student #2 tried to perform some **auxiliary** actions, and then they stopped using these features. Student #3 could focus on viewing topics (**reading** actions), after they spent some time to exploit all the features provided. Student #4 switched between **social interaction** and **navigation** more often than others, with forays into **reading** and **auxiliary** actions. Student #5 could not concentrate on viewing topics (**reading** actions), but they were curious to exploit all the provided features instead, though they focused more on the **social interaction** actions.

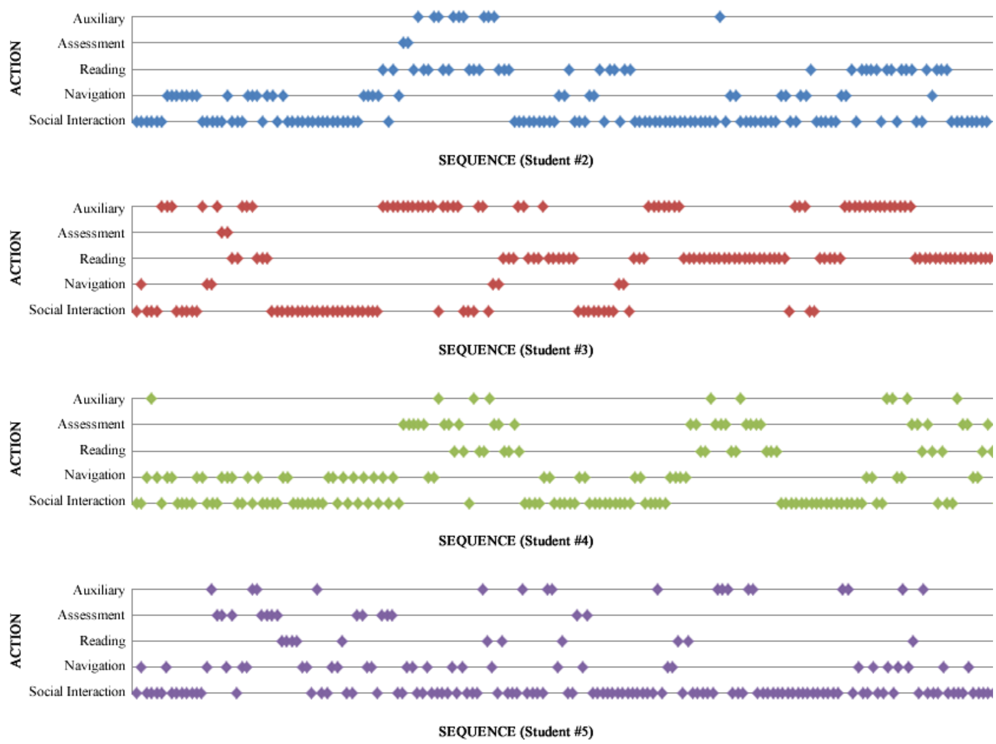


Figure 22 List of action sequences (partially)

(chronological order against action category)

For further investigation, we summarised all of these *action sequences* into a *Directed Acyclic Graph* (DAG). As shown in Figure 23, the DAG consisted of coloured nodes, representing the grouped repetitive actions belonging to the same categorisation, and the edges representing routing relationships. Lower-level actions were performed after higher-level actions (e.g., action 5 in level-2 were performed after action 1 in level-1). The numbers labelled on the edges represent the probabilities that the actions in the lower-level end of the edges performed while routing from the entry point (e.g., the probability of performing actions in the order of 1-5-2-3 was 0.125).

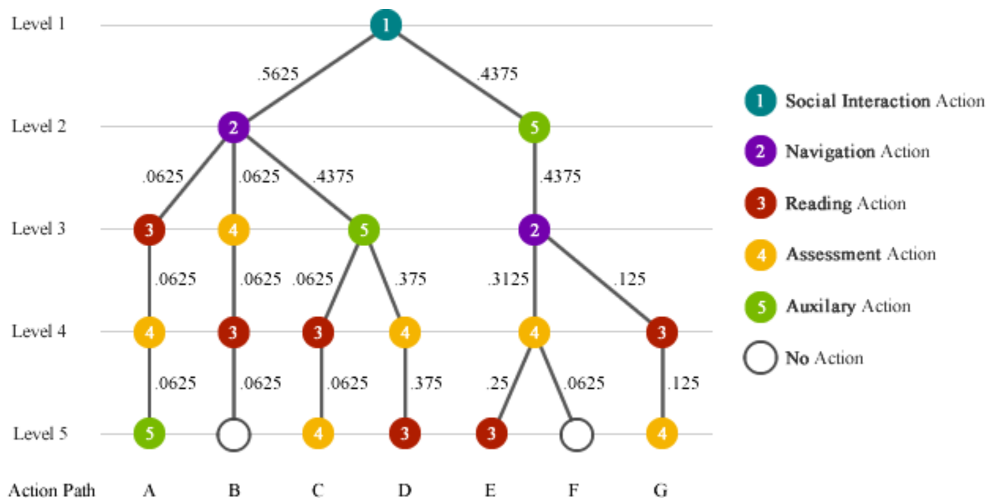


Figure 23 Directed Acyclic Graph (DAG) of possible action paths

From the DAG shown in Figure 23, we have the following observations.

- **Social interaction** actions were the entry points (level-1) for all the possible action paths. The second performed actions were navigation actions or auxiliary actions. The former occurred with probability of 0.5625, and the latter occurred with probability of 0.4375.
- **Navigation** actions were performed relatively earlier than other actions (only occurred at level-2 and level-3), and they had more follow-up routes if they occurred in level-2. We can thus assume that, as routers, navigation actions played an important role during the learning process. Students exploited the features in Topolor by firstly performing navigation actions.

Besides, students might have liked the filtering tools provided by Topolor, as they used them to find interesting topics and questions & answers, before they accessed the detail pages and performed further actions.

- **Auxiliary** actions were relatively dispersed (occurred from an early level – level-2 to the last level – level-5). We assume that different students had different demands from auxiliary tools, so it would be necessary to enhance the personalisation and adaptation features for these tools.
- **Reading** actions were performed relatively late (the majority occurred at level-4 and level-5). It might be because the topic learning pages were not attractive enough, especially the reading content themselves had no interactional features, such as a manipulatable chart.
- **Assessment** actions were also performed relatively later (the majority occurred at level-4 and level-5). The reason for this might be that the assessment actions should be performed right before or right after performing reading actions. We know that some assessment actions were performed before reading actions, because the students could take a pre-test for the whole module before they started to learn a topic in the module.

The DAG represented 7 possible action paths. Table 12 summarised them in descending order based on their probabilities. The observations from Table 12 are as follows.

- The most performed action path was D: 1-2-5-4-3 (0.375), followed by E: 1-5-2-4-3 (0.25) and then G: 1-5-2-3-4 (0.125).

- Most of the action paths (5 out of 7) included all the categorisations of actions.
- The action paths could end after performing **reading** actions or **assessment** actions.
- There was 6.25% chance that **reading** actions were never performed, and the same with **auxiliary** actions.

Table 12 Possible action paths

(1: Social Interaction; 2: Navigation; 3: Reading; 4: Assessment; 5: Auxiliary)

Label	**Action path**	**Probability**
D	1-2-5-4-3	.375
E	1-5-2-4-3	.25
G	1-5-2-3-4	.125
A	1-2-3-4-5	.0625
B	1-2-4-3	.0625
C	1-2-5-3-4	.0625
F	1-5-2-4	.0625

The above observations suggest some potential improvement of implicit user modelling. For instance, if the students are following the same action path, it might be useful to cluster them into the same group, because they might have similar cognitive styles of learning or similar preferences of using an e-learning system. As some action paths had higher probabilities to be performed, the system may recommend related tools (e.g., by making them to be more attractive) for the students to use, when the system detects they have already performed the actions following an action path.

5.4 Discussions

Analysing the visualised learning behaviour data helps in suggesting improvements for the overall learner experience for an e-learning system (from a system designers' perspective). At the same time, these visualisations might also be helpful for online course authors, teachers and students. For instance, an author might need to consider adjusting the course structure, if they found the frequency of **navigation** actions performed by the students was too high. A teacher might need to consider providing more interpretations for a particular topic, if they found the students performed too many **social interaction** actions on that topic. A student might need to consider taking more quizzes, if they found the **reading actions** they had performed were much more than that of **assessment** actions. This points to the demands of *learning behaviour data visualisations* on the client-site of the system for different participants, leading to the new features developed in Topolor, as well as the hypotheses to test in follow-up research (as described in Chapter 7).

Additionally, the generated learning behaviour patterns also suggested the likeness and *perceived efficiency (ease of use)* of the provided features and tools for supporting further improvements to Topolor.

1) **Social interaction** actions were performed most frequently, so they can be considered as the most popular features provided by Topolor. Therefore, they should be further supported and consolidated, without losing sight of the ultimate goal, which is to increase

learning outcomes. Further work has been done towards addressing this aim, as presented in section 6.3.3.

2) Not all the students performed **assessment** actions. This suggests the need to improve the quiz tools, to be more attractive and easier to use, considering the importance of assessment in e-learning. The new quiz tools have been implemented in the next version of Topolor. The description of new features related to this issue can be found in sections 6.3.2 and 7.3.1.
3) The observation that of not all the students perform **auxiliary actions**, made us initially consider the usability and necessity of *to-do* and *note* tools. However, in Topolor version 2, both *to-do* and *note* tools have been removed. Instead, other features have been introduced/enhanced to support such functionality (e.g., a personal reminder) in an easier way. For example, a new powerful *filtering* tool has been implemented in Topolor version 2, as described in section 6.3.1. It can help learners easily find the topics, share, discuss, comment, etc. (topics in which they have been involved and/or have bookmarked).

The results have also indicated that when students start to use a new e-learning system, they are inclined to explore every single available operation rather than focusing on the learning itself, which, however, may not necessarily be a bad thing, because it is normal to try and get familiar with the system, which can be helpful for their later learning, but from the research point of view, it would be better that we made the newly tested tools more familiar to the students, so that the usage data we collected reflect the long term use. In fact, the features that many of the learners are familiar with from social networking websites remain missing from current e-learning systems. For instance, sharing a learning status, engaging in a simple question/answer exchange and sharing notes remain cumbersome or impossible in many of the available systems. Therefore, on the one hand, in the follow-up research we investigate the use of more social interaction features in e-learning system (as described in Chapter 7); and on the other hand, we also explore mechanisms that can reduce 'off-topic conversations' and provide a high level of motivation amongst learners (as described in Chapter 6).

There were some limitations to this work. For example, during the 2 hours session, as it was the first time for the students to use Topolor, it is possible that their curiosity resulted in their exploration of the system rather than a purely learning process, as previously discussed. However, whilst they all started this way, a continuous exploration activity is considered unlikely, as the log data shows that, after the core functions were quickly examined, the students rapidly fell into observable patterns other than that of exploration. Nevertheless, data logging may also obscure some information behind the recorded actions. For example, data logging can only record the actions performed at a certain time, but the information about what is really happening between the times is missing. That is to say, although the information, e.g., time span, can be detected, there is no insight into the reasons for a certain time span.

5.5 Conclusions

This chapter has presented the analysis of the log data within Topolor, the initial social personalised adaptive e-learning system introduced in Chapter 4. The data were collected during the real-life online learning session described in section 4.4.2. Based on the 2175 raw actions identified from the log data, students' learning behaviour patterns were analysed, using the combination of data mining methods and visualisation tools.

From the analysis on *action frequency* and *action sequence*, some interesting individual learning behaviour patterns as well as some common learning behaviour patterns have been found, as described in section 5.3. The analysis has helped to understand learners' *participation* and *engagement* within the system, and to suggest the likeness and *perceived ease of use* of the targeted interaction features.

Additionally, the empirical investigative study has suggested how to utilise the combination of data mining methods and visualisation tools to analyse learning behaviour patterns in social personalised adaptive e-learning systems. The promising discoveries suggested the possible directions to improve user modelling and social interactions for such systems. Furthermore, the discoveries have suggested the directions to improve Topolor in the follow-up research.

In conclusion, the study presented in this chapter has partially addressed the research objective **O3**: "based on the hypotheses and conclusions from **O1** and **O2** (as defined in section 1.2), developing a social personalised adaptive e-learning system that fosters social, personalised and adaptive e-learning experience, and evaluating it from the perspectives of learner effectiveness, efficiency, satisfaction and engagement". In particular, this chapter has focused on the perspective of *engagement* (the perspectives of perceived *effectiveness*, *efficiency* and *satisfaction* have been addressed in Chapter 4). The process of addressing this research objective has also partially contributed to answering the research question **R1**: "how can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and **engagement (the focus of this chapter)** amongst learners?" The answer at this stage is "the combination of classical adaptation based on user modelling, fine-grained social interaction features, and a Facebook-like appearance, can ensure e-learning systems provide a high level of **engagement** amongst learners".

Chapter 6

Gamifying Social Interactions

6.1 Introduction

The main objective of the work presented in this chapter is to answer the research question **R2**: "how can we implement gamification techniques and technologies, in order to enhance social e-learning systems, and thus provide a high level of motivation amongst learners?"

The evaluation results of the initial social personalised adaptive e-learning system – Topolor – have indicated a high level of learners' effectiveness, efficiency and satisfaction, as reported in Chapter 4, and a high level of learners' engagement as reported in Chapter 5, which indicates that the approach presented in the previous work is promising. Nevertheless, some side effects of the extensive social interaction features have also been detected, such as 'noise', i.e., learners' off-topic conversations through 'chitchat' socialisation. It is undeniable that, in principle, informal 'chitchat' plays an important role in motivating and scaffolding peer learning [105] in a social e-learning context. In particular, positive social dialogue (e.g., greetings) may help students to relieve anxiety or promote participation in discussions. However, there are also negative outcomes of such interaction [95].

Thus, reducing the negative side effects whilst maintaining a reasonable scale of informal ‘chitchat’ is still a crucial challenge to address.

Gamification is “the use of gameplay mechanics for non-game applications” [134]. It describes an efficient way of utilising game design elements to engage users and motivate their activities, in order to solve problems and promote learning [86]. It has been incorporated into numerous domains such as marketing, work and education systems (especially social ones) as a way of creating strong connections between users and the systems [54]. This trend is increasingly catching researchers’ attention – to explore theories and practices of gamification in social e-learning, aiming to increase learner motivation, driving desirable learning behaviours and achieving pre-specified learning goals [100]. Gamification and social e-learning have various mechanics in common, such as achievement, collaboration, discovery, and virality. It is therefore likely that their combination may have a great impact on e-learning. Previous studies have shown some benefits brought by this combination, and its influences on the learning process [54, 175].

As follow-up research, the work presented in this chapter particularly aims to explore the impact of gamification on social personalised adaptive e-learning. Compared with existing studies, this work introduces a specific blend of *light gamification*, to symbiotically build upon social interaction features, rather than replace the already existing social learning features within the system. Moreover, as connectedness and interactivity can potentially satisfy learners’ basic innate needs such as autonomy, competence and relatedness [144], and thus lead to an increase of motivation in social e-learning [34], this work has proposed the *contextual gamification strategies* rooted in Self-Determination Theory (SDT) [135] – a well-known motivation theory that has been supported the three basic innate needs, as stated in section 2.4. Applying these *contextual gamification strategies*, the initial social personalised adaptive e-learning system introduced in Chapter 4, i.e., Topolor, has been further implemented with new gamification features, in order to promote learners' intrinsic motivation, and hereby build an efficient self-determined learner experience [64, 177].

The remainder of this chapter is organised as follows. Firstly, section 6.2 details the *contextual gamification strategies* that have been proposed, based on motivation theories, and then section 6.3 outlines the implementation of the second version of Topolor – Topolor 2 – which focuses on the new gamification features – i.e. the proposed *contextual gamification strategies*. Section 6.4 presents the evaluation procedure, followed by section 6.5, which summarises the findings.

6.2 Contextual Gamification Strategies

Self-Determination Theory (SDT) [143] proposes three basic innate needs that are essential to be met for promoting intrinsic motivation. According to SDT, people strive for as much *autonomy* over their own actions and decisions as possible; they also aim to obtain *competence* in their actions and surroundings. Since activities such as learning often occur in a social context, *relatedness* is proposed as the third essential innate need. In all, SDT defines three basic innate needs [144] to be satisfied:

- *Autonomy*: a sense of internal assent of one's own behaviours;
- *Competence*: a sense of controlling the outcome and experience mastery;
- *Relatedness*: a sense of connection with others within a community.

The *contextual gamification strategies* proposed in this work consist of three groups. Each group covers each of the three basic innate needs defined by SDT.

6.2.1 To Satisfy the Need for Autonomy

Experiencing *autonomy* means feeling in charge of one's behaviour and in control of the whole learning process. To satisfy the need of *autonomy*, we suggest providing learners with meaningful and flexible choices, such as learning goals and the paths that may be taken to achieve them, as well as learning peers to interact with (and the respective interaction tools), in order to continuously balance their curiosity, skills and goals against a finite pool of resources. In such a way, learners feel their behaviours are based on their own intentions, and they may acquire desired behaviours in certain contexts. Additionally, to reduce overjustification effects and maintain intrinsic motivation, it is important to provide intrinsic choices for voluntary behaviours [70], e.g., competition and collaboration, because learners usually tend to notice the loss of autonomy (being controlled), which can demotivate them. Furthermore, to maintain the satisfaction of autonomy, we suggest providing learning goals and progress markers with clear descriptions, tasks at hand with clear and immediate feedback, and customisable learning context, so that learners can advance through different challenges, according to their own skill levels. In summary, in order to satisfy the *autonomy* need, a system needs to provide:

A-1. A set of learning goals with a clear description and multiple paths to achieve each goal;

A-2. Various interaction tools to complete a task;

A-3. Clear and immediate feedback for learning activities;

A-4. Meaningful options with consequences;

A-5. Customisable learning context that can be adjusted by learners themselves.

It is noteworthy that the design of above strategies have also taken into consideration some of the system requirements suggested by learners, as detailed in Table 4, section 3.7. For example, they are meant to further meet the adaptation requirements "adapt learning path according to learning progress", "adapt social interaction tools according to students user-level" and the social networking requirement: "use feedback & questions forum at the end of each lesson".

6.2.2 To Satisfy the Need for Competence

Experiencing *competence* means feeling mastery of skills and confidence in the current context, where cognition and expectation are consistent with system responses, so as to be able to obtain further skills and confidence with relative ease. To satisfy the *competence* need, we suggest to support the perceived extent of learners' own behaviours as the cause of desired consequences; multiple choices of learning paths to achieve learning goals according to their mastery of the tasks; and customised interaction tools according to their mastery of interacting with peers, so that learners can build their own *competence*. To enhance *competence* feelings, it is essential to provide unexpected, direct and positive feedback, optimal challenges and freedom of demeaning evaluations [144]. Furthermore, when experiencing enjoyment and fun, learners can become intrinsically motivated [145], so they often even do not realise that they are completing a complicated task or achieving a hard learning goal. Hence, it is important to offer interesting challenges, which can be reached by combining well-defined rules and goals [70]. Additionally, we suggest breaking a learning goal into small and achievable pieces and increase the difficulties during the learning process, so that they can be aware of every instant achievement, feel the increase of skills, and make decisions frequently and accordingly. Therefore, the suggestion on satisfying the *competence* need is to provide:

C-1. Reasonable small chunks of learning goals with increasing difficulties;

C-2. Tasks with pleasantly surprised positive feedback;

C-3. Multiple choices to go along and retrace the learning paths;

C-4. Frequent decision-making to keep the learning process moving forward;

C-5. Enjoyable and fun learning activities.

The system requirements suggested by learners, as detailed in Table 4, section 3.7, have also been considered in the design of the above strategies. For example, they are meant to further meet the learning requirement “view learning progress as a percentage”, the adaptation requirement “recommend topics according to the student’s knowledge level”, and the usability requirement “get instructions and tips”.

6.2.3 To Satisfy the Need for Relatedness

Experiencing *relatedness* means feeling connected to peers, belonging to communities, and contributing to things ‘bigger’ than oneself. Note that a lower feeling of *relatedness* can reduce the learner’s motivation to interact with the system, which in turn would affect the satisfaction of the other two basic innate needs, i.e., *autonomy* and *competence* [185]. To satisfy the need of *relatedness*, we suggest letting learners feel free to be themselves and accepted by the community. *Relatedness* might be supported by various social interactions such as tagging, rating, commenting and sharing that contributes to the community, and the visualisation of social status and reputation such as levels, badges and a leaderboard that connect learners to a meaningful community with the same interests [143]. With *relatedness* feelings, even when the rewards may be boring or meaningless, learners may still retain motivation if they enjoy the community. Therefore, the suggestion for satisfying the *relatedness* need is to provide.

R-1. Opportunities to discover and join learning communities;

R-2. Connections of interest and goals between learners and communities;

R-3. Various tools for collaboration, discussion and mutual assistance;

R-4. Visualisations of social status, reputation and contribution;

R-5. Promotions to show appreciation to others such as 'like'.

The above strategies have been designed also taking account the system requirements suggested the learners, as detailed in Table 4, section 3.7. For example, they are meant to further meet the social networking requirements "discuss the current learning topic with other students", "ask and answer questions of other students", and "share and/or recommend learning materials".

6.3 Implementation

This section focuses on the implementation of Topolor 2's new gamification features – the application of the proposed *contextual gamification strategies*. However, in addition to these gamification features, Topolor 2 has also some other features, based on the initial social, personalisation and adaptation features – that existed in the first version of Topolor, introduced in Chapter 4. Therefore, before going into details of the gamification features in sections 6.3.2 and 6.3.3, an overview of Topolor 2 is first presented in section 6.3.1.

6.3.1 Overview of Topolor 2

Compared to Topolor – the initial social personalised adaptive e-learning system, Topolor 2 has more powerful tools for asking questions, sharing and filtering learning content as well as for social interactions. These new features have been implemented based on the suggestions described in Table 4, section 3.7, and evaluation results detailed in sections 4.4 and 5.4. As shown in Figure 24 (a), it has finer categories especially for sharing (Figure 24 (1)), i.e., text content (Figure 24 (1.2)), an image (Figure 24 (1.3)), a quote (Figure 24 (1.4)), a link (Figure 24 (1.5)), audio (Figure 24 (1.6)) and a video (Figure 24 (1.7)), while in the first version of Topolor learners could only share a 'learning status' in a text format. Learners can specify related topics when they share a learning resource (Figure 24 (1.2) – (1.7)) or ask a question (Figure 24 (1.1)). It has also finer filters (Figure 24 (2)), i.e., only showing questions (Figure 24 (2.2)), learning resources (Figure 24 (2.3)), learning activities (Figure 24 (2.4)), those the learner bookmarked (Figure 24 (2.5)), those the learner participated in (Figure 24 (2.6)), those the learner shared (Figure 24 (2.7)) and those that are featured (Figure 24 (2.8)), while in the first version, learning resources, for instance, can only be filtered by their tags. This allows the recommendations of learning resources and peers to be more personalised and therefore have more effective adaptability. More images of the user interface can be found in Appendix J: User Interface of Topolor 2.

(a) The Home Page (b) A Topic Page

Figure 24 New features in Topolor 2: (a) the Home Page and (b) a Topic Page

6.3.2 Applying the Contextual Gamification Strategies

This section explains how the proposed *contextual gamification strategies* have been applied in the implementation of Topolor 2. The new gamification features will be described within three categories, and mapped to the specific strategies.

1) Structured and Chunked Goals with Increasing Challenges

The gamification features belonged to this category have been implemented based on the suggestions **A-1** (*a set of learning goals with a clear description and multiple paths to achieve each goal*), **A-5** (*customisable learning context that can be adjusted by learners themselves*), **C-1** (*reasonable small chunks of learning goals with increasing difficulties*), and **C-3** (*multiple choices to go along and retrace the learning paths*) from the proposed *contextual gamification strategies* (section 6.2).

In Topolor 2, a *course* is composed of structured *topics*, thus learners have various 'layers' of goals (**A-1**). They have a *long-term goal* to complete the *course*, a *medium-term goal* to finish each *topic*, and a *short-term goal* to achieve each *objective* (**C-1**). They cannot jump goal layers, but they can decide which unlocked topic to learn next (**A-5** and **C-3**), as shown in Figure 25. Besides, a higher-level goal is usually more difficult and complicated (**C-1**). In such a way, learners can incrementally master new skills, and practice before they demonstrate mastery.

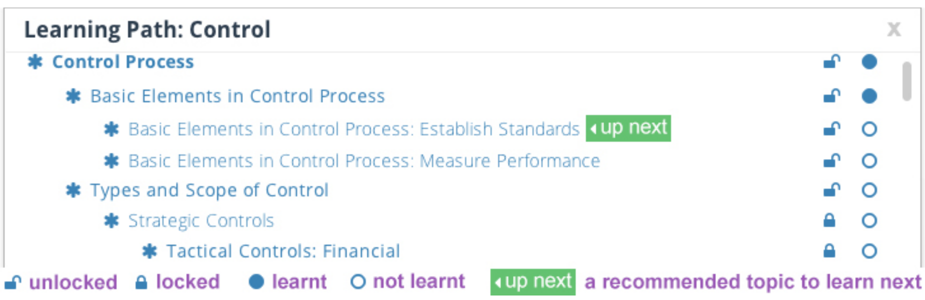


Figure 25 Visualised course structure (learning path for a course)

2) Immediate and Positive Feedback with Guidance on Next Step

The gamification features that belong to this category have been designed based on suggestions **A-3** (*clear and immediate feedback for learning activates*), **A-4** (*meaningful options with consequences*), **C-2** (*tasks with pleasantly surprised positive feedback*), **C-4** (*frequent decision-making to keep the learning process moving forward*) and **R-1** (*opportunities to discover and join learning communities*) from the proposed *contextual gamification strategies* (section 6.2).

Topolor 2 provides clear, immediate and positive feedback for learning activities, in order to satisfy learners' needs of *autonomy* and *competence*. For instance, after finishing the pre-test of a course, Topolor 2 shows "congratulations" and encourages learners to start the course (**A-3**, **C-2** and **R-1**). When a learner shares a new post, such as an image or video, a reminder shows so that the learner can click on it to update the post list (**A-3** and **C-4**). After submitting a test, Topolor 2 immediately shows the result and recommends the topics that the learner may need to review (**A-3** and **A-4**), as shown in Figure 26. It is noteworthy to mention that this *testing* feature has been implemented also based on the follow-up work discussed in section 5.4 – enhancing assessment tools.

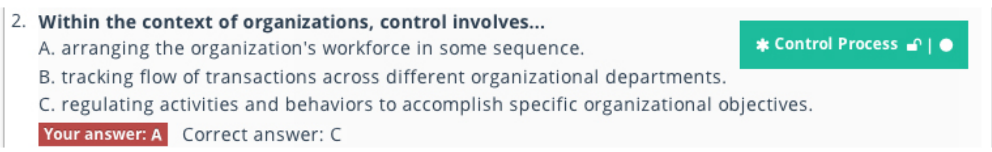


Figure 26 Immediate feedback when taking a quiz

3) Visualisation of social status, comparisons, learning progress

The gamification features belonged to this category have been designed based on suggestions **C-5** (*enjoyable and fun learning activities*), **R-2** (*connections of interest and goals between learners and communities*), **R-3** (*various tools for interaction, collaboration, discussion and mutual assistance*) and **R-4** (*promotions to show appreciation to others such as 'like'*) from the proposed *contextual gamification strategies* (section 6.2).

Topolor 2 supports various visualisations of individuals and communities for learners to feel *competence* and *relatedness*. For example, the comparison of learner performance (Figure 27) and contribution (Figure 28) potentially encourages users to contribute more to the community (**C-5**, **R-2** and **R-3**), as seeing each other's status may simulate imitation and competition. Learners can 'like' an image, a video, etc. shared by others (**C-3**, **R-3** and **R-4**). These features have been implemented in line with the discussion in section 5.4.

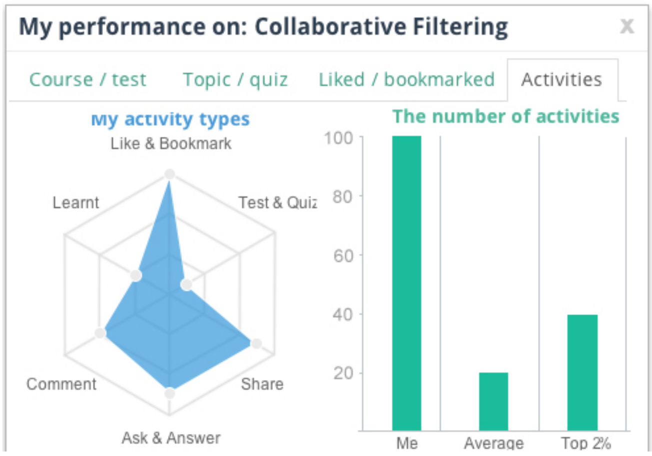


Figure 27 Pop-up view of comparison – performance

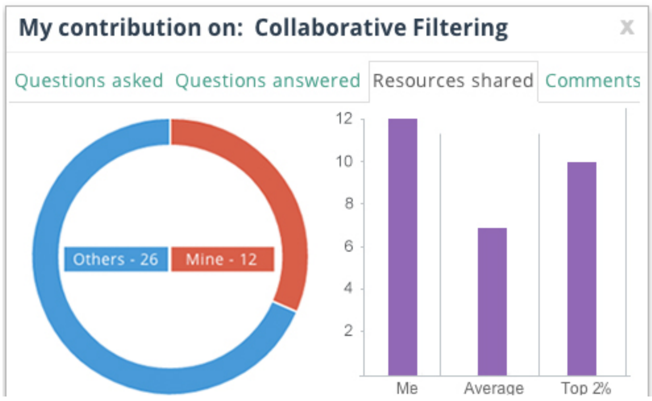


Figure 28 Pop-up view of comparison – contribution

6.3.3 Gamified Social Interaction

This section explains how the social interaction features of the initial social personalised adaptive e-learning system – the first version of Topolor – have been improved by introducing gamification techniques.

1) Peer-Reviewed Posting

Topolor 2 introduces a new blend of powerful tools for querying, sharing (Figure 29) and filtering (Figure 30) learning resources. As described in section 6.3, it has finer categories, especially with regards to sharing content, such as text, an image, a quote, a link, an audio and a video (while in the first version of Topolor, students can only 'share a learning status' as a text). In fact, these categories are widely used in Web 2.0 tools (e.g., Tumblr.com and some online teaching/learning systems that recommend teachers to use these external Web 2.0 tools for delivering learning materials), but it is rare that they are seamlessly integrated into an e-learning system. These features are implemented to further support the system requirements suggested in Table 4, section 3.7, such as the Learning requirements "use multiple types of files; e.g. PDFs, photos, videos, slides", "access open learning resource, e.g. Wikipedia", and the Social Networking requirement "share and/or recommend learning materials".

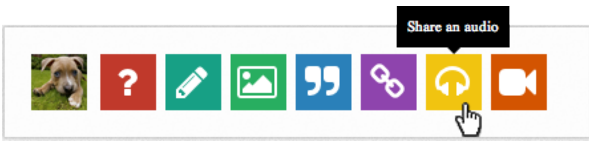


Figure 29 Sharing widget in Topolor 2

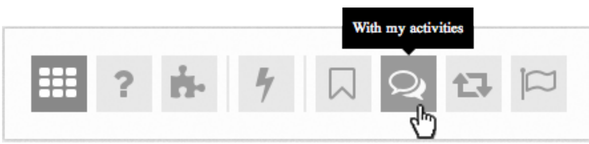


Figure 30 Filtering widget in Topolor 2

Moreover, students can express 'like/dislike' for any of these categories of posts, including for comments on a post and the answers to a question. This has been introduced for quality control, i.e., to prevent students from abusing social interactions by (for example) writing an irrelevant comment on a course video, as suggested in section 5.4. This also encourages students to improve their reputation – a part of a user model. A student with higher reputation has more benefits. For example, a higher weight for their posts, signifying a higher level of authority to their peers'. Moreover, posts can be filtered and sorted based on their perceived quality (as the difference between 'like' and 'dislike' votes from students). More importantly, this method can potentially improve the *quality* of user modelling by filtering out low quality data, as well as reducing the burden of the user modelling process, and thus improving system efficiency.

2) Visualised Social Status

Topolor 2 additionally provides student profile pages as another information and interaction 'hub', which in turn leads to various features of recommendation, adaptation, personalisation and social interaction. For example, by clicking on a student's avatar in a post list, a pop-up view appears (see Figure 31), containing statistics of their learning status, a shortcut to send them a message or to go to their profile page to see their learning status and activities in detail. In a profile page (see Figure 14 in Appendix J) several gamified social interaction features are provided. For instance, by clicking on the button PK[8], a pop-up view shows a comparison of the performance (e.g., quiz score trends) and a comparison of the contribution (e.g., the number of questions answered) to the learning community between the current user and the profile page's owner.

Apart from students' profile pages, the graphical and interactive view of contribution and performance allows students to operate *multi-context comparisons* (i.e., in the context of a specific course or a specific topic) and *multi-group comparisons* (i.e., comparison to another student, the top 20% of students, or all other students). This can increase student motivation by triggering competitive instincts [82]. The implementation of these features has taken into consideration the need for self-reflection, as described in section 2.5. It has also been meant to provide end-users with visualisations and comparisons of learning analytics, as discussed in section 5.4.

Note that these features are implemented also to further support the system requirements suggested in Table 4, section 3.7, such as the social networking requirements "ask and answer questions of other students", "share and/or recommend learning materials", "use communication tools to chat and leave messages" and "write comments/notions wherever and whenever wanted"; usability requirements "view system status" and "use graphical user interfaces".

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[8] PK (Player killing): in a Player(s) Versus Player(s) (PvP) gaming environment, PK means one player attack another without warning. This can result in a character's death [11].

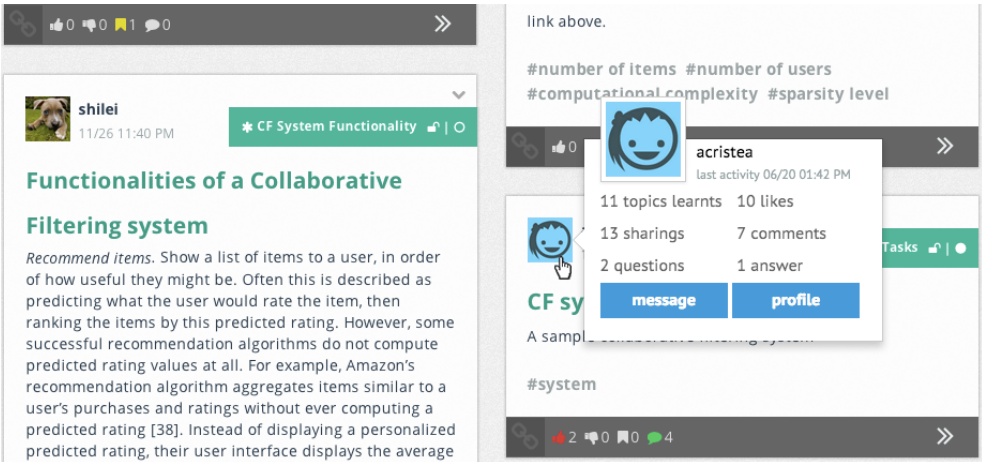

Figure 31 Pop-up view when clicking on an avatar

3) Adaptive Leaderboard

Leaderboards are embedded into different contexts. They adapt to the students and the learning content by adjusting the order and display of the student information. For instance, in a course page, the students can be displayed according to how many topics they have learnt in this course. Meanwhile, in a topic page, students can be displayed according to how many questions related to the topic they have answered correctly (see Figure 32). Students can adjust the order, and Topolor remembers their preference for the next time. Each item on the leaderboard can be separately viewed as a student 'info-card', containing the student's learning status information, buttons for sending them a message or for seeing their profile page. Additionally, the information about the item is device-adaptive, e.g., for a certain size of the browser, smaller icons replace big ones. In Topolor 2, leaderboards allow students to see each other's status publicly and can therefore be instantly recognised. This is designed to create a sense of community by providing opportunities for students to directly interact with each other and to compare their learning progress with each other. These features are implemented to further support the system requirements suggested in Table 4, section 3.7, such as the social networking requirement "use communication tools to chat and leave messages", and the adaptation requirement "recommend other students according to the current topic". They have also been designed to provide end-users with visualisations and comparisons of learning analytics, as discussed in section 5.4.

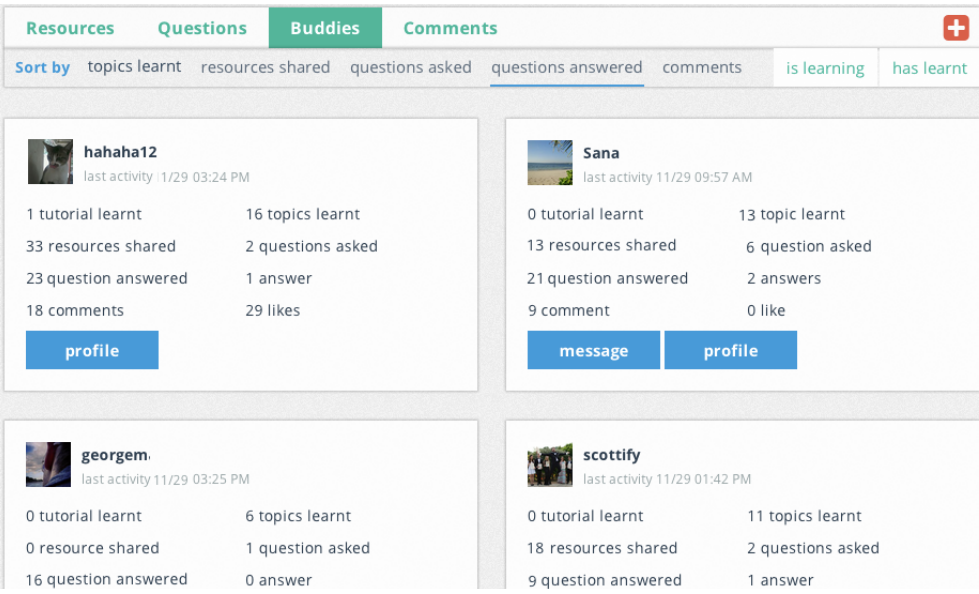

Figure 32 Leaderboard

6.3.4 Requirement Revision

Table 13 below revisits the requirements (suggested in Table 4, section 3.7), which have been implemented in two versions of Topolor, as well as comment upon the level of implementation.

Table 13 System requirements – revisited (2)

	Requirement	Comment
Learning	Use multiple types of files; e.g. PDFs, photos, videos, slides.	Implemented in Topolor 2.
	Take tests after learning a topic.	Implemented in Topolor, and revisited in Topolor 2.
	Get assessment and feedback from teachers.	This is possible via interaction toolsets and comments on the learning pages.
	View learning progress in percentage.	Implemented in Topolor, and revisited in Topolor 2.
	Tag and flag up topics in the learning path.	Open and closed topics in the learning path are flagged up, according to the Learner Model.
	Access open learning resource, e.g. Wikipedia.	Implemented in Topolor 2.
	Search learning resource within and outside of the system.	Future plan.
	Use interactive learning content, e.g. debugging tools.	This is further planned in collaboration with Peter Brusilovsky, Pittsburgh, USA.
	Contribute to learning content by creating and uploading files.	Implemented in Topolor 2.
	Choose to view the whole or partial learning path.	Implemented in Topolor.
Social Interaction	Create groups that are registered for the same topic.	Implemented in Topolor.
	Discuss the current learning topic with other students.	Implemented in Topolor.
	Set access rights for learning materials.	Implemented in Topolor 2.
	Set access rights for groups.	Implemented in Topolor 2.
	Ask and answer questions of other students.	Implemented in Topolor.

	Create groups that share common learning interests.	Implemented in Topolor.
	Use feedback & questions forum at the end of each lesson.	Implemented in Topolor.
	Share and/or recommend learning materials.	Implemented in Topolor.
	Use communication tools to chat and leave messages.	Implemented in Topolor.
	Write comments/notions wherever and whenever wanted.	Implemented in Topolor.
	View history discussion when selecting a particular topic.	Implemented in Topolor.
	Design and publish courses for others to use.	Whilst whole courses cannot be published by the students, contributions can.
Adaptation	Recommend other topics according to current learning topic.	Implemented in Topolor.
	Recommend topics according to student's knowledge level.	Implemented in Topolor.
	Recommend topics by referring to other students' rating.	Implemented in Topolor 2.
	Adapt learning path according to learning progress.	Implemented in Topolor.
	Adapt learning tools according to student's user-level.	Implemented in Topolor 2.
	Adapt social interaction tools according to students user-level.	Implemented in Topolor 2.
	Recommend other students according to the current topic.	Implemented in Topolor.
	Recommend other groups according to student's interests.	Implemented in Topolor.
Usability	View system status.	Implemented in Topolor 2.
	Use graphical user interfaces.	Implemented in Topolor 2.
	Get instructions and tips.	Implemented in Topolor 2.
	Select full screen option.	Future plan.
	Set themes, layout, etc.	Future Plan.

6.4 Evaluation

A case study has been performed to evaluate the Self-Determination Theory (SDT) rooted gamification features of Topolor 2. Both qualitative and quantitative data were collected and analysed. This section presents the evaluation procedure and the analysis results, aiming to answer the research question **R2**: “How can we implement gamification techniques and technologies, in order to enhance social e-learning systems, and thus provide a high level of motivation amongst learners?”

6.4.1 Hypotheses

Self-Determination Theory (SDT) has been guiding the design of the *contextual gamification strategies*, which have been then applied in the implementation of Topolor 2. This evaluation hereby targets SDT’s three basic innate needs, i.e., *autonomy*, *competence* and *relatedness*. Research question **R2** has been addressed by constructing the following hypotheses and sub-hypotheses.

H2.1 The proposed *contextual gamification strategies* are able to positively affect learners’ perceived satisfaction of the **autonomy** need (this hypothesis aims to evaluate the first group of *contextual* gamification *strategies* including **A-1**, **A-2**, **A-3**, **A-4** and **A-5**, as detailed in section 6.2.1).

- **H2.1.1** Learners perceive themselves in control of the learning process.
- **H2.1.2** Learners perceive themselves to be interested in using the system.
- **H2.1.3** Learners perceive themselves to be confident in using the system.

H2.1.4 Learners perceive their learning experience to be personalised.

H2.2 The proposed *contextual gamification strategies* are able to positively affect learners' perceived satisfaction of the **competence** need (this hypothesis aims to evaluate the second group of *contextual gamification strategies* including **C-1**, **C-2**, **C-3**, **C-4** and **C-5**, as detailed in section 6.2.2).

H2.2.1 Learners perceive themselves as having fun using the system.

H2.2.2 Learners perceive that it was only a few steps to complete tasks.

H2.2.3 Learners perceive it was easy to know why they were getting recommendations.

H2.2.4 Learners perceive it was easy to find the content they needed.

H2.3 The proposed contextual gamification strategies are able to positively affect learners' perceived satisfaction of the **relatedness** need (this hypothesis aims to evaluate the third group of *contextual gamification strategies* including **R-1**, **R-2**, **R-3**, **R-4** and **R-5**, as described in section 6.2.3).

H2.3.1 Learners perceive it was easy to share content with peers.

H2.3.2 Learners perceive it was easy to access shared resources from peers.

H2.3.3 Learners perceive it was easy to tell peers what they like/dislike.

H2.3.4 Learners perceive it was easy to discuss with peers.

To test the above hypotheses, a questionnaire (Appendix F) has been developed with the following statements:

S1. I felt in control of my learning process. (For **H2.1.1**)

S2. I was interested in using Topolor. (For **H2.1.2**)

S3. I felt confident to use Topolor. (For **H2.1.3**)

S4. I felt my learning experience was personalised. (For **H2.1.4**)

S5. I enjoyed and had fun using Topolor. (For **H2.2.1**)

S6. I felt I only needed a few steps to complete tasks. (For **H2.2.2**)

S7. I felt it was easy to understand why I received recommendations. (For **H2.2.3**)

S8. I felt it was easy to find the content I needed. (For **H2.2.3**)

S9. I felt it was easy to share content with peers. (For **H2.3.1**)

S10. I felt it was easy to access the shared resources from peers. (For **H2.3.2**)

S11. I felt it was easy to tell peers what I like/dislike. (For **H2.3.3**)

S12. I felt it was easy to discuss with peers. (For **H2.3.4**)

These statements were based on a five-point Likert scale ranging from -2 (strongly disagree) to 2 (strongly agree). Positive mean values and median values of the questionnaire results (**S1-S12**) would support these hypotheses (**H2.1.1-H2.3.4**), whilst the corresponding *null* hypotheses for **H2.1.1-H2.3.4** would be supported if the results of **S1-S12** were negative or zero i.e. not greater than the neutral value.

6.4.2 Experimental Setup

Data was collected through two real-life online sessions, described below.

The first experiment was conducted in November 2013. Fifteen students were involved. They registered for an MSc module 'Dynamic Web-Based Systems', at the University of Warwick, learning a lesson about 'Collaborative Filtering' in

Topolor 2. The experiment was divided into four stages: two time-controlled one-hour learning stages (students sat in a classroom), one flexible (non-time-controlled) learning stage (students accessed Topolor 2 at their preferred time and location), and finally the survey stage (coordinator-led optional questionnaire answering, feature by feature, to make sure they clearly knew which question referred to which feature). Students were explicitly told that their participation in the survey had no impact on module results. Ten of them submitted questionnaires.

The second experiment was conducted at the Department of Economics, Sarajevo School of Science and Technology, Bosnia and Herzegovina, in December 2013. Twenty undergraduate students, two observers and one course instructor participated in the one and half hours online learning session – using Topolor 2 to teach/learn a course about 'Control (management)'. After the online learning session, students were encouraged to further use Topolor 2 to revise the covered materials, for two weeks. After that, students were asked to complete an optional online survey. Out of the twenty students who participated in the online course, fifteen completed the online survey.

In total, twenty-five questionnaires were collected. The analysis presented in this section is based on them.

The reason why these two separate experiments were conducted, as well as the issues that might occurred during the data collating process are further discussed in section 6.4.4.

6.4.3 Results

The questionnaire results corresponding to learners' perceived motivation are shown in Table 14. The *means* range between 0.52 and 1.36, all the *medians* are 1, and the *standard deviations* (**SD**) of the overall results are between 0.49 and 0.78. All the *means* and *medians* are greater than 0 (the neutral response). Additionally, *Cronbach's Alpha* of the scores is 0.808 (>0.8), indicating a 'good' level of reliability [67]. Therefore, all the sub hypotheses related to learners' perceived motivation, i.e., **H2.1.1-H2.3.4**, have been supported, and thus all the hypotheses related to learners' perceived motivation, i.e., **H2.1-H2.3**, have been supported.

Table 14 Scores of learner perceived motivation questionnaire

#	Statement	Mean	Median	Range	SD
1	I felt in control of my learning process.	0.60	1	1	0.50
2	I felt interested in using Topolor.	0.76	1	2	0.60
3	I felt confident to use Topolor.	1.12	1	2	0.78
4	I felt my learning experience was personalised.	1.08	1	2	0.70
5	I felt having fun when using Topolor.	0.80	1	2	0.65
6	I felt I only needed a few steps to complete tasks.	0.64	1	2	0.57
7	It was easy to understand why I received recommendations.	1.36	1	2	0.49
8	It was easy to find the content I need.	1.16	1	2	0.55
9	It was easy to share content with peers.	0.52	1	1	0.51
10	It was easy to access the shared resources from peers.	0.76	1	2	0.60
11	It was easy to tell peers what I like/dislike.	0.80	1	2	0.65
12	It was easy to discuss with peers.	1.00	1	2	0.58

6.4.4 Discussions

For the evaluation, two experiments have been conducted. One reason for performing them was to get more participants involved and thus to collect more data for the analysis. Even with a combined number of participants, the overall, i.e., thirty-five, is still small, and this hereby became the main limitation of this work. The other reason for conducting the two different evaluations was to reduce the bias, by involving students from different disciplines, as computer science students (participants of the first experiment conducted) might have a better view on system development, and thus their response might not purely reflect only perceptions about the learning process.

The fact that students were from two different disciplines, i.e., computer science and economics, despite the potential advantages, might cause some additional issues, such as if the data collected from the two experiments would be too different to be combined together for the analysis. However, the settings of the two experiments were very similar, in order to prevent this issue occurring. For example, both included time controlled and non-controlled learning processes; both used the same questionnaire. Indeed, the pilot analysis (data collected from the two experiments were analysed separately and the results were published in [158]) on the data showed that the results from both experiments were very similar.

Table 14 shows that all the twelve statements gained positive feedback (mean > 0). These results indicate a high level of learners' perceived motivation that was influenced by the newly introduced contextual gamification strategies in Topolor 2. Among these statements, **statement 7** – "it was easy to understand why I received recommendations" – obtained the highest *mean* (mean = 1.36) and the lowest *standard deviation* (SD = 0.49). This is not surprising, as Topolor 2 explains they reason of providing recommendations. For example, in the course structure view (learning path recommendation), the icons on the right explain (when using mouse-over, a tip flows on top of the icon) if a topic has been learnt, as well as if the learner is eligible to learn it. **Statement 8** – "It was easy to find the content I need" received the second highest *mean* (mean = 1.16). This may be due to the new *filtering* tool implemented in Topolor 2. **Statement 3** – "I felt confident to use Topolor" gained the third highest *mean* (mean = 1.12). This confirms our underlying design hypothesis that students nowadays have a high level awareness of game paradigms.

In addition to the quantitative results from the questionnaires, some qualitative feedback was also received from the course instructor, the observers and the students. The general feedback was consistent with the quantitative results, and a number of participants made positive remarks about Topolor 2 and expressed interest in using it in the future for learning other subjects.

However, the observers also provided some negative feedback. For example, they reported that some students, who were using smart phones to access Topolor 2, complained that it was not obvious what they should to do next, indicating the type of device may affect students' motivation as well. Whilst Topolor 2 is mainly aimed at laptop/desktop use, it is clear that nowadays the ability to adapt to the hardware context is essential, as mobile use is widespread, and users perceive it as a natural means of accessing e-learning systems and content.

6.5 Conclusions

Motivation plays a crucial role in the success of the learning process, and gamification has the potential to promote a high level of learners' intrinsic motivation in an e-learning system. In order to tackle the challenge of designing e-learning systems that are able to keep learners motivated to perform desirable learning behaviours and achieving pre-specified learning goals, *contextual gamification strategies* have been proposed, rooted in Self-Determination Theory (SDT).

The proposed *contextual gamification strategies* consist of three parts, and each part aims to satisfy one of the basic innate needs that map to those in Self-Determination Theory (SDT), namely *autonomy*, *competence* and *relatedness*. In contrast to existing studies, this study proposes a specific blend of *light gamification* to symbiotically build upon social interaction features, rather than replace the already existing social learning communities in the system. These *contextual gamification strategies* have been applied in the implementation of a social personalised adaptive e-learning system – Topolor 2. This chapter has explained how these strategies have been applied, by presenting various gamification features, particularly the gamified social features.

The evaluation of the gamification features of Topolor 2 has been conducted in real-life online learning sessions. Both qualitative and quantitative data have been collected and analysed. The high scores of the questionnaire results and their high reliability have illustrated a high level of learners' perceived motivation, indicating that this approach is promising. The additional qualitative feedback from the course instructor, the observers and the students has also shown positive attitudes, which is consistent with the qualitative feedback. This research has also suggested the need for other components in the system, such as the adaption to different hardware contexts to further increase learners' perceived motivation.

In conclusion, the study presented in this chapter has addressed the research objective **O4**: "based on the hypotheses and conclusions from **O3** (as defined in section 1.2), building novel gamification strategies upon the initial social personalised adaptive e-learning system, and examining the impacts of the new gamification features on learners' motivation". The process of addressing this research objective has answered the research question **R2**: "how can we implement gamification techniques and technologies, in order to enhance social e-learning systems, and thus provide a high level of motivation amongst learners?" The answer here is "the implementation of 'contextual gamification' rooted in Self-Determination Theory (SDT), can keep learners motivated in performing desirable learning behaviours and achieving learning goals, and thus provide a high level of motivation amongst learners".

Chapter 7

Opening Learner Data

7.1 Introduction

The main objective of the work presented in this chapter is to answer the research question **R3** – "how can we implement open learner modelling techniques and technologies, in order to enhance e-learning systems, and thus provide a high level of effectiveness, efficiency and satisfaction amongst learners?"

Chapter 6 has presented one follow-up work based on the initial iteration of a social personalised adaptive e-learning approach (Chapter 4), that of promoting learners' motivation by gamifying adaptations and social interactions. This chapter presents the other follow-up research, as suggested in section 5.4, which is to analyse the impact of **learner data visualisation** on the perceived *effectiveness*, *efficiency* and *satisfaction* amongst learners, when using the system.

It is envisaged that learners, especially younger generations who are familiar with Web 2. 0 and Social Web techniques embedded in their daily lives, are expected to have the ability to create and maintain their own personal learning systems, to interact with peers as well as learning resources, and be actively engaged in a social e-learning context. However, the availability of massive open resources and the diversity of connections and interactions have led to many challenges. Successful social e-learning requires tools to assist learners in directing their own learning and having a higher level of presence and engagement in order to participate in meaningful interactions [94], similar to popular social software. Towards tackling these challenges, open learner modelling (OLM) approaches have been adopted in the existing studies.

OLM makes it possible for a learner to observe their learning status, so as to promote metacognition (e.g., self-reflection, self-direction and transparency) [181]. It has been suggested that learners studying together may benefit from accessing peers' models and group models [186]. Studies have been conducted to explore the use of OLM [27, 109]. Several of them take into consideration also the social aspect of learning [22, 76]. Yet, much further research needs to be performed to enhance OLM, especially in terms of social personalised visualisation and interaction, which can potentially improve the social e-learning experience.

Following from existing studies, the work presented in this chapter aims to enable interactive visualisation of different *Social-OLM* (OSLM) angles, which could potentially enhance e-learning systems, and thus provide a high level of effectiveness, efficiency and satisfaction amongst learners. In particular, this work explores the design of *multifaceted Open Social Learner Models* (multifaceted-OSLM) in a social personalised adaptive e-learning system.

In the following, firstly, section 7.2 sketches up the new open learner modelling approach – *Multifaceted Open Social Learner Modelling* (Multifaceted-OSLM), and then, section 7.3 presents the implementation of the Multifaceted-OSLM in Topolor 2. Thirdly, section 7.4 reports the evaluation procedure and results. Finally section 7.5 concludes the findings of this research.

7.2 Multifaceted Open Social Learner Modelling

The OSLM proposed in this work is called 'multifaceted' because, firstly, a learner can access their model and their peers' models ubiquitously, and the system adapts the visualisations to fit *various contexts*, corresponding to the hierarchy of course pages, topic pages, resource pages and profile pages. Additionally, it provides various visualisation modes, such as comparison between individuals, to a certain group of learners, and to all other learners. These modes of *multi-context* and *multi-cohort* comparisons require enhancements of both adaptivity and adaptability, and are expected to further promote metacognitive activities.

Unlike existing approaches providing a single complex view of OSLM with many criteria to manually select in order to adjust visualisations (e.g., [22, 101], detailed in section 2.5), the proposed multifaceted-OSLM seeks to seamlessly and adaptively integrate OSLM with learning content, so that its ubiquity and context-awareness can support new adaptation and personalisation methods for social e-learning. It emphasises the possibility and necessity of visualising both *performance* and *contribution*, reflecting not only a learner's role as a knowledge consumer, but also that of a knowledge producer, which could better integrate in the Web 2.0 and Social Web era.

7.3 Implementation

7.3.1 Visualisation of Performance

Visualisation of performance is a common feature in existing OSLM approaches, such as [22], potentially promoting motivation [76]. Topolor 2 emphasises the importance of a timeline by presenting, e.g., test score trends, and the importance of comparisons, e.g., via the comparison of success rate in tests between learners. On a course page or a topic page Figure 24 (b), by clicking on the button 'My Performance', a pop-up view shows a learner's performance on the current course or topic. Figure 33 shows the pop-up view of performance on a course page. The default view contains the test score trends and the comparison of success rates of tests (Figure 33). For brevity not all tabs are shown here, but in short: the tab-view 'topic / quiz' shows a two column charts presenting the comparisons of the average quiz score between a learner, the whole class and the top 20% learners. The tab-view 'liked / bookmarked' shows a two column charts presenting how many times the shared resources were 'liked' / bookmarked. The tab-view 'activities' shows a radar chart and a column chart comparing activities (Figure 33).

Figure 34 illustrates the respective pop-up views of performance in a topic page, showing the comparison of quiz scores, and the learner's corrected quiz answers.

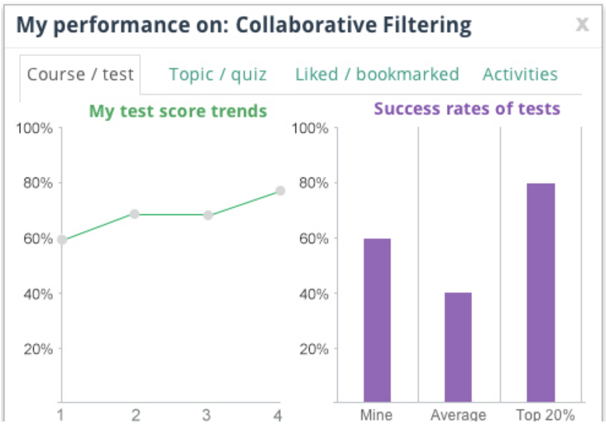

Figure 33 Pop-up view of performance at a course level – activities

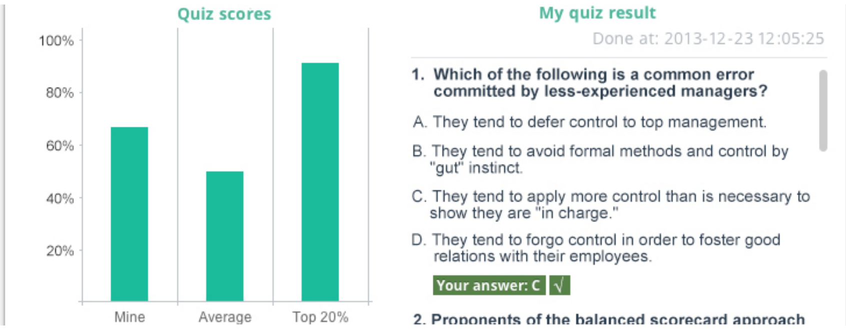

Figure 34 Pop-up view of performance at a topic level

7.3.2 Visualisation of Contribution

In a social e-learning system, learners act not only as learners, but also authors of learning content. They contribute by, e.g., sharing, commenting, asking, and answering. Visualisation of one's own contribution potentially encourages contributing more, as seeing each other’s contribution may stimulate imitation and competition. By clicking on the button ‘My contribution’ on a course page or a topic page a pop-up view of the contribution shows, as shown in Figure 35, presenting comparisons of resources shared, the number of questions asked and answered, and comments.

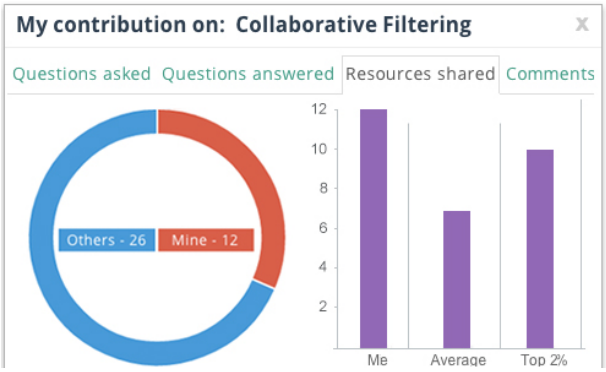

Figure 35 Pop-up view of contribution, comparison to others

7.3.3 The PK Mode

The PK mode is designed drawn from educational gamification [171], as an acronym for 'Player Killer'. On a profile page (Figure 36), by clicking on the button 'PK', a pop-up view shows, presenting comparisons of *performance* and *contribution* between a learner and the profile page's owner (Figure 37). Contributions are questions asked and answered, resources, and comments shared. Performances include correct tests, topic completion rate, and the number of shared ('liked' and bookmarked) resources.

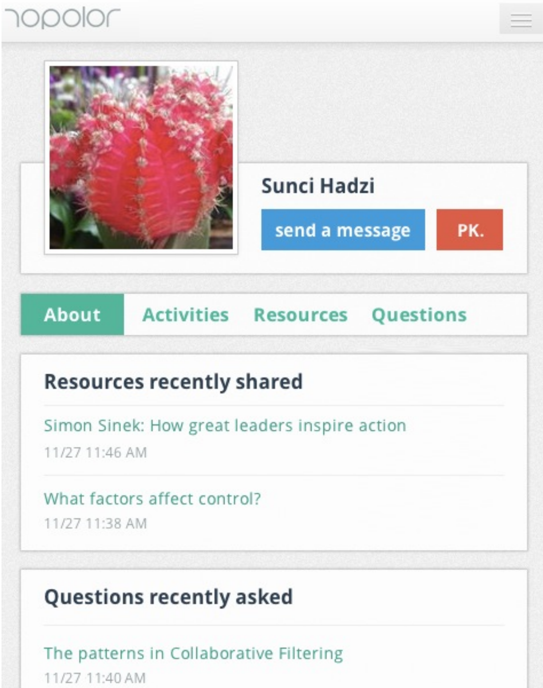

Figure 36 Profile page (via a smart phone client-side)

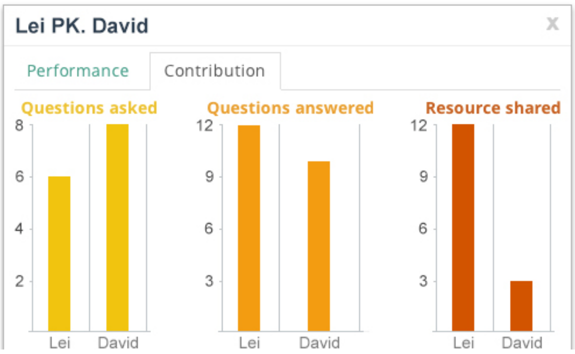

Figure 37 The PK mode: 1-to-1 comparison of contribution of 2 learners

7.3.4 Visualisation of Learning Path

On a course page or a topic page, by clicking on the button 'Learning Path', a *learning path visualisation* view pops-up, as shown in Figure 38. The tree structure graph represents the whole course structure, and the icons represent the learner's progress. For instance, a *hollow circle* means the learner has not learnt this topic yet; a *solid circle* means the learner has already learnt this topic; an *unlocked lock* means the learner is ready to learn this topic; a *locked lock* means the learner should finish learning all the prerequisite topics before start to learn this topic; and the *blue-coloured-background label* with the text 'Up next' recommends the learner that this topic is the most appropriate topic to learn for the next step.

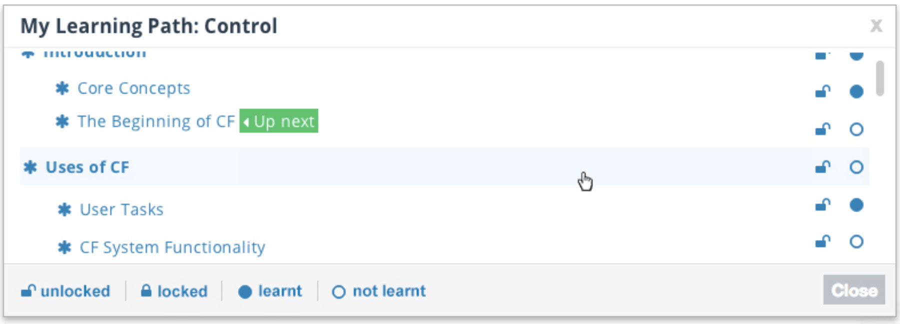

Figure 38 Pop-up view of learning path

7.3.5 Visualisation of Learning Activities

Topolor 2 exposes the learners' activity logs to learners, and they can 'like' and comment on each other's activity logs. This feature is designed based on our hypothesis that *observation of activity logs of a learner and their peers' can stimulate interactions, hereby improve the system's engagement.* There are two ways of viewing learners' activity logs. One is on the Topolor 2 home page, as shown in Figure 39, where a learner can filter to view their own activity logs or to view all learners' activity logs; the other is on a profile page (Figure 36) by clicking on the button ‘Activities’, where a learner can view the profile owner’s activity logs, to show various paths to information.

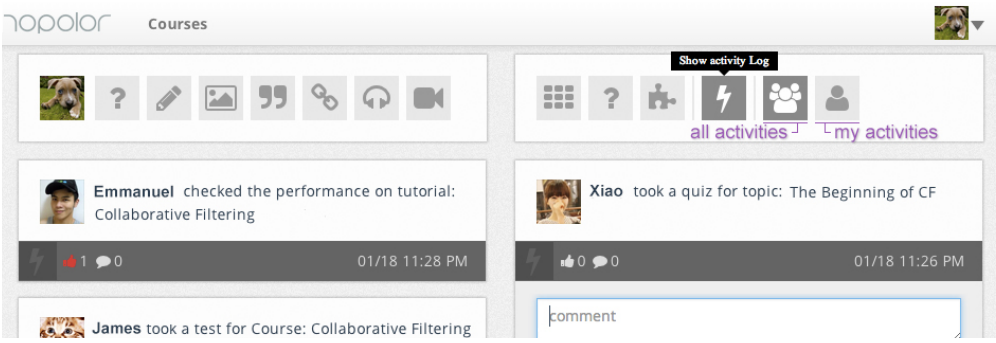

Figure 39 List of activity logs on homepage

7.4 Evaluation

The case study presented in section 6.4.2 has also been performed for the evaluation of the *multifaceted Open Social Learner Modelling* (multifaceted-OSLM) proposed in this chapter. Besides the questionnaires used for evaluating the gamification features, as described in section 6.4.1, additional questionnaires were used for evaluating the multifaceted-OSLM. This section presents the specific hypotheses for the evaluation of the multifaceted-OSLM, and the questionnaire designed to test the hypotheses, aiming to answer the research question **R3** – “How can we implement open learner modelling techniques and technologies, in order to enhance e-learning systems, and thus provide a high level of effectiveness, efficiency and satisfaction amongst learners?”

7.4.1 Hypotheses

The main motivation for the implementation of Topolor 2 is the assumption that *the seamless and adaptive integration of interactive visualisation of learner data with learning content, and various comparisons of learner performance and contribution,* can *provide a high level of perceived* ***effectiveness****,* ***efficiency*** *and* ***satisfaction*** *amongst learners*. Therefore, the evaluation aims to test the following hypotheses.

1) Effectiveness and Efficiency

As discussed in section 2.6, in this work we evaluate *effectiveness* by asking learners if the system (or the functionality, or the feature) is useful (fit for purpose), and we evaluate *efficiency* by asking learners if the system (or the functionality, or the feature) is easy to use (effort required to use). Similar to section 4.4, this study assesses two levels of granularity of the system's functionalities, i.e., the 'system as a whole' level, and the '’multifaceted OSLM-related Features' level.

The *System Usability Scale* (SUS) questionnaire survey (Appendix D) has been used for evaluating the system at the 'system as a whole' level. The hypothesis regarding learners' *effectiveness* and *efficiency* at 'the system as a whole' level for this study has been defined as follows.

H3.1 Learners perceive high *effectiveness* (usefulness) and *efficiency* (ease of use) of using the system as a whole.

The SUS score that is greater than 70 would support this hypothesis (**H3.1**), whilst the corresponding *null* hypothesis for **H3.1** would be supported if the SUS score is less than 70.

To evaluate learners' perceived *effectiveness* and *efficiency* at the 'multifaceted-OSLM related Features' level, the following forty-eight features related to the proposed *multifaceted-OSLM* have been tested, as shown in Table 15.

Table 15 Features related to Multifaceted-OSLM

#	Feature	#	Feature
Home page			
01	Filter by everyone's activities	02	Filter by my activities
Course Page			
03	Learning path - Tree View[@]	04	Performance - Pop-up View[@]
05	Score trends - Line Chart[@]	06	Contribution - Pop-up View[@]
07	Test success rates - Bar Chart[*]	08	Average quiz score - Bar Chart[*]
09	Topic completion - Bar Chart[*]	10	Number of activities - Bar Chart[*]
11	Bookmarked - Bar Chart[*]	12	Questions asked - Bar Chart[*]
13	'Liked' - Bar Chart[*]	14	Questions answered - Bar Chart[*]
15	Activity types - Radar Chart[@]	16	Questions asked - Donut Chart[&]
17	Resources shared - Bar Chart[*]	18	Questions answered - Donut Chart[&]
19	Comments - Bar Chart[*]	20	Resources shared - Donut Chart[&]
21	Comments - Donut Chart[&]		
Topic Page			

22	Learning path - Tree View@	23	Performance - Pop-up View@
24	Contribution - Pop-up View@	25	Questions asked - Donut Chart&
26	Questions asked - Bar Chart*	27	Questions answered- Donut Chart&
28	Resources shared - Bar Chart*	29	Questions answered -Bar Chart*
30	Comments - Bar Chart*	31	Resources shared - Donut Chart&
32	Comments - Donut Chart&	33	My quiz results - Pop-up View@
34	View quiz scores - Bar Chart*		
Resource Page			
35	Author's name and stats		
Profile Page			
36	Check my performance	37	Check my contribution
38	PK., compare me with another	39	List of resources shared
40	List of questions asked	41	List of questions answered
42	List of courses learned	43	List of topics learned
44	List of topics learnt	45	Statistics for the profile's owner
46	Waterfall list of activity logs	47	Like an activity log
48	Comment on an activity log		

@: my data; &: comparison between me and the rest of the class;
*: comparison between me, the whole class and the top 20% of the class.

All the above features presented in Table 15 have been evaluated from two perspectives, i.e., perceived *usefulness* and *ease of use*, on a five-point Likert scale ranging from -2 (very useless/hard to use) to 2 (very useful/easy to use). The Multifaceted-OSLM feature questionnaire is detailed in Appendix G.

The hypothesis regarding learners' perceived *effectiveness* and *efficiency* of using these forty-eight features has been defined as follows.

H3.2 Learners perceive multifaceted-OSLM related features with high level of usability.

This hypothesis (**H3.2**) would be supported if the mean values and median values of both *perceived usefulness* and *perceived ease of use* for all these forty-eight multifaceted-OSLM related features are positive, i.e., greater than the neutral value (0), whilst the corresponding *null* hypothesis for **H3.2** would be supported if one or more above values were negative or zero i.e. not greater than the neutral value.

2) Satisfaction

Similar to the hypotheses regarding the learners' *satisfaction* for evaluation of the initial social personalised adaptive e-learning system, the hypotheses regarding *learners' perceived satisfaction* for this study also include hypothesis **H1.1-H1.10**, as stated in section 4.4.1. However, other six hypotheses regarding the *learners' satisfaction of the 'socialisation quality'* have also been included, i.e., **H3.3-H3.18**. The sixteen hypotheses are as follows.

H3.3 Learners perceive the system helpful for learning more topics.

H3.4 Learners perceive the system helpful for learning more profoundly.

H3.5 Learners perceive the system helpful with for their weak points.

H3.6 Learners perceive the system helpful for planning their classwork.

H3.7 Learners perceive that the system increased their learning interests.

H3.8 Learners perceive that the system increased their learning confidence.

H3.9 Learners perceive that the system increased their learning outcome.

H3.10 Learners perceive the system easy to use.

H3.11 Learners perceive the system easy to learn how to use.

H3.12 Learners perceive the system easy to remember how to use.

H3.13 Learners perceive it was easy to discuss with peers.

H3.14 Learners perceive it was easy to share content with peers.

H3.15 Learners perceive it was easy to access the content shared by peers.

H3.16 Learners perceive it was easy to tell peers what they liked/disliked.

H3.17 Learners perceive the statistic comparison was engaging for learning more.

H3.18 Learners perceive the system was engaging for interacting with peers.

To test these hypotheses, a questionnaire (Appendix C) has been developed with the following statements.

S1. Topolor helped me to learn more topics. (For **H3.3**)

S2. Topolor helped me to learn more profoundly. (For **H3.4**)

S3. Topolor helped me to identify my weak points. (For **H3.5**)

S4. Topolor helped me to plan my classwork. (For **H3.6**)

S5. Topolor increased my learning interests. (For **H3.7**)

S6. Topolor increased my learning confidence. (For **H3.8**)

S7. Topolor increased my learning outcome. (For **H3.9**)

S8. It was easy to use Topolor. (For **H3.20**)

S9. It was easy to learn how to use Topolor. (For **H3.11**)

S10. It was easy to remember how to use Topolor. (For **H3.12**)

S11. It was easy to discuss with the peers. (For **H3.13**)

S12. It was easy to share content with peers. (For **H3.14**)

S13. It was easy to access the content shared by peers. (For **H3.15**)

S14. It was easy to tell peers what I liked/disliked. (For **H3.16**)

S15. The statistic numbers (mine & peers') engaged me to learn more. (For **H3.17**)

S16. Topolor helped me engage in interacting with peers. (For **H3.18**)

These statements are based on a five-point Likert scale ranging from -2 (strongly disagree) to 2 (strongly agree). The positive mean values and median values of the questionnaire results (**S1-S16**) would support these hypotheses (**H3.3-H3.18**), whilst the corresponding *null* hypotheses for **H3.3-H3.18** would be supported if the results of **S1-S16** were negative or zero i.e. not greater than the neutral value.

7.4.2 Experimental Setup

Data have been collected through the same two real-life online sessions, as described in section 6.4.2. In total, twenty-five questionnaires were collected, and hereby the analysis presented in this section is based on them.

7.4.3 Results

1) Effectiveness and Efficiency

1.1) At the 'System as a Whole' Level

Table 16 presents SUS's ten items and the results from the questionnaires. The SUS score for Topolor 2 is 76.1 out of 100 (σ=12.36). *Cronbach's Alpha* of the

SUS scores is 0.982 (>0.9), meaning the results of SUS questionnaires were in an 'excellent' level of reliability [67]. Therefore, the hypothesis related to learners' *effectiveness and efficiency* at the 'system as a whole' level, i.e., **H3.1**, has been supported.

Table 16 Scores of System Usability Scale (SUS) – Topolor 2

#	Statement	Mean	Median	Range	SD
1	I think that I would like to use this system frequently.	3.92	4	2	0.70
2	I found the system unnecessarily complex.	1.80	2	3	0.76
3	I thought the system was easy to use.	4.32	4	2	0.63
4	I think that I would need the support of a technical person to be able to use this system.	1.84	2	3	0.80
5	I found the various functions in this system were well integrated.	4.00	4	3	0.82
6	I thought there was too much inconsistency in this system.	2.08	2	2	0.81
7	I would imagine that most people would learn to use this system very quickly.	4.12	4	2	0.67
8	I found the system very cumbersome to use.	2.12	2	2	0.83
9	I felt very confident using the system.	3.92	4	3	0.86
10	I needed to learn a lot of things before I could get going with this system.	2.00	2	2	0.65

1.2) At the 'multifaceted-OSLM related Features' Level

Table 17 shows the scores of the multifaceted-OSLM features in Topolor 2. For *usefulness*, the *means* of the scores range between 0.56 and 1.76, and the *medians* range between 1 and 2. The *standard deviations* of the overall results are between 0.37 and 0.76. All the *means* and *medians* are much larger than 0 (the neutral response), suggesting learners' attitudes to be generally positive. In terms of *ease of use*, the *means* range between 1.70 and 1.76, and the *medians* range between 1 and 2. The *standard deviations* are between 0.37 and 0.60. As all the *means* are greater than 0, it enables us to infer that most of the students found the social interaction toolset to be relatively *easy to use*. *Cronbach's Alpha* of *usefulness* is 0.849 (>0.8), and *Cronbach's Alpha* of *ease of use* is 0.801 (>0.8), indicating a 'good' level of reliability of the results. Therefore, the hypothesis related to learners' *effectiveness and efficiency* at the 'sub-system functionalities' level, i.e., **H3.2**, is supported.

Table 17 Scores of system functionality scale – new features in Topolor 2

	Usefulness				Ease of Use			
#[1]	Mean	Median	Range	SD	Mean	Median	Range	SD
1	1.20	1	2	0.58	1.12	1	2	0.44
2	1.40	1	1	0.50	1.00	1	3	0.50
3	1.20	1	2	0.58	1.48	2	2	0.59
4	1.12	1	2	0.67	1.32	1	1	0.48
5	0.84	1	2	0.75	1.68	2	1	0.48

	Usefulness				**Ease of Use**			
#[1]	Mean	Median	Range	SD	Mean	Median	Range	SD
6	1.08	1	2	0.64	1.44	1	1	0.51
7	1.00	1	2	0.58	1.24	1	2	0.52
8	1.08	1	2	0.49	1.12	1	2	0.60
9	0.92	1	2	0.40	1.16	1	2	0.47
10	0.92	1	2	0.57	1.32	1	2	0.56
11	0.80	1	2	0.58	1.48	1	1	0.51
12	0.92	1	2	0.49	1.36	1	1	0.49
13	1.00	1	2	0.41	1.28	1	2	0.54
14	1.08	1	2	0.64	1.52	2	1	0.51
15	0.84	1	2	0.69	1.52	2	1	0.51
16	0.84	1	2	0.69	1.60	2	1	0.50
17	0.88	1	2	0.53	1.24	1	2	0.52
18	0.76	1	2	0.52	1.36	1	2	0.57
19	1.00	1	2	0.65	1.40	1	1	0.50
20	0.88	1	2	0.67	1.16	1	2	0.55
21	0.88	1	2	0.53	1.44	1	1	0.51
22	1.56	2	1	0.51	1.64	2	1	0.49
23	1.32	1	1	0.48	1.64	2	1	0.49
24	1.36	1	3	0.70	1.60	2	1	0.50
25	1.24	1	2	0.60	1.52	2	2	0.59
26	1.16	1	2	0.55	1.40	1	2	0.58
27	1.24	1	2	0.60	1.64	2	1	0.49
28	0.96	1	2	0.45	1.24	1	2	0.52
29	0.96	1	2	0.54	1.48	1	1	0.51
30	0.96	1	2	0.54	1.20	1	2	0.50
31	1.20	1	2	0.50	1.08	1	2	0.40

	Usefulness				**Ease of Use**			
#[1]	Mean	Median	#[1]	Mean	Median	#[1]	Mean	Median
32	1.16	1	1	0.37	1.72	2	1	0.46
33	1.60	2	1	0.50	1.56	2	1	0.51
34	1.24	1	1	0.44	1.56	2	1	0.51
35	1.04	1	2	0.54	1.16	1	2	0.55
36	1.60	2	1	0.50	1.64	2	1	0.49
37	1.12	1	2	0.53	1.64	2	1	0.49
38	1.24	1	1	0.44	1.28	1	2	0.54
39	1.48	1	1	0.51	1.16	1	1	0.37
40	1.52	2	1	0.51	1.56	2	1	0.51
41	1.28	1	2	0.54	1.20	1	1	0.41
42	1.48	2	2	0.59	1.32	1	1	0.48
43	1.44	1	2	0.58	1.20	1	2	0.50
44	1.36	1	2	0.64	1.44	1	2	0.58
45	1.76	2	1	0.44	1.20	1	1	0.41
46	0.56	1	3	0.71	1.76	2	1	0.44
47	1.00	1	3	0.76	1.52	2	2	0.59
48	1.20	1	3	0.65	1.24	1	1	0.44

[1]: These numbers in the first column represent the features shown in Table 15, which have the same numbers.

2) Satisfaction

The questionnaire results corresponding to learners' *satisfaction* are shown in Table 18. The *means* range between 0.52 and 1.52, the *medians* range between 1 and 2, and the *standard deviations* (SD) of the overall results are between 0.51 and 0.81. All the *means* and *medians* are greater than 0 (the neutral response).

Additionally, *Cronbach's Alpha* of the scores is 0.854 (>0.8), indicating a 'good' level of reliability [67]. Therefore, all the hypotheses related to *learners' perceived satisfaction*, i.e., **H3.3-H3.18**, are supported.

Table 18 Scores of learner perceived satisfaction scales for Topolor 2

#	Statement	Mean	Median	Range	SD
1	I think that I would like to use this system frequently.	0.64	1	2	0.71
2	I found the system unnecessarily complex.	0.92	1	2	0.81
3	Topolor helped me to identify my weak points.	0.72	1	2	0.61
4	Topolor helped me to plan my classwork.	0.52	1	1	0.51
5	Topolor increased my learning interests.	1.52	2	1	0.51
6	Topolor increased my learning confidence.	0.52	1	1	0.51
7	Topolor increased my learning outcome.	0.76	1	2	0.60
8	It was easy to use Topolor.	1	1	2	0.65
9	It was easy to learn how to use Topolor.	1.24	1	2	0.66
10	It was easy to remember how to use Topolor.	1.08	1	2	0.70

7.4.4 Discussions

The potential benefits of applying the *multifaceted Open Social Learner Modelling* (multifaceted-OSLM) in social personalised adaptive e-learning have been revealed from the evaluation results. The experimental studies on the area of learning both computer science and economics have provided a real-life evaluation environment and have revealed several benefits of the multifaceted-OSLM approach. The high means and medians of the Likert-scale questionnaire survey results, along with the high reliability score, support the hypotheses that *the seamless and adaptive integration of interactive visualisation of learner data with learning content, and various comparisons of learner performance and contribution,* can *provide a high level of effectiveness, efficiency and satisfaction amongst learners*.

The results may appear possibly counter-intuitive, due to the high number of features introduced, which may seem complex to a learner. However, in fact, we have found that using a Facebook-like appearance (Chapter 4), and a gaming inspired paradigm (Chapter 6), quickly get learners used to system experts.

It should be noted that, on the one hand, questionnaires with more statements might reduce the quality of the responses from the students; and on the other hand, a lower quantity of responses might reduce the reliability of the results. Therefore, it was difficult but crucial to find the balance between the quality and quantity of the responses, due to the fact that there was a limited number of participants, i.e., thirty-five students were using the system and twenty-five of them responded to the questionnaires. These were the reasons why there were 'long questionnaires' that included sixteen statements related to learner satisfaction and forty-eight statements related to the multifaceted-OSLM related features. Indeed, with the 'long questionnaire', the reliability of the results was high enough, as the *Cronbach's Alphas* of the scores were all greater than 0.8.

Apart from the quantitative results from the questionnaire survey, some qualitative feedback has been informally received after the course, from the course instructor, the observers and the students. The general qualitative feedback was consistent with the quantitative results. A number of participants made positive remarks about Topolor and expressed interest in keeping using it later on.

In addition to the experimental study, Topolor 2 has also been shown in international conferences such as UMAP (the 22nd Conference on User Modelling, Adaptation and Personalization) and EC-TEL (the 9th European Conference on Technology Enhanced Learning). Expert researchers in this area have given positive feedback. Topolor 2 has received the 'Best Demo Award' from UMAP.

It is noteworthy that the proposed multifaceted-OSLM also maintains attributes that record learning status such as 'know', 'unknown' and 'learning', which are inherited from traditional user modelling approaches in adaptive educational hypermedia area. Besides, though the visualisation of comparisons between a learner and their learning group, e.g., top 20% learners of the class, hides other learners' personal data, in a 'PK' mode it may raise ethical issues about all learners being able to view each other's data. Therefore, further studies are needed to solve this issue, e.g., by introducing privacy management mechanisms to allow learners to expose data to different groups in different ways, which is out of the work scope.

7.5 Conclusions

This chapter has presented the novel approach of *multifaceted open social learner model* (multifaceted-OSLM), as well as its application, i.e., the new multifaceted-OSLM features implemented in Topolor 2. This chapter has also described the evaluation of these new features, in the perspectives of learners' perceived satisfaction and system usability, which indicates a high level learners' perceived effectiveness, efficiency and satisfaction of using the social personalised adaptive e-learning system.

The proposed *multifaceted-OSLM* visualises not only learners' *performance* but also their *contribution* to a learning community, potentially better catering for social personalised adaptive e-learning, where learners are 'prosumer' – both knowledge consumer and producer. Additionally, the *multifaceted-OSLM* provides various comparison modes that allow for visualising the differences between learners' learning history (e.g., in terms of test score trends), between them and another learner, and between them and a group (i.e., the whole class and the top 20% of the class). Moreover, the *multifaceted-OSLM* is integrated and adapted to learning content, so that its ubiquity and context-awareness could enhance any system's adaptivity and adaptability, which potentially improves usability.

In conclusion, the study presented in this chapter has addressed the research objective **O5**: "based on the hypotheses and conclusions from **O3** (as defined in section 1.2), extending the previous system with new open learner modelling, and examining its influence on learners' effectiveness, efficiency and satisfaction". The process of addressing this research objective has answered the research question **R3**: "how can we implement open learner modelling techniques and technologies, in order to enhance e-learning systems, and thus provide a high level of effectiveness, efficiency and satisfaction amongst learners?" The answer is "multifaceted open social learner modelling that visualises both learners' performance and contribution, provides various comparison modes, and is integrated and adapted to learning content, can enhance e-learning systems, and thus provide a high level of effectiveness, efficiency and satisfaction amongst learners".

Chapter 8

Conclusions

8.1 Introduction

The work presented in this thesis has ultimately led to exploring an innovative method of combining, threading and balancing the amount of adaptation, social interaction, gamification and open learner modelling for e-learning. In particular, this research has explored a novel combination of classical adaptation based on user modelling, fine-grained social interaction features and a Facebook-like appearance, in order to achieve a high level of learner effectiveness, efficiency, satisfaction and engagement amongst learners in social personalised adaptive e-learning systems. It has also investigated gamification and open learner modelling techniques and technologies to achieve a high level of learner motivation and further support a high level of effectiveness, efficiency and satisfaction amongst learners, and thus provide social personalised adaptive e-learning systems with a rich learner experience. Two versions of a social personalised adaptive e-learning system – **Topolor** and **Topolor 2** – have been implemented and evaluated in real-life online learning sessions. The evaluation results have been helpful with gaining new insights on the influence of new approaches proposed in this work.

The process of addressing the research objectives and answering the research questions has provided theoretical and practical suggestions, which are expected to help other researchers to develop their own research as well as contribute to this research area. In particular, we have suggested a new approach to conduct participatory design experiments for collecting end-user's requirements of designing a social personalised adaptive e-learning system, a new approach to synthesis social interactions and adaptations, a new approach to implement gamification and gamify social interactions, a new approach to visualise user data, a new approach to analyse log data, and a new approach to define and evaluate learning experience.

The main aim of this chapter is to conclude the thesis through a review of the general research progress, discuss the overall research achievements, contributions and impacts, and recommend potential directions and areas in which future research could be undertaken.

In the remainder of this chapter, firstly, section 8.2 summarises the research process in which the umbrella research question and the follow-up main working research questions have been answered, and discusses how well the respective research objectives have been achieved. Secondly, section 8.3 enumerates the research achievements and contributions. Thirdly, section 8.4 presents the research impacts. At last, in section 8.5, it recommends potential directions and areas in which future research could be undertaken.

8.2 Summary

This research has explored various techniques and technologies, in order to answer the umbrella research question:

R0. "How can we ensure that e-learning systems achieve rich learner experience, in terms of a high level of effectiveness, efficiency, satisfaction, motivation and engagement amongst learners?"

The umbrella research question has been transformed into three main working research questions of the thesis, which build upon each other:

R1. "How can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and engagement amongst learners?"

R2. "How can we implement gamification techniques and technologies, in order to enhance social e-learning systems, and thus provide a high level of motivation amongst learners?"

R3. "How can we implement open learner modelling techniques and technologies, in order to enhance e-learning systems, and thus provide a high level of effectiveness, efficiency and satisfaction amongst learners?"

Aiming to answer the above research questions, this research has been implemented via five individual research objectives (as stated in section 1.2). In the following, the achievement of each of the research objectives is discussed, as well as its relation to the main working research questions, articulating how they have been answered.

O1. Review the state of art in the fields of adaptive e-learning, social e-learning, gamification and open learner modelling to investigate their influence on the e-learning process.

This research objective has been achieved through an intensive and continuous study of related fields, summarised and filtered, based on its direct relevance and impact on this work, in the chapter on background and related work (Chapter 2). It is not surprising that the adaptive e-learning research field has embraced a social orientation. We believe that the investments and achievements in this social personalised adaptive e-learning branch are shaping the future of learning, which is one of the reasons why we are pursuing this particular research direction. Adaptive e-learning allow personalisation, meanwhile social web tools enable learners to create, publish and share content, facilitating interaction and collaboration. The integration of social web tools into adaptive e-learning systems can potentially offer new ways of learner engagement and extended user modelling.

Social techniques and technologies in e-learning can promote learners to interact with each other, and generate trails for other learners to follow, encourage them to create and share learning content, and engage them to participate in various learning activities. The integration of social techniques and technologies into adaptive e-learning systems has attracted researchers' attention, and some recent work [40, 164, 166] has highlighted the need for creating adaptive and highly interactive integrated learning environments; however, only limited numbers of mechanisms for enabling social interaction have been suggested [114, 163]. Therefore, the gap for extending and evaluating social web tools in adaptive e-learning settings has been identified for this research to fill.

Gamification techniques and technologies in e-learning can leverage learners' basic desires and needs that revolve around the understanding of competition, status, self-expression, achievement and community collaboration. Thus, gamification can encourage desirable behaviours towards performance and the achievement of the designed learning goals. However, gamification has also been criticised for its overjustification effect, which occurs when an expected external incentive de-motivates learners with already existing high intrinsic motivation. Therefore, this research seeks a *light gamification* approach (Chapter 6) that applies motivation theories to promote intrinsic motivation in existing social personalised adaptive e-learning systems, rather than a *full-fledged gamification* approach that may 'over-gamify' the existing mechanics.

Open learner modelling techniques and technologies in e-learning can visualise data within learner models to support self-reflection in the learning process, and explain the reason for getting a specific personalised recommendation. However, recent studies [22, 76, 101] merely focus on the learning progress visualisation and social navigation support. Additionally, we have identified many limitations of the existing systems (section 2.5), such as limited level granularity representation of learning performance comparison and limited ability of adjusting comparison views. Hence, this work seeks a 'multifaceted' approach to address the limitations.

The achievement of the first research objectives, i.e., **O1**, provides background knowledge for answering research questions **R1**, **R2** and **R3**.

O2. Explore and understand the needs of the learners, the end-users, for a social personalised adaptive e-learning system, aiming at gathering requirements for the implementation of the research environment.

This research objective has been achieved through an experimental study of the system requirement analysis (Chapter 3). In this experimental study, a Participatory Design (PD) methodology has been adopted to gather the authentic needs from the learners in the early design stage. In particular, the We!Design framework, one of the PD methodologies, has been applied. Both designers and learners were involved in participating the design process together. The experiment led to an ordered list of initial system implementation requirements, as well as gather issues and initial preferences for the development of the initial social personalised adaptive e-learning system, which is the next research objective to achieve. This work has been published in [166, 167].

O3. Based on the hypotheses and conclusions from **O1** and **O2**, develop a social personalised adaptive e-learning system that fosters social, personalised and adaptive e-learning experience, and evaluate it from the perspectives of learner effectiveness, efficiency, satisfaction and engagement.

This research objective has been achieved through designing, implementing and evaluating Topolor – the initial social personalised adaptive e-learning system (Chapter 4 and Chapter 5). Topolor has been developed to foster effective social and adaptive e-learning experiences by providing the combination of 1) *classical adaptation based on user modelling*, 2) *fine-grained social interaction features*, and 3) *a Facebook-like appearance*. This combination has been proposed, on the one hand, based on the system requirements suggested in Chapter 3, and on the other hand, inspired by the literature discussed in Chapter 2.

Based on the study on the research background and related work (sections 2.2 and 2.3), and the suggestions on system requirements (Table 4 in section 3.7), the architecture of the initial social personalised adaptive e-learning system has been designed. The architecture adopts a classical layered structure (inspired by the Dexter model [71]), extended with a social flavour: a *Storage Layer*, a persistence infrastructure for physical entities; and a *Runtime Layer*, parsing adaptation strategies to present adaptations and social interactions, and tracking learner behaviours.

To evaluate the framework, the architecture and the system, learners' perceived effectiveness, efficiency and satisfaction have been assessed. Learners' perceived efficiency and effectiveness were explored at different granularity levels of Topolor functionality, including the levels of 'system as a whole', 'sub-system functionalities', and 'single tasks'. Furthermore, ten criteria were defined (section 4.4.1) to assess learners' perceived satisfaction. A case study was conducted in a real-life online learning session for the evaluation. The results indicated a high percentage of the learners perceiving a high level of effectiveness, efficiency and satisfaction. Therefore, we claim that this research objective has been met successfully. Additionally, these results and feedback also suggested further improvements for the initial social personalised adaptive e-learning system.

During the online learning session, Topolor also kept tracking distinct user actions, e.g., clicking on a button. Each of the actions was recorded in a database with a timestamp. Chapter 5 has analysed these log data to investigate learning behaviour patterns, in order to gain new insights into learners' participation and engagement. In particular, the combination of data mining methods and data visualisation tools has been used to analyse learning behaviour patterns in terms of action frequency and action sequence. From the analyses, we have found some interesting individual learning behaviour patterns as well as common learning behaviour patterns, which helped to understand learners' participation, which also indicated a high level of engagement amongst learners. These discoveries led to the follow-up research: 1) exploring design strategies of gamifying adaptation and social interaction, and their impacts on learners' motivation (implemented in Chapter 6), and 2) investigating design strategies of visualising learners' data to themselves and/or each other, and their influences on learners' effectiveness, efficiency and satisfaction (implemented in Chapter 7).

The achievement of research objective **O2** and **O3** has led to answering the first research question:

R1. "How can we synthesise social interaction and adaptation techniques and technologies, in order to ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and engagement amongst learners?"

Answer for R1. "The combination of classical adaptation based on user modelling, fine-grained social interaction features, and a Facebook-like appearance, can ensure e-learning systems provide a high level of effectiveness, efficiency, satisfaction, and engagement amongst learners."

The work related to design, implementation of the system has been published in [168–170]. The work related to evaluating various perspectives of the system has been published in [154, 155, 159, 161, 172].

O4. Based on the hypotheses and conclusions from **O3**, build novel gamification strategies upon the initial social personalised adaptive e-learning system, and examine the impacts of the new gamification features on learners' motivation.

This research objective has been achieved through designing, implementing and evaluating the gamification strategies and functionalities introduced in the second version of the social personalised adaptive e-learning system – Topolor 2 (sections 6.3 and 6.4). The side effect of extensive social interaction features detected from the prior study of this research (section 5.4), the discussions on the further improvement of the initial social personalised adaptive e-learning system (section 4.4.4), and the literature study on influences of gamification on e-learning (section 2.4) have been the inspiration of carrying out this follow-up research.

Fifteen *Contextual gamification strategies* have been proposed applying Self-Determination Theory (SDT) [143], with the aim of keeping learners motivated in performing desirable learning behaviours and achieving learning goals. The *Contextual gamification strategies* contains three parts, each of which targets satisfying one of the basic innate needs mapping to those in SDT, namely autonomy, competence and relatedness. Unlike existing studies, this research adopts a specific blend of light gamification to symbiotically build upon social interaction features, rather than replace the already existing social learning communities in the system.

Guided by these *Contextual gamification strategies* (section 6.2), Topolor 2, the second version of the social personalised adaptive e-learning system, has been implemented. Section 6.3.2 has explained how these *Contextual gamification strategies* were applied, and presented various gamification features in Topolor 2, such as peer-reviewed posting, visualised social status and an adaptive leaderboard.

To evaluate the new gamification strategies and functionalities, learners' perceived motivation has been assessed. Criteria include learners' perceived autonomy, competence and relatedness, in line with each of the three basic innate needs from Self-Determination Theory (SDT). Two case studies were conducted in real-life online sessions. The results indicated a high level of learners' perceived motivation. Therefore, we claim that this research objective has been met successfully – the contextual gamification strategies and functionalities can increase learners' perception of motivation.

The achievement of research objective **O4** has helped in answering the second research question:

> **R2.** "How can we implement gamification techniques and technologies, in order to enhance social e-learning systems, and thus provide a high level of motivation amongst learners?"

> **Answer for R2.** "The implementation of 'contextual gamification' rooted in Self-Determination Theory (SDT), can keep learners motivated in performing desirable learning behaviours and

achieving learning goals, and thus provide a high level of motivation amongst learners."

This work has been published in [158, 160, 171].

O5. Based on the hypotheses and conclusions from **O3**, extend the previous system with a new open learner modelling, and examine its influence on learners' effectiveness, efficiency and satisfaction.

This research objective has been achieved through designing, implementing and evaluating the new open learner modelling introduced in Topolor 2 (section 6.3.1). This follow-up research has been inspired by the discussion on the learner data visualisation (section 5.4) and the literature review on open learner modelling (section 2.5).

Having learnt from existing open learner modelling research and systems, we have proposed the new *multifaceted open social learner modelling* approach (section 7.2). Unlike existing approaches introduced in section 2.5, this new approach aims to seamlessly and adaptively integrate open social learner modelling with learning content, so that its ubiquity and context-awareness can support new adaptation and personalisation methods for social e-learning. This new approach emphasises the possibility and necessity of the visualisation of both learners performance and contribution, which can better reflect a learner's role in a social personalised adaptive e-learning system as both knowledge consumer and producer. This new approach also underlines the importance of comparisons between a learner and different groups of learners, e.g., the top 20% of the class.

To evaluate the proposed *multifaceted open social learner modelling* approach, learners' perceived effectiveness, efficiency and satisfaction have been assessed. The criteria included the same ten ones described in *achieving **O3***, but another six new ones regarding learners' perceived satisfaction of 'socialisation quality' were additionally considered. The data for the assessment were collected through the same case study described in *achieving **O4***. The results analysis supported all the hypotheses, and thereby we claim that that this research objective has been met successfully.

The achievement of research objective **O5** has helped in answering the third research question:

> **R3.** "How can we implement open learner modelling techniques and technologies, in order to enhance e-learning systems, and thus provide a high level of effectiveness, efficiency and satisfaction amongst learners?"

> **Answer for R3.** "Multifaceted open social learner modelling that visualises both learners' performance and contribution, provides various comparison modes, and is integrated and adapted to learning

> content, can enhance e-learning systems, and thus provide a high level of effectiveness, efficiency and satisfaction amongst learners."

This work has been published in [156, 157, 163].

Note that before commencing this work, a Chair's Approval was received from the University of Warwick Biomedical and Scientific Research Ethics Sub-Committee, in order to safeguard conducting the study as well as to protect the rights, safety, dignity and well-being of research participants.

8.3 Contribution

The major contribution of this research is to answer the research question **R0** "how can we ensure that e-learning systems achieve rich learner experience, in terms of a high level of effectiveness, efficiency, satisfaction, motivation and engagement amongst learners?" We have explored techniques and technologies that can provide a high level of effectiveness, efficiency, engagement and motivation amongst learners. In addition, we have contributed to the methodology of doing such research. The following sub-sections present the specific contributions that have been made in this work.

8.3.1 Contribution to Socialisation of Adaptive E-Learning

Brusilovsky [17] and later Knutov *et al.* [90] have classified the adaptation techniques utilised in adaptive hypermedia into three broad areas including *content adaptation techniques*, *adaptive presentation techniques* and *adaptive navigation techniques*. However, none of these takes into account any information about the user's social connections. Indeed, the review of the previous work indicates that current adaptive e-learning systems have only marginally explored the integration of social interaction features and adaptation techniques. Therefore this research combines benefits offered by existing adaptive e-learning systems with the social affordances of social web tools, and thereby offers a great potential to improve e-learning systems and the overall learner experience.

Other than other adaptive e-learning research that are often limited in their strategies for adapting to social needs or in their social features, other than some recent work that suggest only a limited number of mechanisms for enabling social interactions, this research has tried addressing this gap by extending and evaluating social interaction tools in adaptive e-learning settings.

8.3.2 Contribution to Gamification in Social E-Learning

We have proposed *contextual gamification strategies* rooted in motivation theories including Self-Determination Theory (SDT), for increasing learners' intrinsic motivation, so as to keep them motivated in performing desirable learning behaviours and achieving learning goals, in social personalised adaptive e-learning systems. These contextual gamification strategies can be symbiotically built upon social interaction features without replacing the existing social learning communities, in order to reduce the side effects of social interactions, mitigate potential negative overjustification effects, and increase learners' motivation and engagement in social personalised adaptive e-learning.

We have investigated the three basic innate needs to fulfil suggested by SDT [143], in order to enhance learners' intrinsic motivation. The proposed fifteen *contextual gamification strategies* are grouped into three categories for addressing each of the SDT needs, i.e., autonomy, competence and relatedness, and thereby it is clear and convenient to apply them in both the design process and the evaluation process. We have showcased how to apply these strategies in a real-life system implementation process; we have also proposed matrices to evaluate the implementation from three perspectives that map to the three SDT needs.

8.3.3 Contribution to Open Learner Modelling

This research has proposed a new *Multifaceted Open Social Learner Modelling* approach – *Multifaceted-OSLM*, which can assist learners in self-directed and self-determined learning in a social context and promote metacognitive activities. Unlike other open learner modelling approaches, *multifaceted-OSLM* components can be seamlessly integrated with learning content in order for its prospect of ubiquity and context-awareness to enrich the adaptive potential of social e-learning systems and improve system usability.

In addition, unlike most other approaches that only focus on learner performance visualisation, or providing complex tools for social navigation, our approach, additionally, emphasises the importance of visualising both learners' performance and their contribution to a learning community. Importantly, the visualisation is built on a Facebook-like appearance, and on features inspired from popular games, instead of on traditional learning system visualisations. This can support new adaptation and personalisation methods for social e-learning.

It is also noteworthy that the proposed *multifaceted-OSLM* also maintains attributes that record learning status such as 'know', 'unknown' and 'learning', which inherit the traditional user modelling approach in adaptive educational hypermedia area.

8.3.4 Contribution to Participatory Design Methodology

This research has explored how to apply Participatory Design (PD) methodology in the early stage of system development. The experiment conducted for the system requirement analysis applied the We!Design framework as a PD methodology, but we further developed this framework and proposed some advice for better conduct of such experiments. The main difference between our approach and the original We!Design framework is the use of an additional questionnaire survey. This provides more information about the system requirements from the end-user point of view. This also avoids middleman bias influenced by experiment coordinators, as the structured questionnaires have uniform questions standardising the responses for easier analysis and does not interrupt students' thinking.

Additionally, unlike other approaches that 'questionnaires come first', in our approach, the questionnaires were delivered after the *application synthesis phase*, because, on the one hand, on the fact that the designers had already analysed the requirement proposed by the students, they would be able to ask pointed questions to further understand students' opinions, and on the other hand, since the students had already gone through the design session, they would like to have more chances to propose extra expectations as well as helping the system designers to understand the priorities of the previously extracted requirements.

Furthermore, according to the observation of the experiment in progress, the key to better conduct the experiment is to encourage the students to participate in discussion and presentation. Due to limited time, coordinators should keep the balance between the detail level of discussion and time controlling, and it is better that they provide some tools and tips during the experiment, e.g., personas and scenarios. It is also necessary to keep in mind the importance of mutual understanding between the system designers and the students. A feasible way is to ask the students to check the consistency.

8.3.5 Contribution to Learning Behaviour Analysis

This research has shown a novel practice of learning behaviour analysis, which uses the combination of data mining methods and data visualisation tools to elicit common and individual learning behaviour patterns from the perspectives of action frequency and action sequences. This approach helps to unobtrusively and ubiquitously learn from learners' experiences and characteristics, in order to adapt systems and services to their personal needs and thus improve learners' effectiveness, efficiency and satisfaction.

Data mining or knowledge discovery in databases (KDD) is a process of analysing and extracting knowledge from data contained within a database [139]. Evidently, educational data mining (EDM) has great potential and it is particularly useful for improvement of e-learning systems, but most of the approaches focus on the development of data mining algorithms rather than empirical analyses of e-learning systems. In contrast, this research focuses on finding out which learning data need to be analysed, what learning behaviour patterns can be captured, and how to analyse them. The combination of data mining methods and data visualisation tools in this work helps with representing learning behaviour data and exploring learning behaviour patterns. In our approach, researchers can be directly involved in the data mining process, as well as gain insight into the data and come up with new discoveries.

Using the proposed approach, our empirical investigation has found some interesting individual learning behaviour patterns as well as some common learning behaviour patterns, which suggest the possible directions to improve implicit user modelling for social personalised adaptive e-learning systems, and thus to improve the overall learner experience.

8.4 Impacts

The progress and results of this research have led to twenty papers published in journals, book chapters and A-level conference proceedings, and they have been presented in various formats including oral presentations, demos and posters, at international conferences including the top ones in the research field of user modelling and e-learning, such as UMAP, EC-TEL, ICALT and ICWL.

Five awards have been received for this research, including Best Student Paper Award from ICWL, Best Demo Award from UMAP, Best Poster Award from ICALT, Best Paper Award from IADIS-EL, and Best Extended Abstract Award from YDS.

This research has led to the creation of a series of innovative social personalised adaptive e-learning systems: Topolor was launched in November 2012; Topolor 2 was launched in November 2013. They have been used as online learning environments for undergraduate and postgraduate students in Western and Eastern Europe and Middle Eastern universities, including the University of Warwick, UK;

Jordan University, Jordan; Taibah University, Saudi Arabia, and Sarajevo School of Science and Technology, Bosnia and Herzegovina. The produced data, including questionnaire data and log data, have been collected and analysed to support the work presented in this thesis. The results and informal feedback from those students and lectures indicates this approach is promising, as well as suggests further implementation of the systems and follow-up research. Topolor was further demonstrated successfully in Brasilia, Brazil, among others. The worldwide use of Topolor has also promoted potential international collaboration.

This research has inspired other follow-up research. For example, Afaf Alamri, a PhD student from the Intelligent and Adaptive Systems Group, University of Warwick, has started her research based on the legacy of this research. Her research focuses on utilising social, personalisation, and virtual teams in the e-learning context to support group coursework and projects, with the aim of exploring the combination of social, virtual teamwork concepts with personalised e-learning, and investigating if such combinations can achieve more acceptance in comparison to current traditional e-learning systems.

Moreover, this work has led to several research collaborations, as its results are already underway to create a more generic methodology and framework for the intelligent e-learning area. Consequently, an interdisciplinary collaboration has been recently built-up, between the Intelligent and Adaptive Systems Group (IAS), Department of Computer Science, University of Warwick, and the Educational Development & Research Team, Warwick Medical School. Another collaboration which is to build on this research, is between the IAS, Warwick and the Personalized Adaptive Web Systems Lab (PAWS Lab), led by Peter Brusilovsky, School of Information Sciences, University of Pittsburgh, USA.

8.5 Future Research

The work presented in this thesis has led to a novel approach to thread appropriate balance and granularity of adaptation, social interaction, gamification and open learner modelling techniques and technologies, in order to trigger synergetic interactions and thus ensure e-learning system to deliver a high level of learner experience in terms of learner effectiveness, efficiency and satisfaction. The approach has been indicated successful through several experimental studies and evaluations of its various perspectives. Based on these results we suggest the following directions for the future research.

8.5.1 Learner Analytics

This research has investigated learning behaviours and found both individual and common learning behaviour patterns. These results could be further used in enhancing the implicit user modelling. For example, it may be useful to cluster learners who have been following the same action path into the same group, as they may have similar cognitive styles of learning or similar preferences of using the system, and they may benefit from a specific type of adaptation support. It may be useful to remind learners when the system detected that they are following a particular action path, which has less probability to be performed by other learners within the system, as following the action paths that have less probability to be performed may result in off task behaviours. Therefore, the future research questions could ask how to efficiently find out learning behaviour patterns, how to efficiently detect which pattern an individual learner may have been following, and which patterns could be tracked for predicting and adapting to various characteristics.

8.5.2 Adaptive Gamification

This work has explored how to build gamification upon adaptation and social interaction, in order to motivate learners to perform desirable learning behaviours and achieve learning goals, but the other way around, it would be also useful to make gamification adaptive and personalised, after all, learners are usually different from one another. For example, rewards, punishments and arguments may need to be adaptive and personalised, as learners differ in interests; performance feedback, emotional support and ambitiousness of goals to set may need to be adaptive and personalised, as learners differ in personality; level of goal and social comparisons may need to be adaptive and personalised, as learners differ in ability. Therefore, several questions could be answered in the future research, such as what characteristics of a learner need to obtain and how to obtain, what gamification techniques and features can be personalised and how to personalise, where and when to apply adaptation and personalisation of gamification, and how to employ adaptive gamification in social e-learning.

8.5.3 Private Data Explosion

This work has proposed visualisations of learning performance and contribution to learning communities, and the comparison of these visualisations between a learner and different learning groups, as essential components of the proposed *multifaceted open social learner modelling* (multifaceted-OSLM). In fact, there is still space to expand the approach of visualisations, such as visualising metacognitive activities to promote self-reflection, self-direction and transparency. Additionally, although the proposed multifaceted-OSLM allows learners to manipulate the visualisations, such as choosing different learning groups (top 20% learners of the class or the whole class) to compare with their data, more options could be potentially opened to the learner to choose, such as allowing learners to choose different ways (types of graphs) to visualise the same data. More importantly, as learners' data are exposed to others, the ethic and privacy issues have been highlighted as a strong challenge. Therefore, it is crucial to investigate learners' perceptions of personal data exposure, and explore techniques and technologies of privacy management.

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Appendix A

System Requirement Survey

This survey will help us with research and design next generation e-learning systems.

Please answer all these questions according to their types:
○ is a single-choice ☐ is a multi-choice ___ is a text-field

Thank you for your contribution!

A. Personal Background

Age: ____________________ Nationality: ______________________
Gender: _________________ Field of Study: ____________________

B. E-learning System(s) that you have used or are using

1. **What e-learning system(s) have you used?**

☐ Moodle ☐ Sakai
☐ WebCT ☐ Blackboard
☐ ATutor ☐ Janison
☐ Others: ____

2. If you haven't used any e-learning system(s), why?

☐ Not sure of the possibilities ☐ Not relevant to my learning area
☐ Lack of time ☐ Do not like the technology
☐ Lack of confidence ☐ Others: _____________________

3. If you currently use e-learning system(s), why?

☐ Compulsory to use ☐ Good levels of assessment
☐ Save time and effort ☐ Increase output and creativity
☐ Multimedia resources ☐ Others: _____________________

4. What e-learning system(s) do you currently use?

- [ ] Moodle
- [ ] Sakai
- [ ] WebCT
- [ ] Blackboard
- [ ] ATutor
- [ ] Janison
- [ ] Others: ______________________

5. What features of the e-learning system(s) do you like best?

6. What features of the e-learning system(s) do you dislike most?

7. What functions of e-learning system(s) do you use most commonly?

8. What equipment(s) do you use most commonly for the e-learning system(s)?

- [ ] Desktop
- [ ] Tablet
- [ ] Laptop
- [ ] Smartphone
- [ ] Others: ______________________

Product name (e.g. Mac Pro): ______________________

9. How often do you use the e-learning system(s)?

- ( ) Very Frequently
- ( ) Frequently
- ( ) Occasionally
- ( ) Rarely
- ( ) Very Rarely

10. What do you rate overall experience in using e-learning system(s)?

- ◯ Very satisfied
- ◯ Satisfied
- ◯ Neither
- ◯ Dissatisfied
- ◯ Very dissatisfied

11. What website(s) do you use to learn/collect learning resources?

- ☐ Facebook
- ☐ YouTube
- ☐ Twitter
- ☐ Google Plus
- ☐ LinkedIn
- ☐ Wikipedia
- ☐ Others: ______________________________

C. New E-learning System(s) that you expect

12. Which do you prefer?

- ◯ Use a nickname to prevent others to know who I am
- ◯ Use my real name to let others know who I am

13. Which do you prefer?

- ◯ Knowledge space based social network
- ◯ Social network based knowledge space

14. Which do you prefer?

- ◯ A specific learning path
- ◯ A dynamic learning path

15. Which do you prefer?

- ◯ Specific learning content
- ◯ Dynamic learning content

16. Which do you prefer?

- ◯ Depth-first Learning
- ◯ Breadth-first Learning

17. Which do you prefer?

- ◯ View the whole learning path and then learn every items in an order
- ◯ Learn every learning items until traverse the whole learning path

18. Which do you prefer?

- ○ Recommended learning items ranked by rating and correlation degree
- ○ Recommended learning items which are ranked by popularity

19. Which do you prefer?

- ○ A learning path that statistically calculated via peers' learning path
- ○ A learning path which is designed by a teacher

20. Which do you prefer?

- ○ Have all the web2.0 functions at the beginning of using the system
- ○ Have more web2.0 functions when I move up to a higher user-level

21. Which do you prefer?

- ○ Every user can organize and share courses for others to learn
- ○ Only teachers can author and publish courses

22. Which do you prefer?

- ○ Synchronous feedback from teachers
- ○ Asynchronous feedback from teachers

23. Which do you prefer?

- ○ Synchronous interaction with other students
- ○ Asynchronous interaction with other students

24. Which do you prefer?

- ○ Learning under time pressure with time management tools
- ○ A relaxed Learning environment without time pressure

25. What do you prefer to access e-learning system(s)?

- ☐ Desktop
- ☐ Laptop
- ☐ Tablet
- ☐ Smartphone
- ☐ Others: ____

26. What are you more concerned about?

- ☐ Friendly usability
- ☐ Timely feedback
- ☐ Learning outcomes
- ☐ Others: ____________________

27. To whom do you like to expose your learning experience/process?

- ☐ Other students
- ☐ Potential employers
- ☐ My teacher
- ☐ Keep private

28. Scale of importance

	Very	Quite	Fairly	Slightly	Not at all
1. Share learning experience & materials	○	○	○	○	○
2. Exchange of knowledge and approaches	○	○	○	○	○
3. Trust of user-generated learning content	○	○	○	○	○
4. Trust of group members and teachers	○	○	○	○	○
5. Instructions and tips	○	○	○	○	○
6. Revision exercises	○	○	○	○	○
7. Feedback of learning progress and results	○	○	○	○	○
8. Review or assessment of each other's work	○	○	○	○	○
9. Collaborative learning and group activities	○	○	○	○	○
10.Multimedia delivery	○	○	○	○	○
11.Interactive learning content	○	○	○	○	○
12.Recommendation of learning path	○	○	○	○	○
13.Recommendation of related learning content	○	○	○	○	○
14.Recommendation of group and other peers	○	○	○	○	○

29: Please provide more suggestions on design new e-learning systems:

Appendix B

Learner Satisfaction Survey (1)

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Topolor helped me to learn more topics.	-2	-1	0	1	2
Topolor helped me to learn more profoundly.	-2	-1	0	1	2
Topolor helped me to identify my weak points.	-2	-1	0	1	2
Topolor helped me to plan my classwork.	-2	-1	0	1	2
Topolor increased my learning interests.	-2	-1	0	1	2
Topolor increased my learning confidence.	-2	-1	0	1	2
Topolor increased my learning outcome.	-2	-1	0	1	2
It was easy to use Topolor.	-2	-1	0	1	2
It was easy to learn how to use Topolor.	-2	-1	0	1	2
It was easy to remember how to use Topolor.	-2	-1	0	1	2

Appendix C

Learner Satisfaction Survey (2)

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Topolor helped me to learn more topics.	-2	-1	0	1	2
Topolor helped me to learn more profoundly (deeply).	-2	-1	0	1	2
Topolor helped me to identify my weak points.	-2	-1	0	1	2
Topolor helped me to plan my classwork.	-2	-1	0	1	2
Topolor increased my learning interests.	-2	-1	0	1	2
Topolor increased my learning confidence.	-2	-1	0	1	2
Topolor increased my learning outcome.	-2	-1	0	1	2
It was easy to use Topolor.	-2	-1	0	1	2
It was easy to learn how to use Topolor.	-2	-1	0	1	2
It was easy to remember how to use Topolor.	-2	-1	0	1	2
It was easy to discuss with the peers.	-2	-1	0	1	2
It was easy to share content with peers.	-2	-1	0	1	2
It was easy to access the content shared by peers.	-2	-1	0	1	2
It was easy to tell peers what I liked/disliked.	-2	-1	0	1	2
The statistic numbers engaged me to learn more.	-2	-1	0	1	2
Topolor helped me engaged in interacting with peers.	-2	-1	0	1	2

Appendix D

System Usability Scale

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I think that I would like to use this system frequently.	1	2	3	4	5
I found the system unnecessarily complex.	1	2	3	4	5
I thought the system was easy to use.	1	2	3	4	5
I think that I would need the support of a technical person to be able to use this system.	1	2	3	4	5
I found the various functions in this system were well integrated.	1	2	3	4	5
I thought there was too much inconsistency in this system.	1	2	3	4	5
I would imagine that most people would learn to use this system very quickly.	1	2	3	4	5
I found the system very cumbersome to use.	1	2	3	4	5
I felt very confident using the system.	1	2	3	4	5
I needed to learn a lot of things before I could get going with this system.	1	2	3	4	5

Appendix E

Sub-System Functionalities Survey

Value	Usefulness (should we have this feature?)	Ease of Use (is this feature easy to use?)
-2	Completely useless	Very hard to use
-1	Useless	Hard to use
0	Neither useless nor useful	Neither hard nor easy to use
1	Useful	Easy to use
2	Very	Very easy to use

Functionality	Usefulness					Ease of Use				
Overall-Sub	-2	-1	0	1	2	-2	-1	0	1	2
Status (post)	-2	-1	0	1	2	-2	-1	0	1	2
Messaging	-2	-1	0	1	2	-2	-1	0	1	2
Q&A (questioning and answering)	-2	-1	0	1	2	-2	-1	0	1	2
Note	-2	-1	0	1	2	-2	-1	0	1	2
To-do	-2	-1	0	1	2	-2	-1	0	1	2
Module	-2	-1	0	1	2	-2	-1	0	1	2
Topic	-2	-1	0	1	2	-2	-1	0	1	2
Testing	-2	-1	0	1	2	-2	-1	0	1	2
Statistics	-2	-1	0	1	2	-2	-1	0	1	2

Appendix F

Learner Motivation Survey

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I felt in control of my learning process.	-2	-1	0	1	2
I was interested in using Topolor.	-2	-1	0	1	2
I felt confident to use Topolor.	-2	-1	0	1	2
I felt my learning experience was personalised.	-2	-1	0	1	2
I enjoyed and had fun using Topolor.	-2	-1	0	1	2
I felt I only needed a few steps to complete tasks.	-2	-1	0	1	2
I felt it was easy to understand why I received recommendations.	-2	-1	0	1	2
I felt it was easy to find the content I need.	-2	-1	0	1	2
I felt it was easy to share content with peers.	-2	-1	0	1	2
I felt it was easy to access the shared resources from peers.	-2	-1	0	1	2
I felt it was easy to tell peers what I like/dislike.	-2	-1	0	1	2
I felt it was easy to discuss with peers.	-2	-1	0	1	2

Appendix G

Multifaceted-OSLM Features Survey

Functionality	Usefulness					Ease of Use				
Home Page										
Filter by everyone's activities	-2	-1	0	1	2	-2	-1	0	1	2
Filter by my activities	-2	-1	0	1	2	-2	-1	0	1	2
Course Page										
Learning path - Tree View@	-2	-1	0	1	2	-2	-1	0	1	2
Performance - Pop-up View@	-2	-1	0	1	2	-2	-1	0	1	2
Score trends - Line Chart@	-2	-1	0	1	2	-2	-1	0	1	2
Contribution - Pop-up View@	-2	-1	0	1	2	-2	-1	0	1	2
Test success rates - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Average quiz score - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Topic completion - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Number of activities - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Bookmarked - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2

Questions asked - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
‘Liked’ - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Questions answered - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Activity types - Radar Chart@	-2	-1	0	1	2	-2	-1	0	1	2
Questions asked - Donut Chart&	-2	-1	0	1	2	-2	-1	0	1	2
Resources shared - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Questions answered - Donut Chart&	-2	-1	0	1	2	-2	-1	0	1	2
Comments - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Resources shared – Donut Chart&	-2	-1	0	1	2	-2	-1	0	1	2
Comments - Donut Chart&	-2	-1	0	1	2	-2	-1	0	1	2
Topic Page										
Learning path - Tree View@	-2	-1	0	1	2	-2	-1	0	1	2
Performance - Pop-up View@	-2	-1	0	1	2	-2	-1	0	1	2
Contribution - Pop-up View@	-2	-1	0	1	2	-2	-1	0	1	2
Questions asked - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Questions asked - Donut Chart&	-2	-1	0	1	2	-2	-1	0	1	2
Resources shared - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Questions answered- Donut Chart&	-2	-1	0	1	2	-2	-1	0	1	2
Comments - Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Questions answered -Bar Chart*	-2	-1	0	1	2	-2	-1	0	1	2
Comments - Donut Chart&	-2	-1	0	1	2	-2	-1	0	1	2

Resources shared - Donut Chart[&]	-2	-1	0	1	2	-2	-1	0	1	2
View quiz scores - Bar Chart[*]	-2	-1	0	1	2	-2	-1	0	1	2
My quiz results - Pop-up View[@]	-2	-1	0	1	2	-2	-1	0	1	2
Resource Page										
Author's name and stats	-2	-1	0	1	2	-2	-1	0	1	2
Profile Page										
Check my performance	-2	-1	0	1	2	-2	-1	0	1	2
Check my contribution	-2	-1	0	1	2	-2	-1	0	1	2
PK., compare me with another	-2	-1	0	1	2	-2	-1	0	1	2
List of resources shared	-2	-1	0	1	2	-2	-1	0	1	2
List of questions asked	-2	-1	0	1	2	-2	-1	0	1	2
List of questions answered	-2	-1	0	1	2	-2	-1	0	1	2
List of courses learned	-2	-1	0	1	2	-2	-1	0	1	2
Profile Page										
List of topics learned	-2	-1	0	1	2	-2	-1	0	1	2
List of topics learnt	-2	-1	0	1	2	-2	-1	0	1	2
Statistics for the profile's owner	-2	-1	0	1	2	-2	-1	0	1	2
Waterfall list of activity logs	-2	-1	0	1	2	-2	-1	0	1	2
Like an activity log	-2	-1	0	1	2	-2	-1	0	1	2
Comment on an activity log	-2	-1	0	1	2	-2	-1	0	1	2

[@]: my data.
[&]: comparison between me and the rest of the class.
[*]: comparison between me, the whole class and the top 20% of the class.

Appendix H

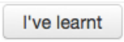
Tasks to Perform in Topolor

1. For all the tasks below, consult the User Guide on how to perform them if necessary.
2. Go to: http://www.topolor.com
3. Register in the system, and enter it
4. Things to do on the Home sub-system (Please note that these are all things which you can do repeatedly later on, when you are studying the module)
    a. Things to do on 'Status'
        i. Create your own 'status', briefly describing (e.g., 1-2 words) your current state (you can say anything related or non-related to the learning topics)
        ii. Edit the 'status'
        iii. Comment on the 'status'
        iv. Share the 'status'
        v. 'Favourite' and 'Unfavourite' the 'status'
        vi. Delete the 'status' (unless you want to keep it and it is relevant)
    b. Things to do on the Message
        i. Send messages to others
        ii. Reply to messages to others
    c. Things to do on the Q&A
        i. Ask questions about learning topics with some tags
        ii. Edit questions
        iii. Answer questions
        iv. Share questions
        v. 'Favourite' and 'Unfavourite' questions
        vi. Add tags to questions
        vii. Edit tags of questions

viii. Go to learning topics (concepts) or module related to the questions
ix. Filter questions by tags and learning topics (concepts)
x. Filter 'My questions ' and 'My answers'
xi. Delete question(s) (unless you want to keep it and it is relevant)

d. Things to do on Notes
   i. Create notes about learning topics with some tags
   ii. Edit notes
   iii. Share notes
   iv. 'Favourite' and 'Unfavourite' notes
   v. Add tags to notes
   vi. Edit tags of notes
   vii. Go to learning topics (concepts) or module related to the notes
   viii. Filter notes by tags and learning topics (concepts)
   ix. Filter notes according to when they are created
   x. Delete note(s) (unless you want to keep it and it is relevant)
e. Things to do on To-Do
   i. Create todos about learning topics with some tags
   ii. Edit todos
   iii. Change the status of todos, i.e. 'On Going', 'Done' and 'Cancel'
   iv. Add tags to todos
   v. Edit tags of todos
   vi. Go to learning topics (concepts) or module related to the todos
   vii. Filter todos by tags and learning topics (concepts)
   viii. Filter todos according to when they should be done
   ix. Filter todos according to their status
   x. Delete todo(s) (unless you want to keep it and it is relevant)

5. Things to do on the Module Centre sub-system
   a. Register in the Collaborative Filtering module
   b. Click 'Module Structure' on the top left of the page to read the module structure.

c. Read the information about the module on the module dashboard page
d. Do a Pre-test
e. Click tags of the module and get into the related learning topics (concepts)
f. Read about all concepts in the Collaborative Filtering module (depending on time)
    i. Start from the main Collaborative Filtering page, Click 'Up Next->Start' and follow with 'Next>' button.
    ii. Whilst reading about concepts, do at least one Quiz
    iii. Comment on (at least one of) the concepts that you are reading
    iv. Ask and answer questions about the concepts that you are reading
    v. Create 'My note' and 'My todo' about the concepts that you are reading
    vi. Share questions and 'My note' about the concepts that you are reading
    vii. Click  when you finish reading the concept
    viii. Click  to read other concepts
    ix. Click tags to read related concepts
g. Talk to a recommended peer (that has learnt this concept) about it. Ask him/her some questions directly.
h. From the main Collaborative Filtering page, Click 'Recently Learnt' to see the learning topics (concepts) list
    i. Filter/order the learning topics (concepts) with the help of the filter bar
    ii. Click on one or more tags to see related learning topics (concepts)
i. From the main Collaborative Filtering page, review the learning topics (concepts)
j. From the main Collaborative Filtering page, click 'Quizzes' to see the quiz list
    i. Review the quizzes
    ii. Click concepts to see related concepts
    iii. Click tags to see related concept
k. From the main Collaborative Filtering page, click 'My answers' to see my answer list

i. Filter my answer list by using filter bar
ii. Click concepts to see related concepts
iii. Click tags to see related concept

6. Things to do on the Q&A Centre sub-system
   a. Things to do on 'Trends'
      i. Filter questions by using the filter bar
      ii. Answer questions
      iii. Delete questions
      iv. 'Favourite', 'Unfavourite', Share, Tag questions
      v. Go to related learning topics (concepts)
   b. Things to do on 'Concepts'
      i. Filter concepts by using the filter bar
      ii. Click concepts to see related questions
      iii. Create new questions, and than edit, delete, share, favourite them
   c. Things to do on 'Tags'
      i. Filter tags by using the filter bar
      ii. Click tags to see related questions
      iii. Create new questions, and then edit, delete, share, favourite them
   d. Things to do on 'Q&A'
      i. Filter questions by using the filter bar
      ii. Go to learning topics (concepts) or module related to the questions
      iii. Create new questions, and then edit, delete, share, favourite them
      iv. Add and edit tags
   e. Things to do on 'My questions'
      i. Filter, create, delete, them
   f. Things to do on 'My answers'
      i. Filter, create, delete, them
   g. Things to do on 'TOP USERS' below the left menu
      i. Filter recommended peers by 'Answers' and 'Questions' respectively
      ii. Send messages to one or more recommended peers

Appendix I

User Guide for Topolor

Topolor

User Guide

Designed by Shi Lei

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1 Preface

Topolor is an adaptive personalised e-learning system, aiming at integrating social network and knowledge network, in order to provide better learning topic adaptation support, learning path adaptation support and learning expert adaptation support.

Topolor.com v.0.1 is an alpha version system. The objective of this version is to set up the infrastructure and provide basic services. There are several features that seem not as the same as normal web apps, i.e. you have to upload your avatar when you sign up; even you could occasionally find a bug, but please be patient. Sure you are welcome to report bugs to us, as well as tell us your suggestions on the system design.

Why Topolor? The name ‘Topolor’ is from topology, a branch of mathematics. The idea is to connect everything within the system together. For instance, you can easily access related topics according to the tags of the topic that you are currently learning; you can easily access topics related the questions that you incorrectly answered in a quiz; you can easily find who are learning the same topics that you are learning and you can send messages to them for discussion.

Note: a Concept in the system presents a learning item. We named it as concept, because we consider it as a node in the semantic knowledge network. However in this version, the knowledge network has not been built up; instead, we organize the module in a tree structure. Hence in this user guide we call it learning topic instead.

Note: there are two types of question in the system. One type of question belongs to quizzes that you can find in Module Centre, and the other one of question is the questions that user asked that you can find in Q&A Centre and each learning topic’s social interaction panel.

2 Getting Started

- To access Topolor.com, an Internet connection is needed.
- You can access Topolor.com via http://www.topolor.com.
- The system has been tested and can work well on Chrome (v.23), Firefox (v.16), Opera (v.12) and Maxthon (v.3).

2.1 Sign Up

- To use Topolor.com, you need to sign up with your email, username, password and avatar. Your password will be stored encrypted, see consequences in password recovery below.

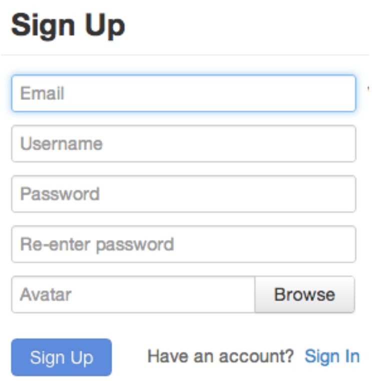

Figure 1 Sign Up

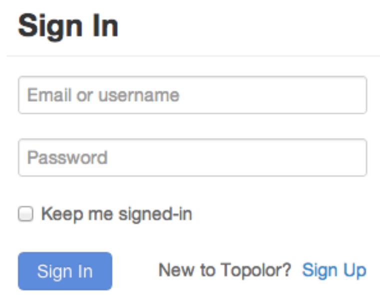

Figure 2 Sign In

2.2 Sign In

You can and must sign in Topolor.com before you use Topolor.com (Figure 2).

2.3 Password Recovery

Password recovery service is not ready in this version. In case you lost your password, please send email to lei.shi@dcs.warwick.ac.uk for help.

2.4 Top Menu

The top menu is the black bar on the top of your screen. Topolor.com includes 3 sub-systems: Topolor – Home, Module Centre and Q&A Centre. As shown in Figure 3, the top menu always stays on the top of the web pages, so you can easily switch among these sub-systems. If your browser window is too narrow, the 3 sub-system names can be found by clicking on the three lines that appear on the right hand side of the top menu.

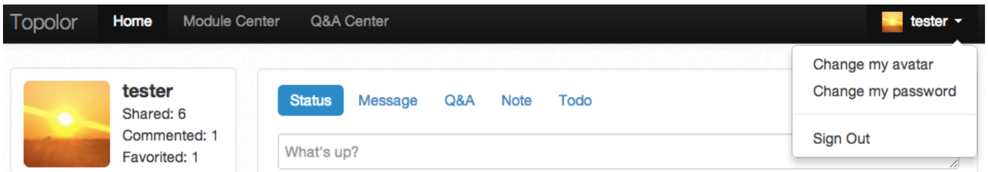

Figure 3 Top Menu

2.5 Sign Out

On the right side of the top menu (Figure 3), you can click a dropdown menu to sign out of system. However, Change my avatar and Change my password are not available in this version.

3 Topolor – Home

Topolor – Home sums up several functions of the system. You can access them via left menu, as shown in Figure 4.

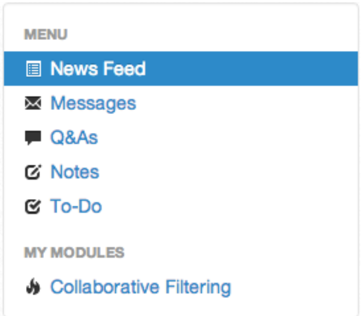

Figure 4 Left menu in Topolor – Home

3.1 Posts and New Posts

If something new comes up, you will find the button shown as in Figure 5 between the post-create form (Figure 6) and the post list (Figure 7), and if you click this button, the post list will be updated.

Figure 5 New Feed Button

Figure 6 Post-create Form

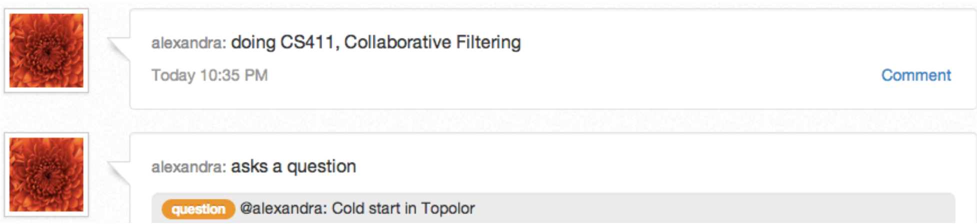

Figure 7 Post List

3.2 News Feed

News Feed is the index page where you can see what is happening to other users in the system. And also, you can create your own post via the post-create form as shown in Figure 8 between the top menu and the post list. There are 5 types of post you can create:

- Status: whatever you want to say and let others know.
- Message: send messages to others.
- Q&A: ask/answer questions about a specific learning topic with several tags.
- Note: create notes for a specific learning topic with several tags, which can be seen only by yourself, but you can choose to share it with others by clicking the share button.
- Todo: create todos in your todo-list, which can only be seen by yourself.

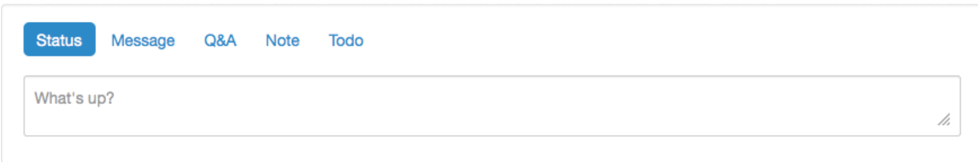

Figure 8 Post-create Form

- You can specify a learning topic for each post, and provide several tags. When you type tags, the system will suggest to you the tags you used before.

3.3 Messages

- You can send messages to others via message-create form from the Home sub-system, by choosing 'Messages' in the left menu, or by choosing 'Message' in the top menu, as shown in Figure 9. If you are in a different sub-system, your study buddies and the top five users can be contacted by clicking on their icon (see later on more explanations on how to do this).

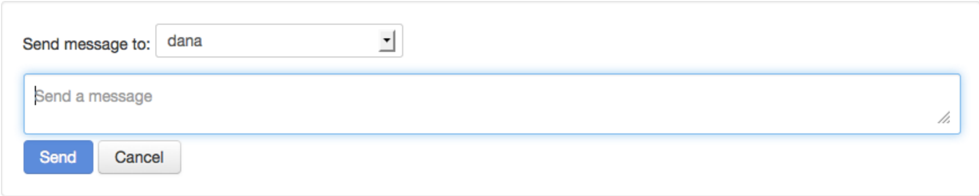

Figure 9 Message-create Form

- A message-list below the message-create form shows every conversation ordered by created time. To see the conversation details and reply to it, please click on it and get into the detail page as shown in Figure 10.

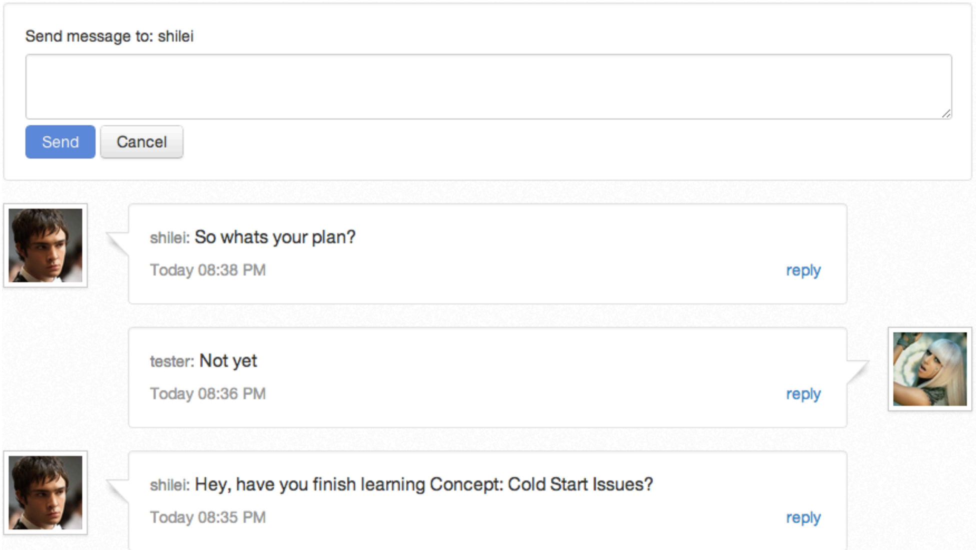

Figure 10 Message Detail Page

- You can see the refresh-button when new messages come up as shown in Figure 11; if you click the button, the message-list will be update.

Figure 11 Message List Refresh Button

3.4 Q&As

- For each question, you can find its detail information if you click as shown in Figure 12, including what learning topic it is related to and what tag it has.
- To edit the title or the description of the question, just simply click the title or the description, and then the edit panel will be activated (if only you are the owner).

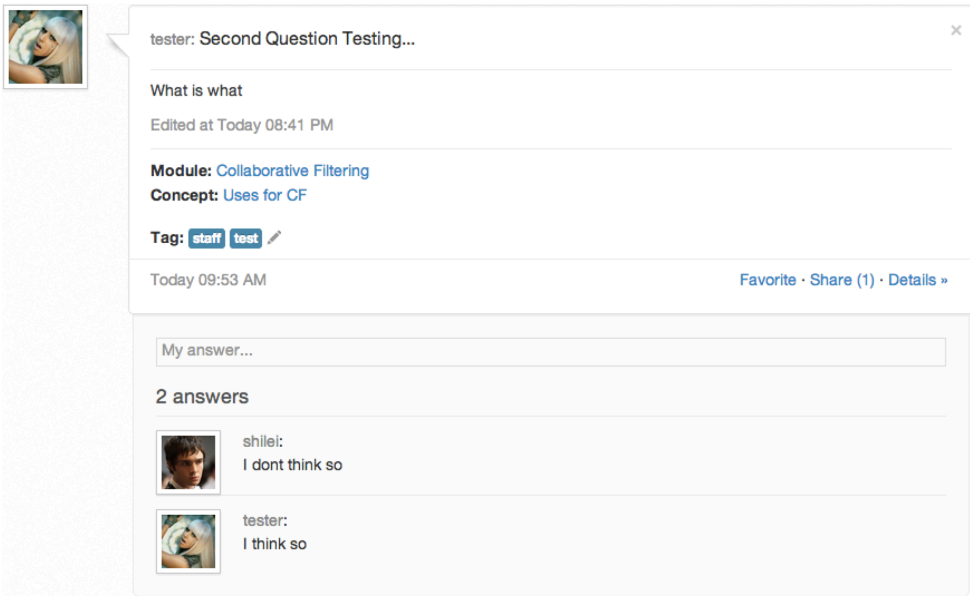

Figure 12 Question - Details

- Besides, you can edit the tags of the question by clicking , and then you can see the tag panel as shown in Figure 13. My-tags shows what tags you have used for Q&A. You can simply click the tag to add it to the question, or you can type new tag in the input field (tags should be divided by ‘, ’, comma + space).

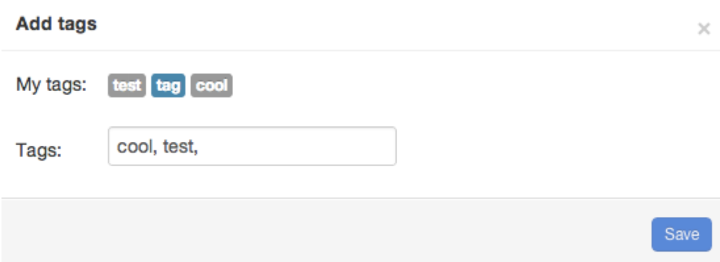

Figure 13 Tag Panel

- You can add new answers to this question and see answers form others in the answer-list below question Details.
- Between the question-create form and question-list, a filter bar as shown in Figure 14 can appear if you click 'All concepts' or 'All tags'.

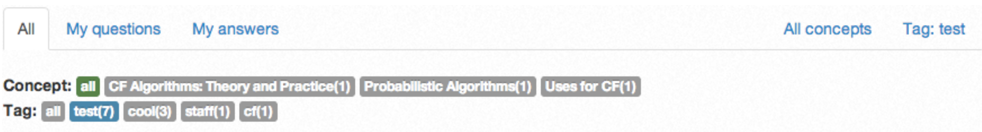

Figure 14 Filter Bar for Q&A

3.5 Notes

As shown in Figure 15, you can specify a learning topic and several tags when you create a note. Notes are normally personal. You can edit, share, select it as favourite, or delete it. You can also filter the note-list by using the filter bar.

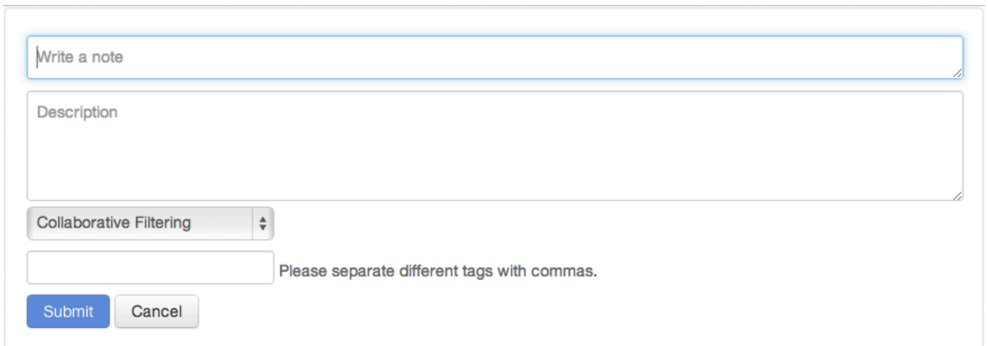

Figure 15 Create a Note

8

3.6 To-Do

- As shown in Figure 16, you can create, modify and delete you todos.

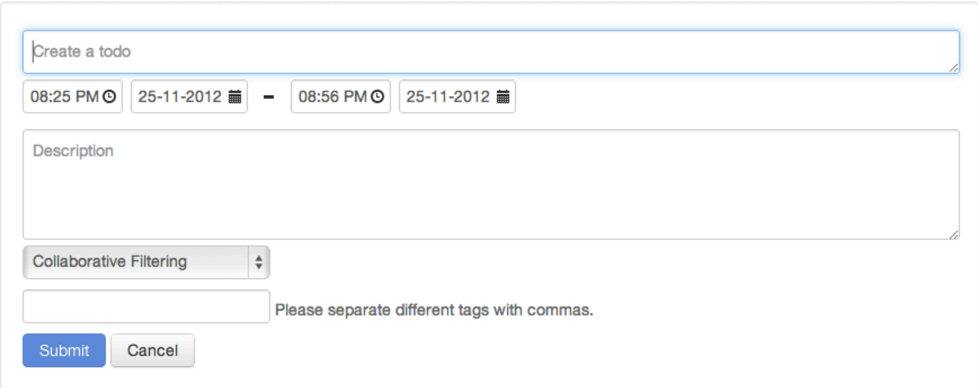

Figure 16 Create a Todo

- There are 3 status options (On Going, Done and Cancelled) for a todo as shown in Figure 17. You can easily switch between them by clicking the dropdown list.

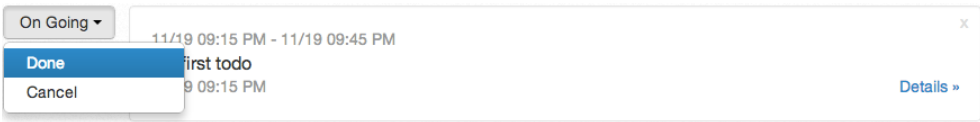

Figure 17 Switch Status for a Todo

- Select different views via the filter bar (Figure 18). This is done similarly to the filtering of Q&As.

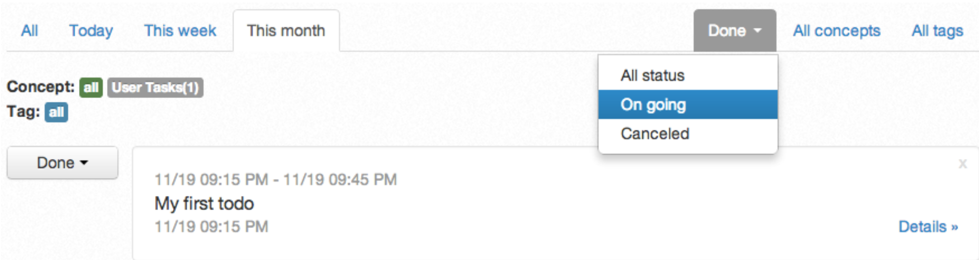

Figure 18 Todo - Filter Bar

4 Module Centre

4.1 Home page

- In the Module Centre sub-system, you can register on modules that you'd like to learn (or check their details by clicking Review) as shown in Figure 19. Or, you can click to enter a module that you've already registered onto, as shown in Figure 20.
- On the left are statistics about concepts of the current module that you are learning/have learnt, module recommendation (based on learners learning them) and user ranking (see Top Users, filtered by number of learning/learnt modules; you can send messages to them, by hovering over the icon) as shown in Figure 21.

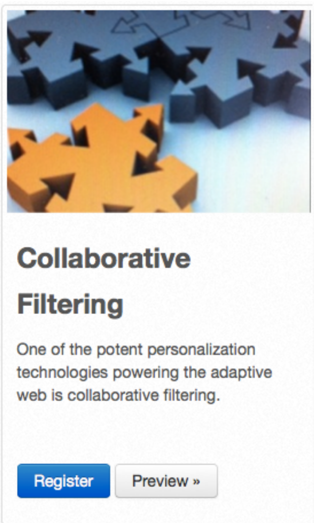

Figure 19 Register or Preview a Module

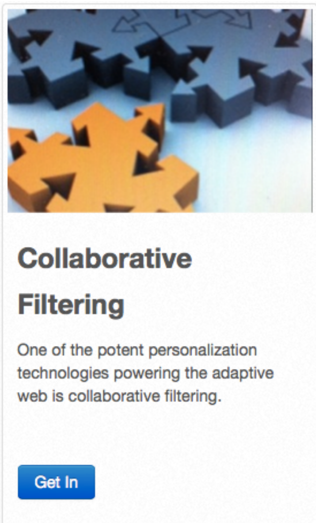

Figure 20 Get in a Module

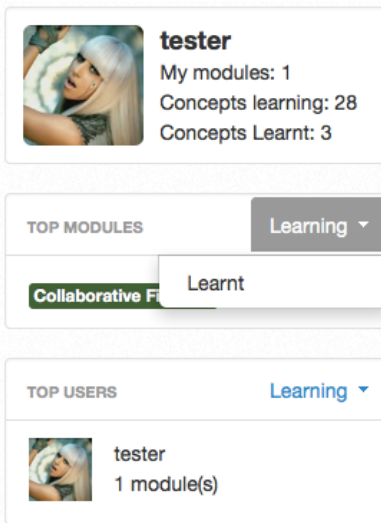

Figure 21 Left Menu of Module Centre

In order to get to the next menus, you need to enter a module.

4.2 Module dashboard

- After you have selected one of the modules, and entered it, you are in the module dashboard.
- Left menus include recommended learning topics list –here, based on how many people have learned it (Figure 22), recommended learning peers – here, based on how many questions they've answers or asked; you can set the filter for one of the other (Figure 23), and study buddies – here, representing all your colleagues learning the same module (Figure 24).

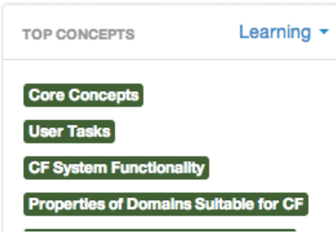

Figure 22 Left Menu – Learning Topic Recommendation

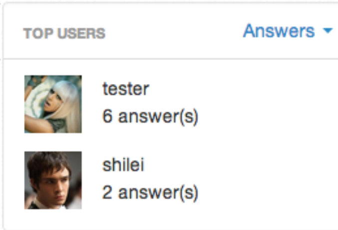

Figure 23 Left Menu – Learning Peer Recommendation

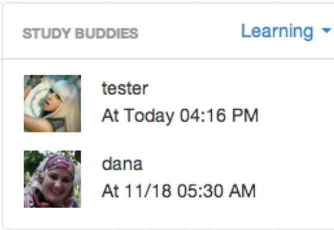

Figure 24 Left Menu – Study Buddies

- Module Structure (Figure 25). You can click Module Structure » on the top right of the screen, to expand or collapse it. Below, you can see an expanded module structure.

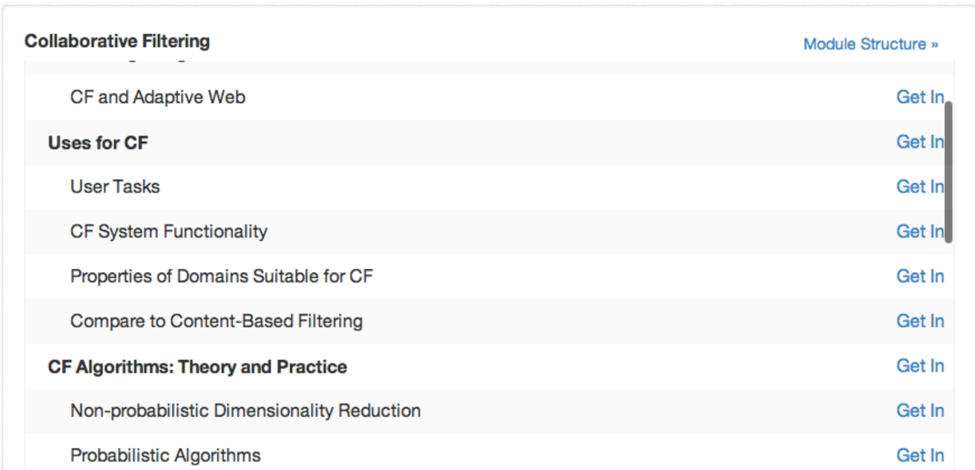

Figure 25 Module Structure

- You can take a pre-test before you start to learn the module, by clicking Pre-test.
- Figure 26 shows the tags and the description for a module. You can click a tag to see related learning topics as shown in Figure 27.

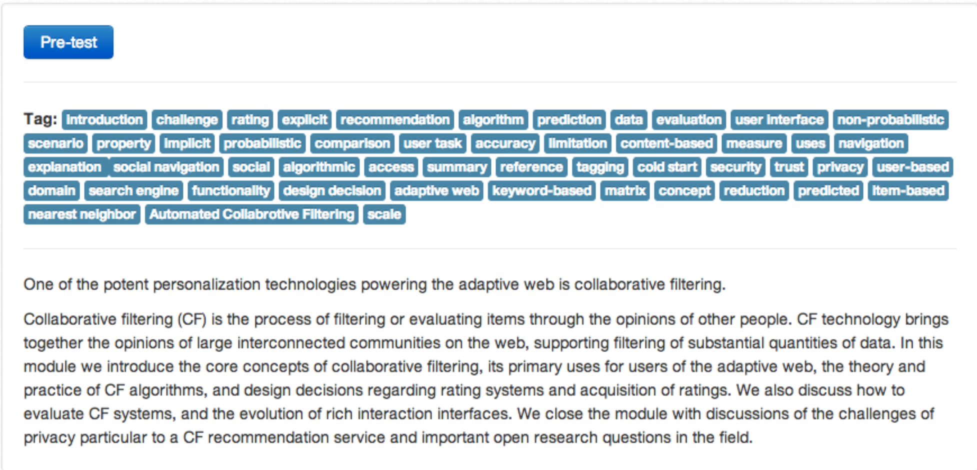

Figure 26 Tags and Structure for a Module

Figure 27 Tags and their related Learning Topics

- Figure 28 shows the next learning topic that you may need to learn according to the module structure. You can also read the first paragraph of this learning topic, to understand what it is about.

Figure 28 Module Dashboard – Up Next

- Figure 29 shows what learning topics you have learnt in reverse chronological order. You can click i.e. on 4 and on 31 in to open a learning topic list, as shown in Figure 30, and you can specify an order to display the list in.

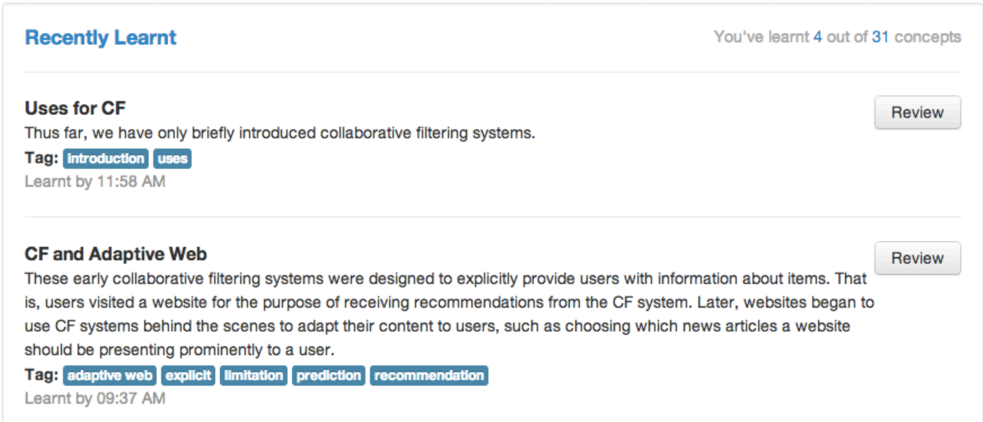

Figure 29 Module Dashboard – Recently learnt

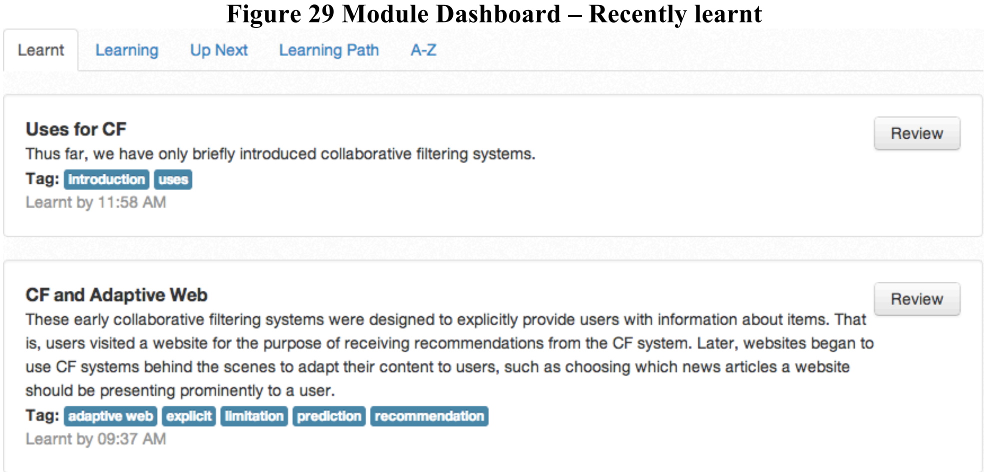

Figure 30 Learning Topic List with Ordering Bar

- As shown in Figure 31, you can review the quizzes that you've taken - click to see the quiz list (Figure 32), and click to see the questions from the quizzes that you've taken and which questions you answered correctly or incorrectly (Figure 33).

- In both Quiz List and My answers, you can click topic (concept) or tag to check the related learning topics, and get into those learning topic pages.

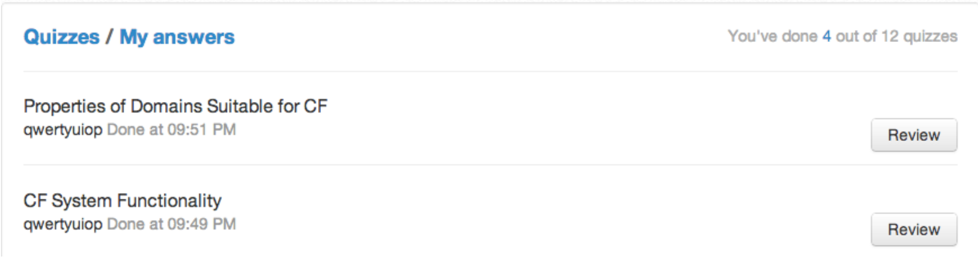

Figure 31 Module Dashboard - Quizzes / My answers

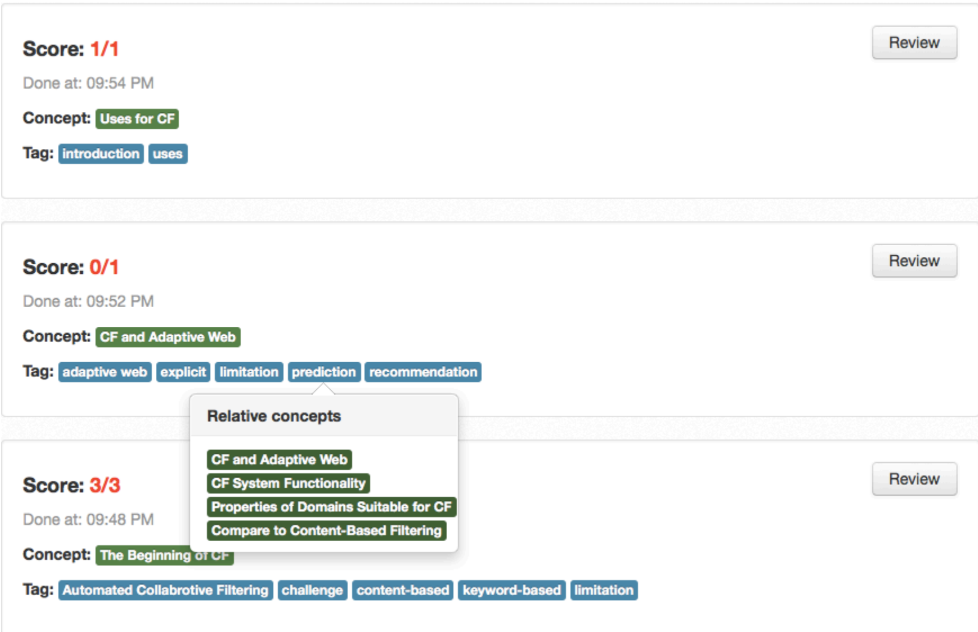

Figure 32 Quiz List

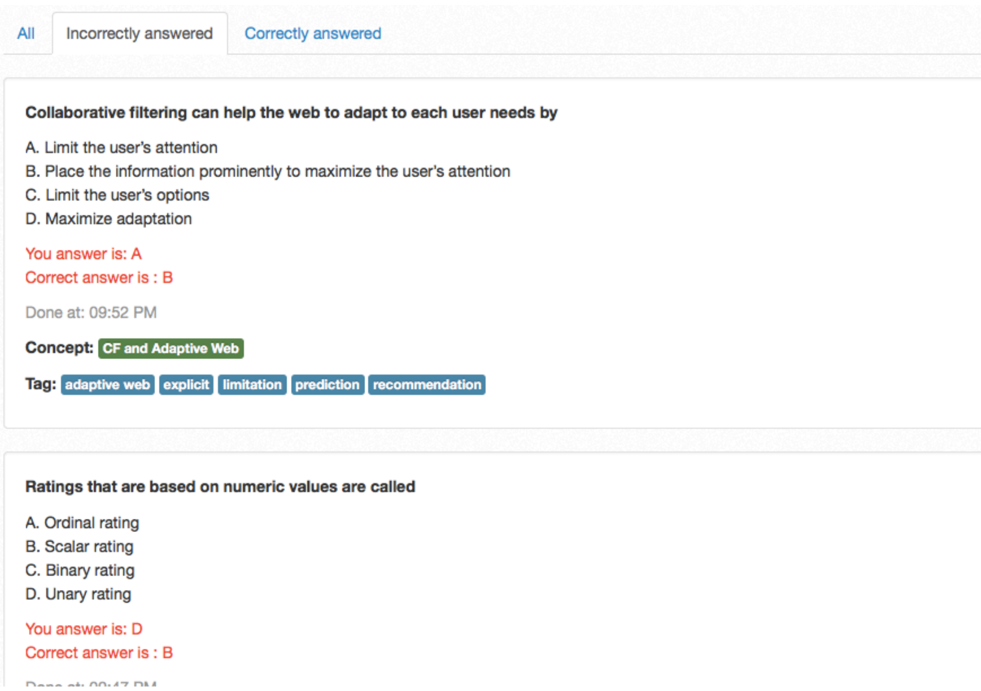

Figure 33 My answers List

- Figure 34 shows the Social Interaction Panel that locates in the bottom part of the Module Dashboard page. You can comment, ask/answer questions, take note and create todos.

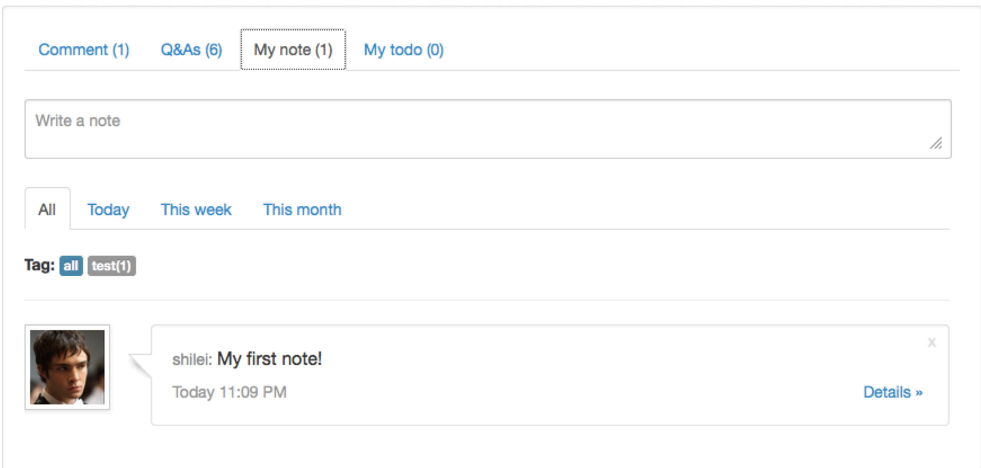

Figure 34 Social Interaction Panel

4.3 Learning Topic

- As shown in Figure 35, you can take a quiz, go to other learning topics, and return to the module dashboard.
- When you finish learning a topic, please click at the top right of the page, which can help the system calculate recommendations for your learning topics as well as your peers (you will be recommended to a peer, if you have declared to have learnt a topic).

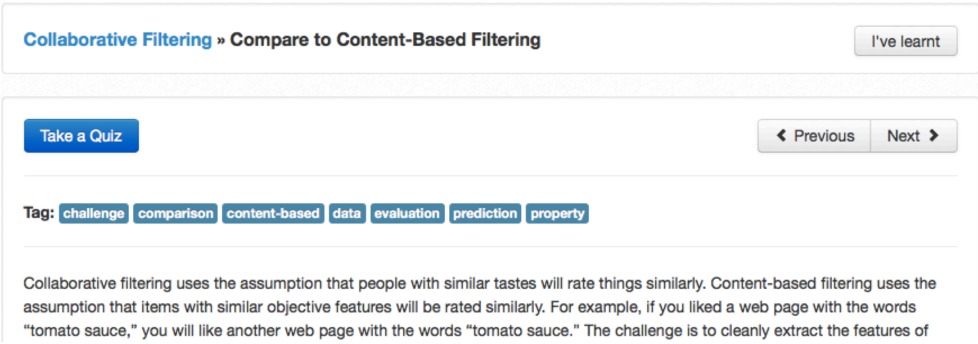

Figure 35 Learning Topic Page

- In the bottom part of learning topic page, you can find a social interaction panel, which is the same to that in the module dashboard page. The difference is that the comments and questions etc. you write here will relate directly to the current concept that you are reading about.

5 Q&A Centre

5.1 Stats

- You can see how many questions you asked and answered in the top left part of the screen, next to your image (Figure 36).
- You can click on statistics numbers to open a Q&A list (Figure 43).

Figure 36 Q&A Centre – Stats

5.2 Left Menu

- There are 6 types of Q&A Lists in Q&A Centre. You can access them by clicking the left menu as shown in Figure 37. See sections 5.4 onwards for the different menu choices.

Figure 37 Q&A Centre – Left Menu

5.3 Top Users: Learning Peers Recommendation

- Learning Peers Recommendation is in the left side of the learning topic page as shown in Figure 38. You can filter according to how many questions they answered or asked to order the list. You can send personal messages to these users.

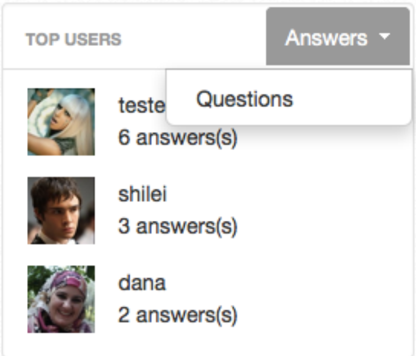

Figure 38 Q&A Centre – Learning Peers Recommendation

5.4 Trends

- Select different orders by clicking the ordering bar in the top of the Trends page as shown in Figure 39.

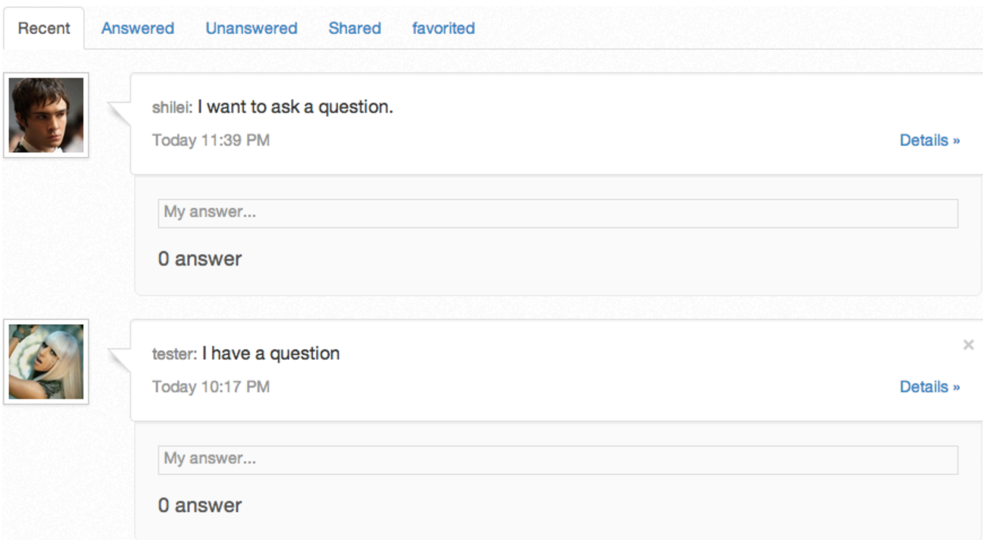

Figure 39 Q&A Centre – Trends

5.5 Concepts

- You can categorize Q&As by Learning Topics (concepts) and filter them by clicking the filtering bar (Figure 40).
- You can click on a Learning Topic to open the questions related to it.

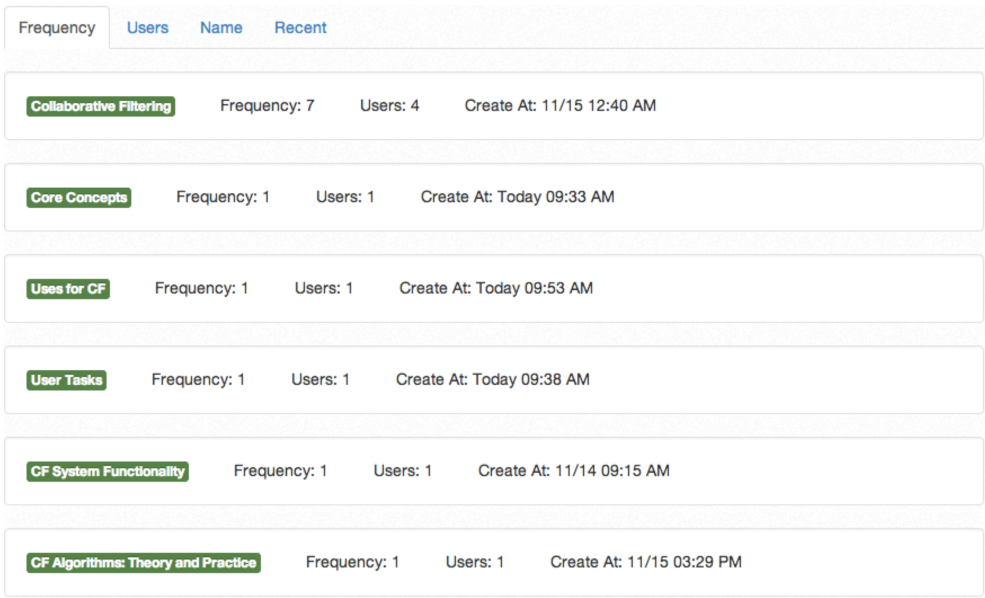

Figure 40 Q&A Centre – Concepts

5.6 Tags

- You can categorize Q&As by Tags and filter them by clicking on the filtering bar (Figure 41). Unlike concepts, which are defined by the administrator, tags are created by users when asking the questions.

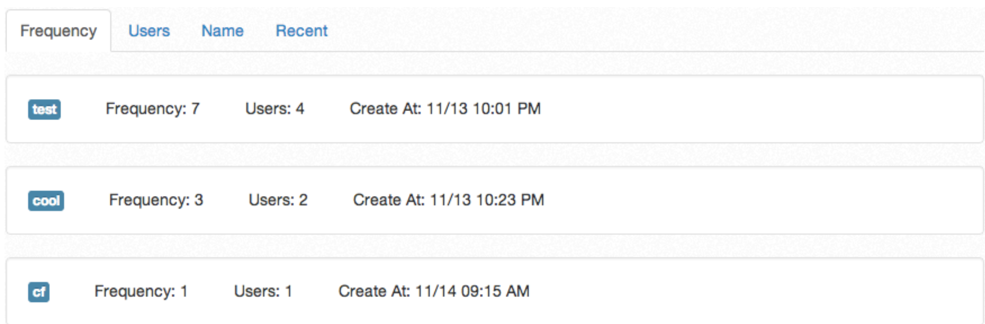

Figure 41 Q&A Centre – Tags

- You can click a Tag to see all related Q&As as shown in Figure 42.

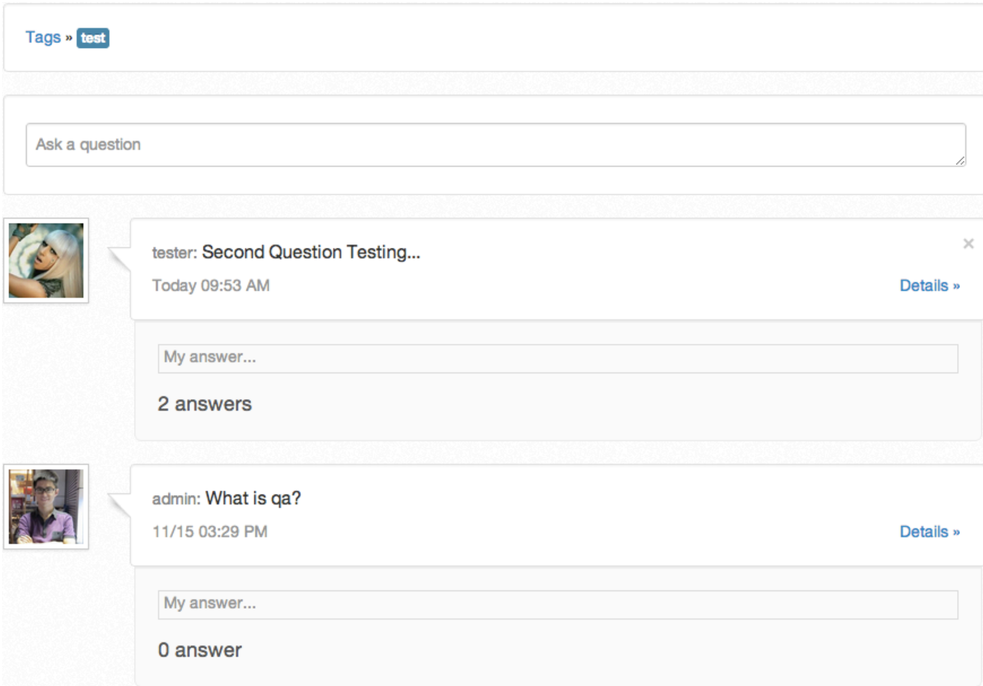

Figure 42 Q&A Centre – Tags – Related Q&As

5.7 Q&As

- Here you can read, ask and answer questions, via the Q&A list. You can also use filters on it, as explained in the following sections (Figure 43).

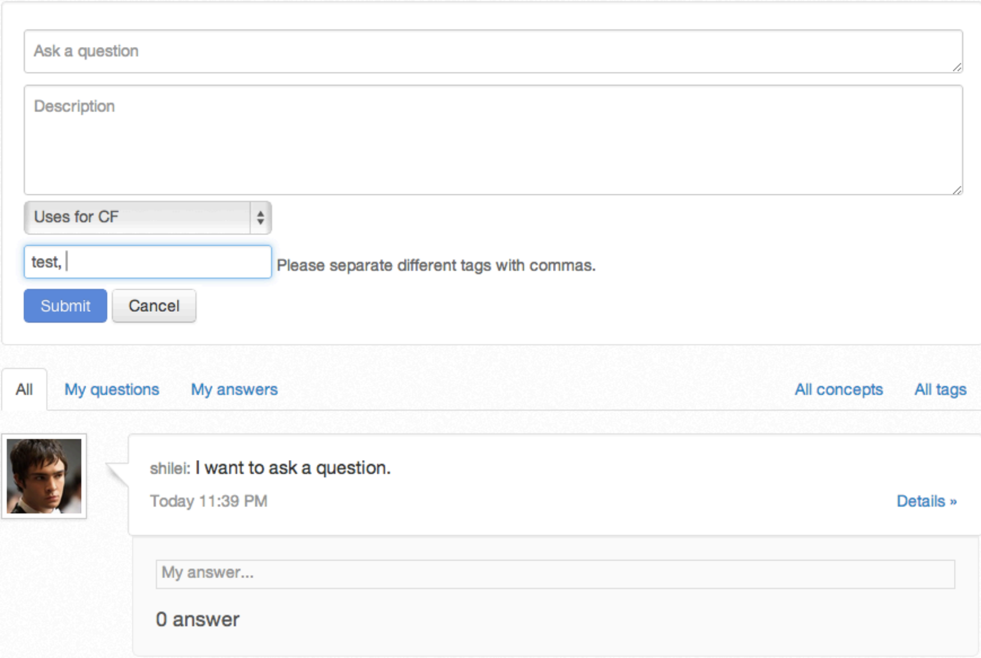

Figure 43 Q&A Centre – Q&A page

5.8 My questions

- Check questions that you have asked (Figure 44).

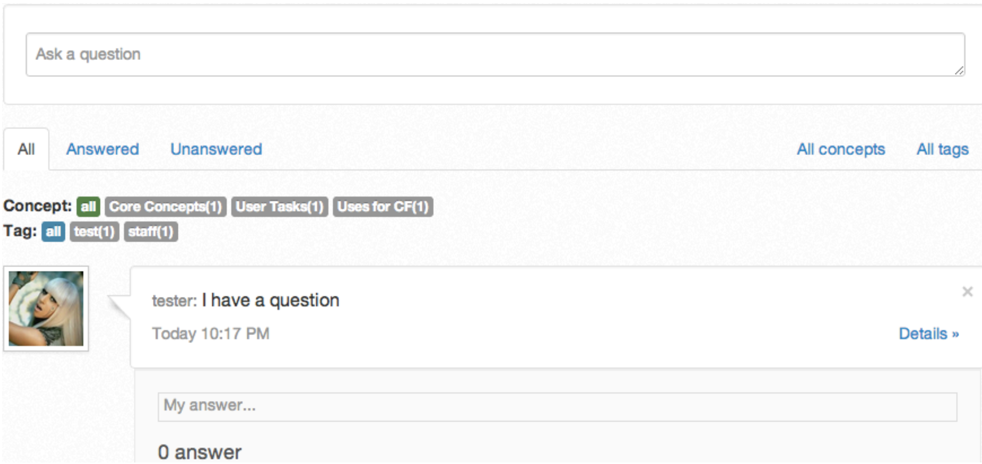

Figure 44 Q&A Centre – My questions

5.9 My answers

- Check questions that you have answered (Figure 45).

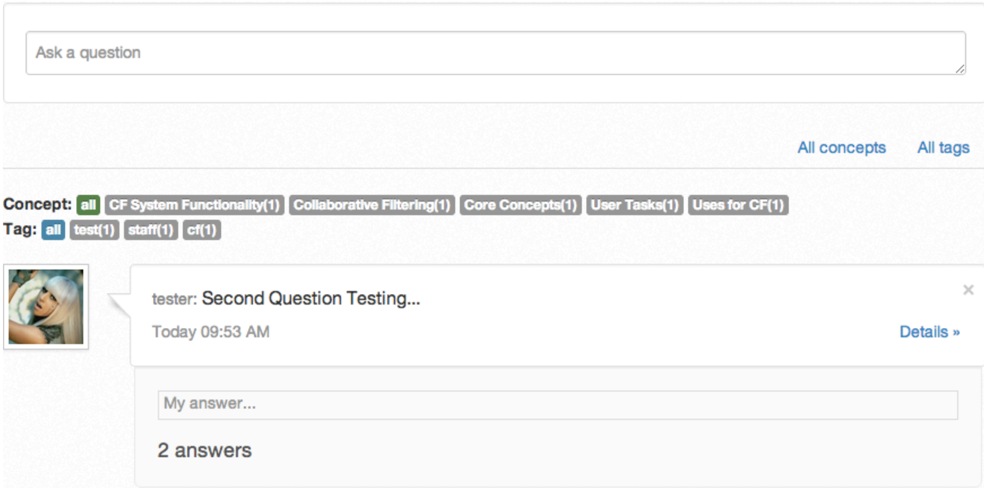

Figure 45 Q&A Centre – My answers

Designed by Shi Lei

Lei.Shi@dcs.warwick.ac.uk

Appendix J

User Interface of Topolor 2

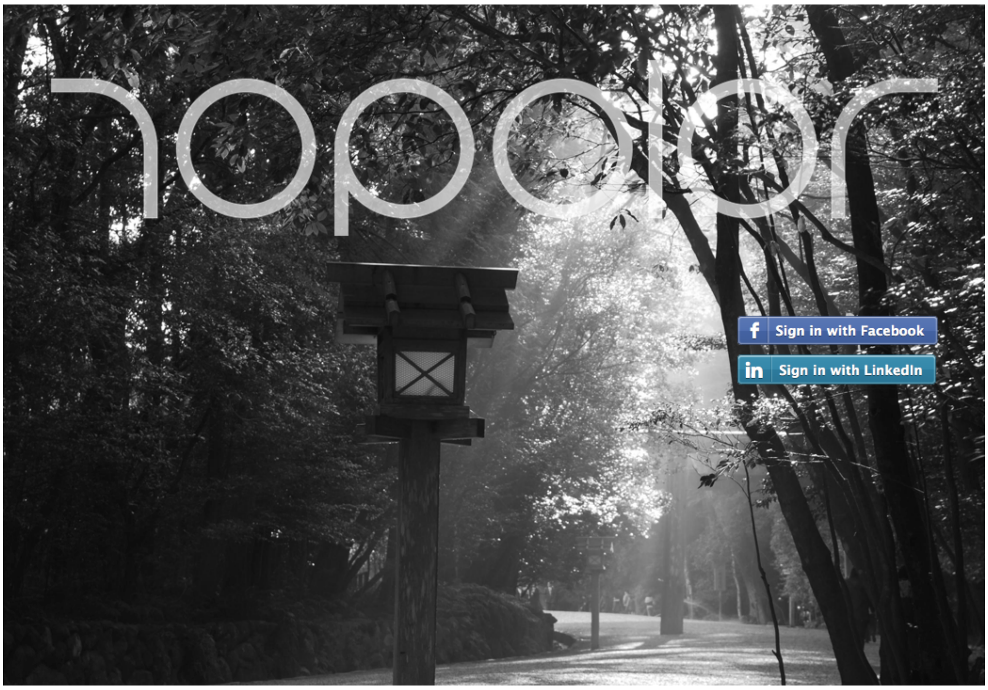

Figure 1 Sign In (when accessing to this Sign In page, Topolor randomly shows a background picture; learners can automatically login using their Facebook or LinkedIn account; Topolor builds learners' profile using their information, e.g., avatar and username, from their Facebook or LinkedIn account)

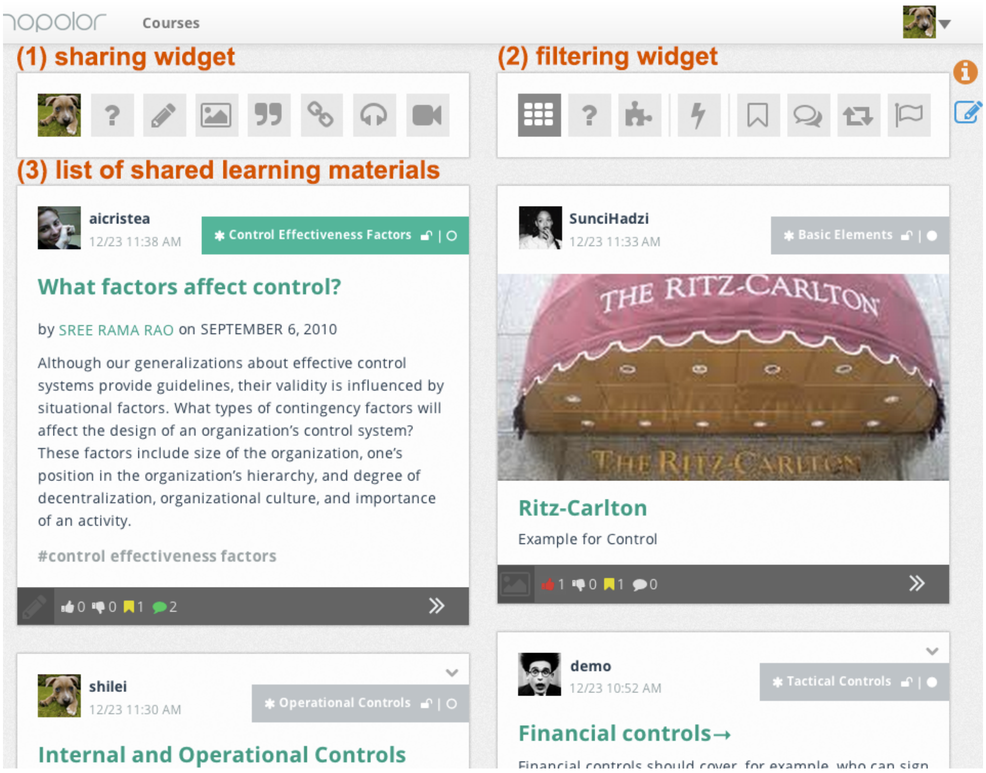

Figure 2 Homepage

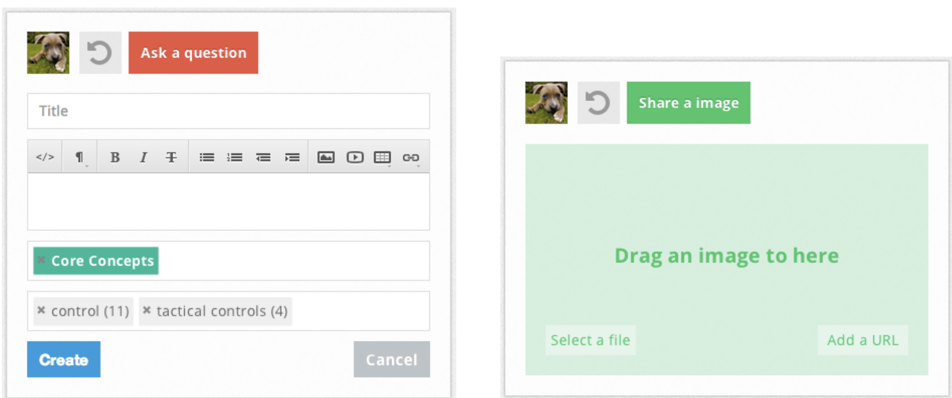

Figure 3 Sharing Tool (when clicking on the first icon of the sharing widget (Figure 2), the a panel for asking questions shows (left); when clicking on the third one, a panel for sharing a image shows (right))

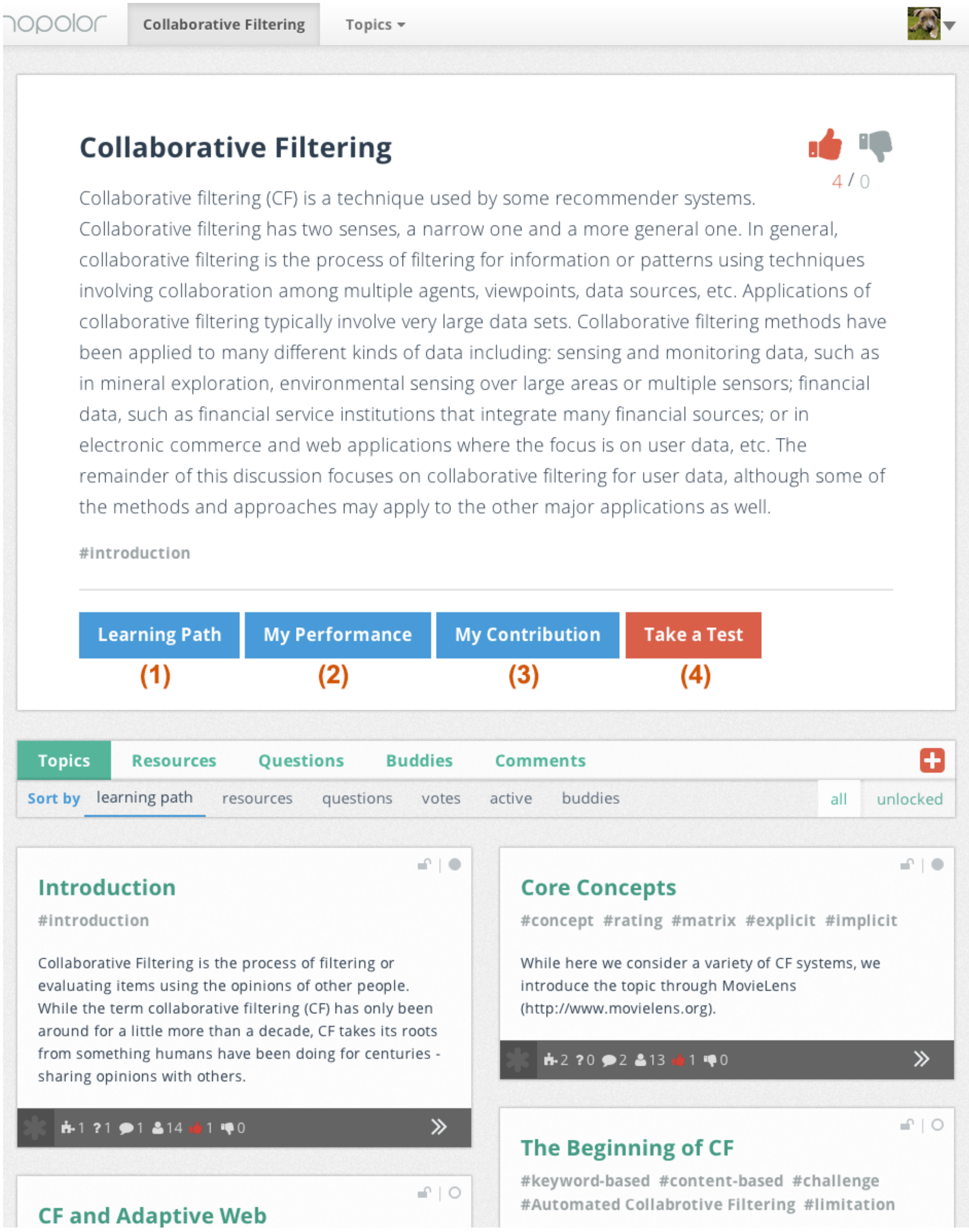

Figure 4 Course Page (when clicking on button (1), Learning Path pop-up view shows (see Figure 5); when clicking on button (2), My Performance pop-up view shows (see Figure 6-9); when clicking on button (3), My Contribution

pop-up view shows (see Figure 10); when clicking on button (4), Take a Test pop-up view shows (see Figure 11))

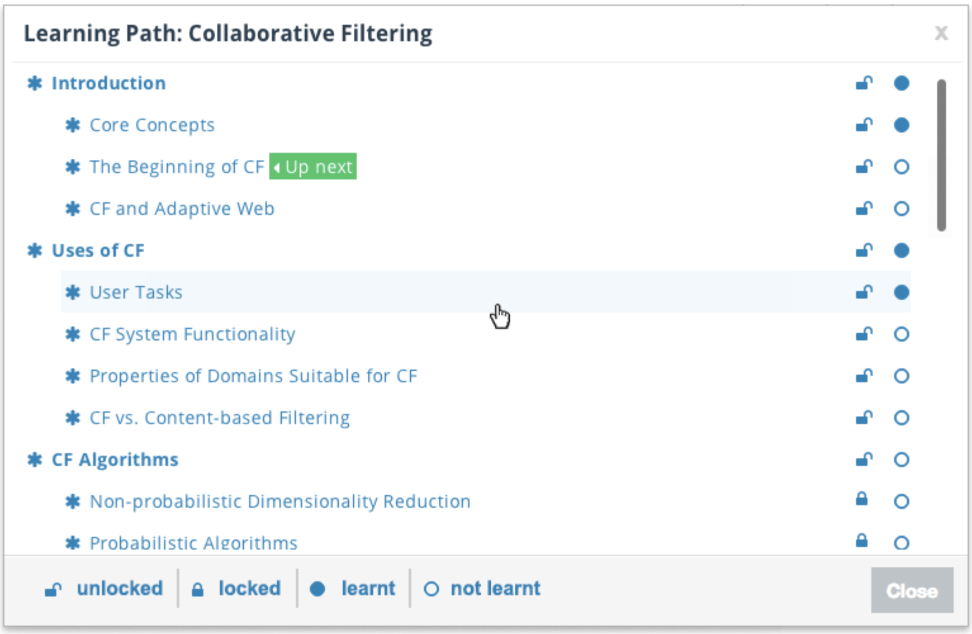

Figure 5 Learning Path (pops-up when clicking on (1) in Figure 4)

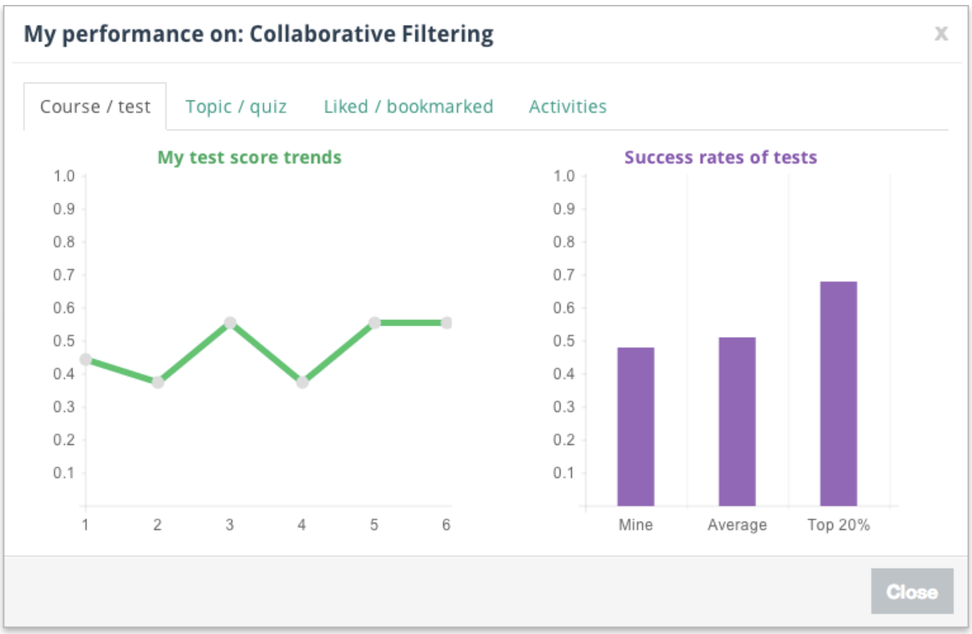

Figure 6 My Performance – Course/test

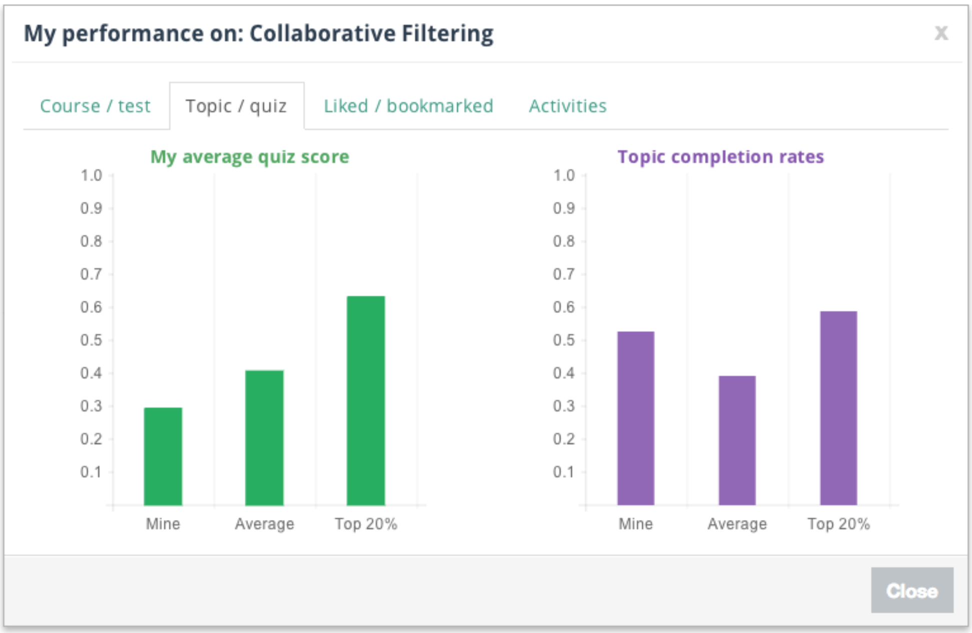

Figure 7 My Performance – Topic/quiz

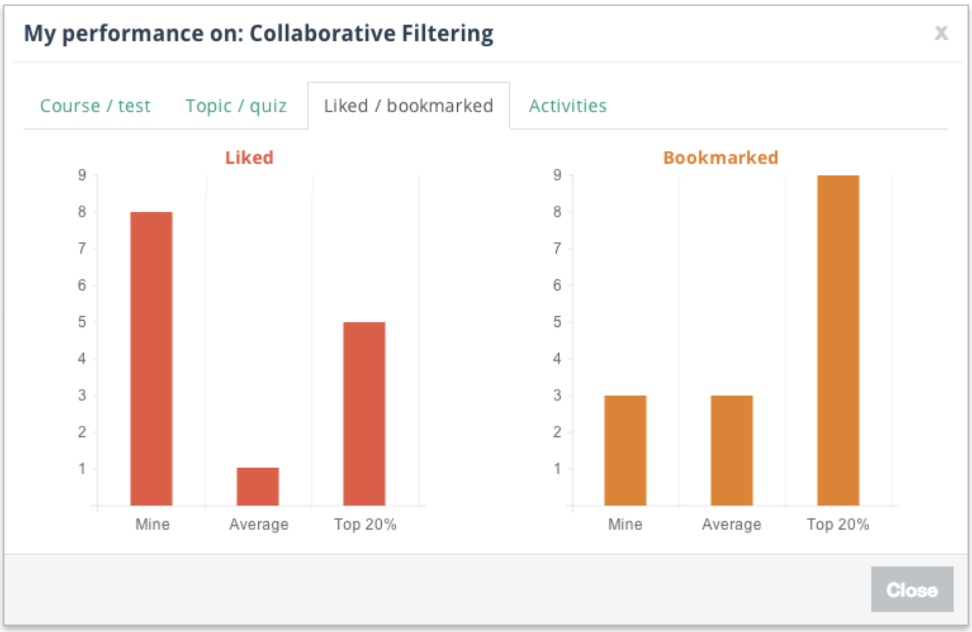

Figure 8 My Performance – Liked/bookmarked

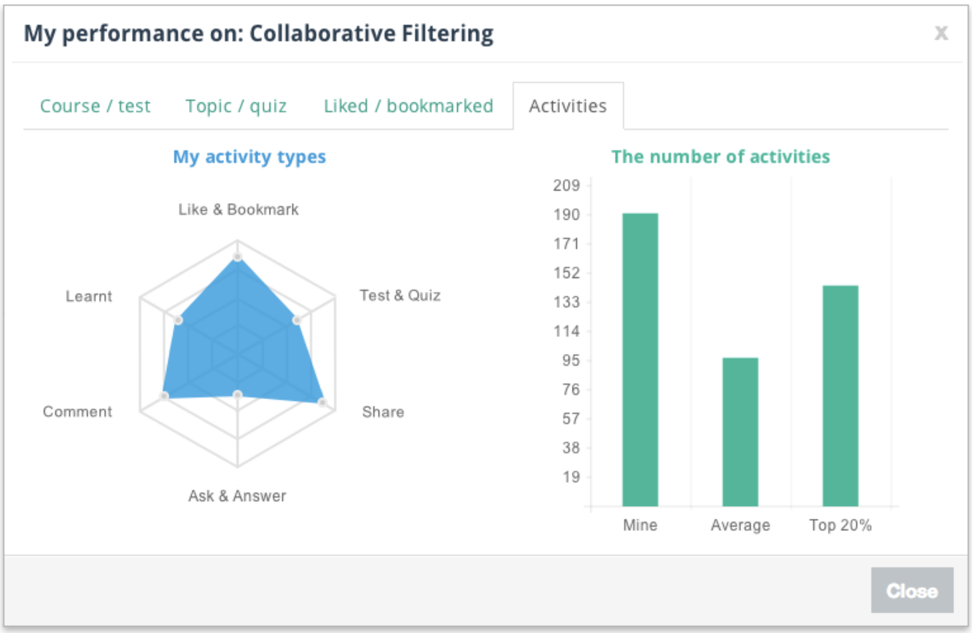

Figure 9 My Performance – Activities

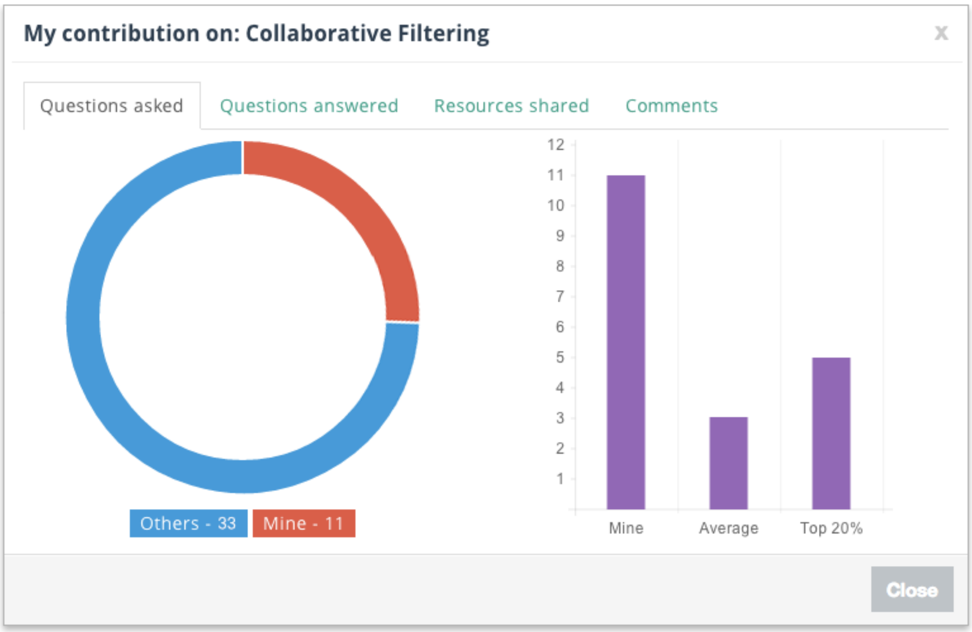

Figure 10 My Contribution – Questions asked

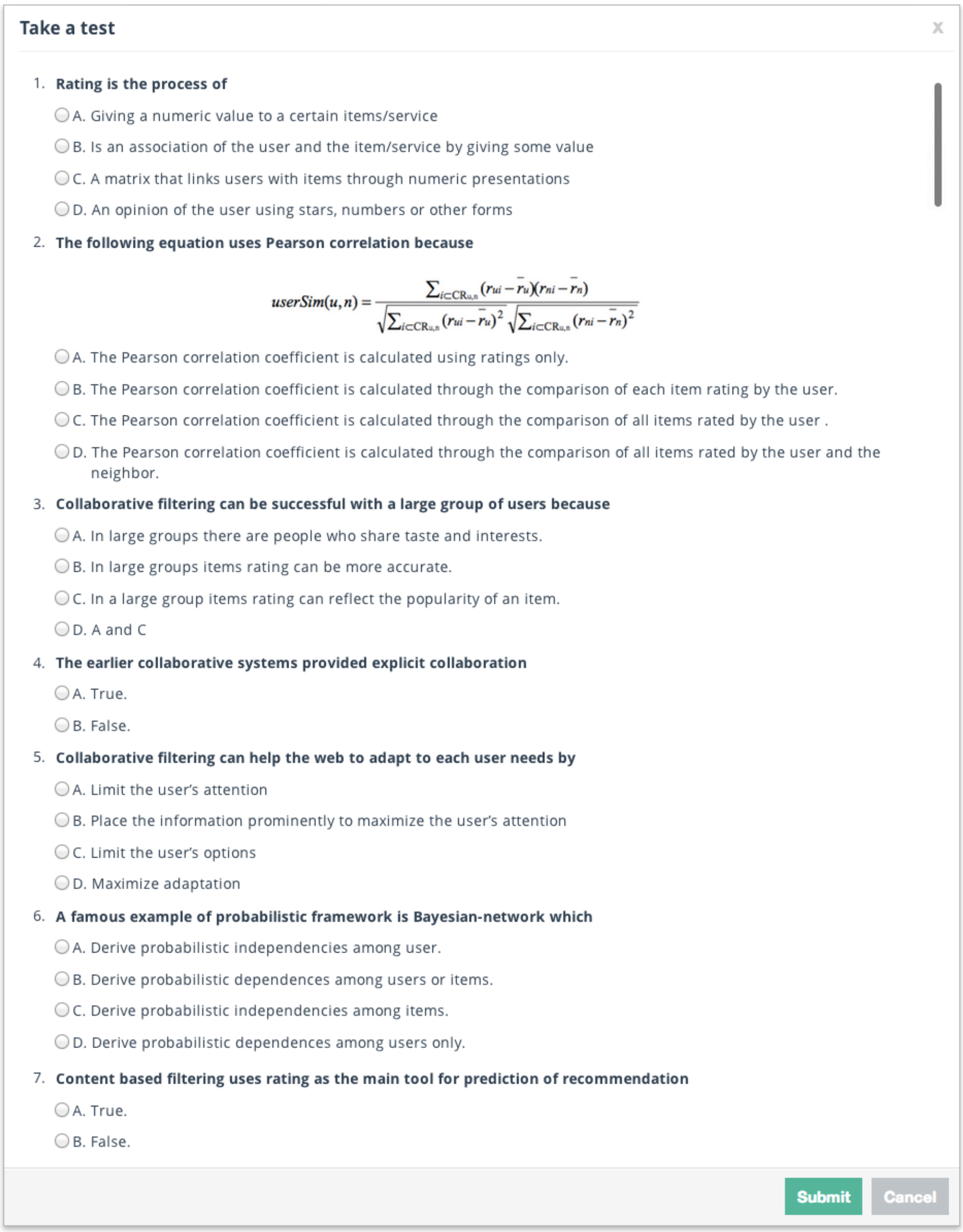

Figure 11 Test pop-up view (when clicking on the submit button the test result shows (Figure 12))

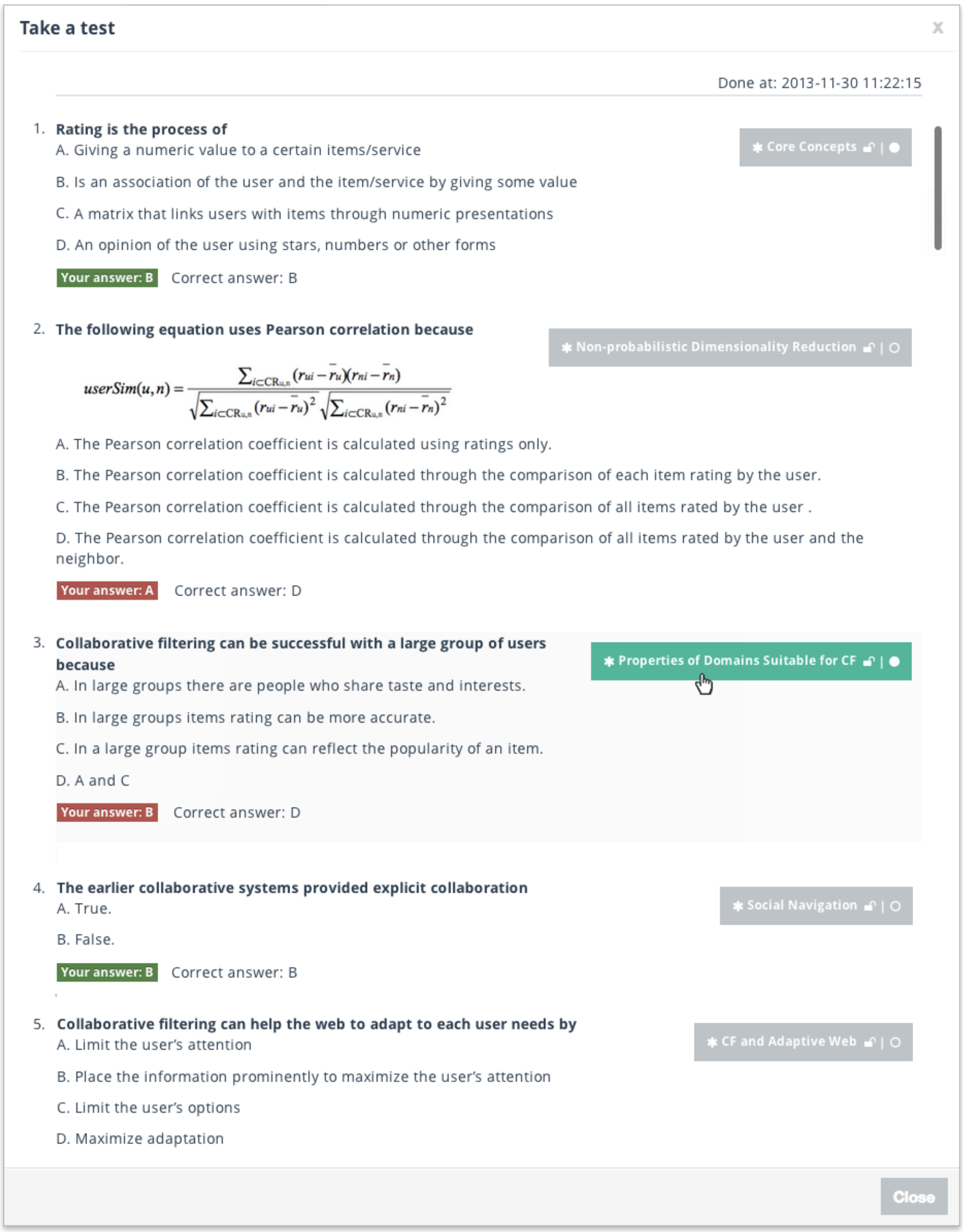

Figure 12 Test results – showing correct and incorrect answers and the related topics (when clicking on the topic title, the topic page shows (see Figure 13))

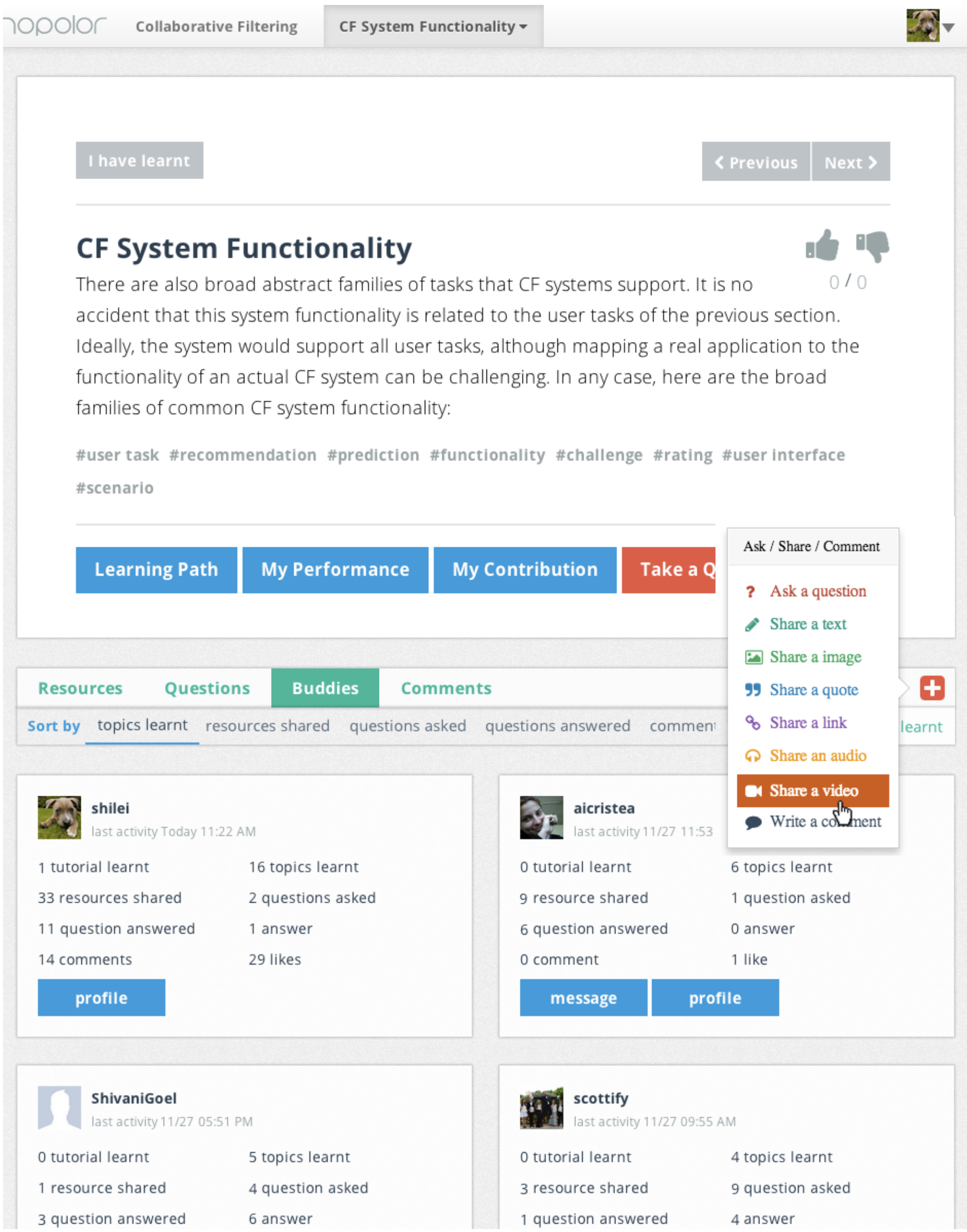

Figure 13 Topic Page – showing related resources, questions, learning peers, comments, etc. (when clicking on the Profile button, the profile page shows (see Figure 14))

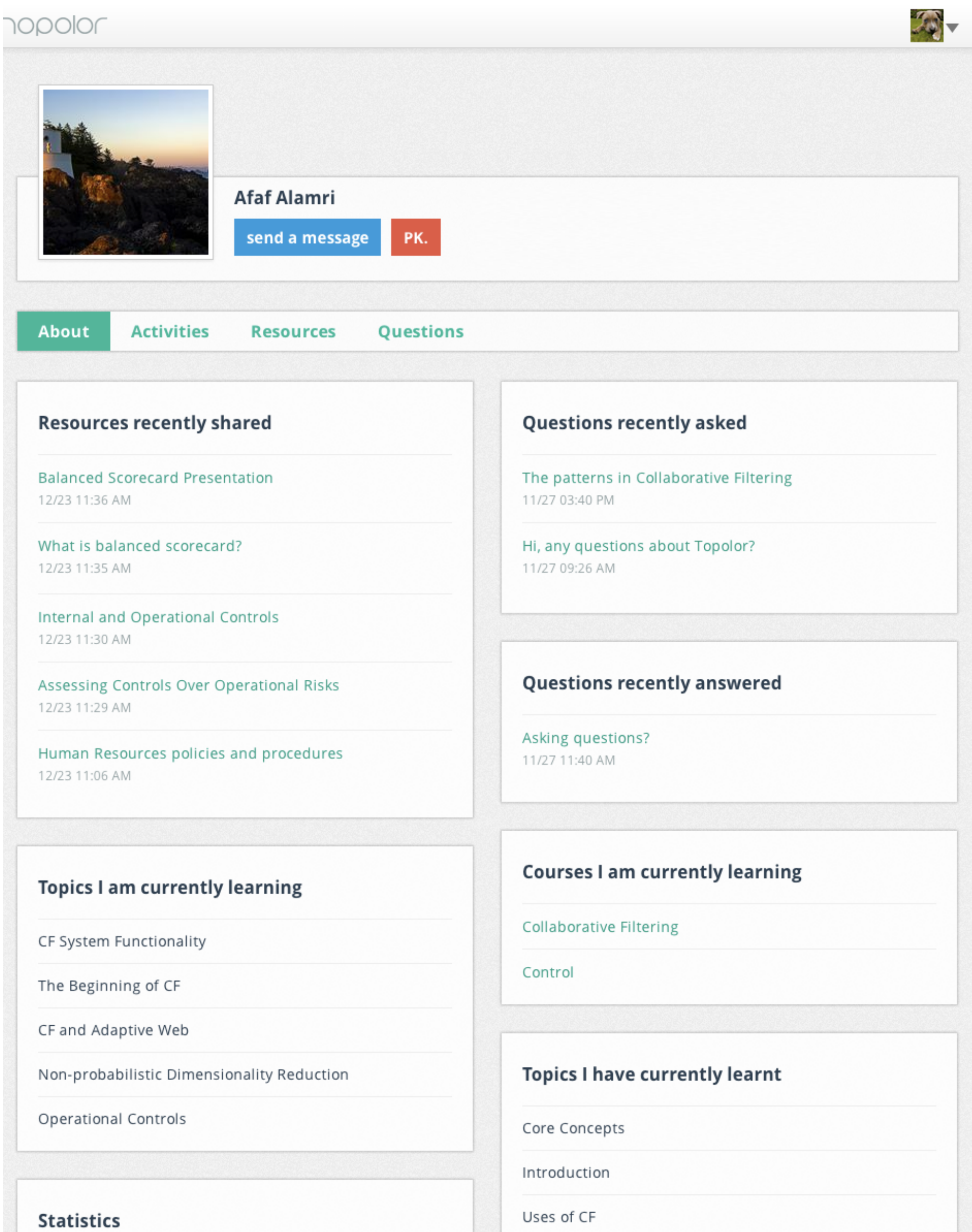

Figure 14 Profile Page – About Tap - showing overall activities of this learner's (when clicking on the PK. button, a comparison view shows (see Figure 15 and 16))

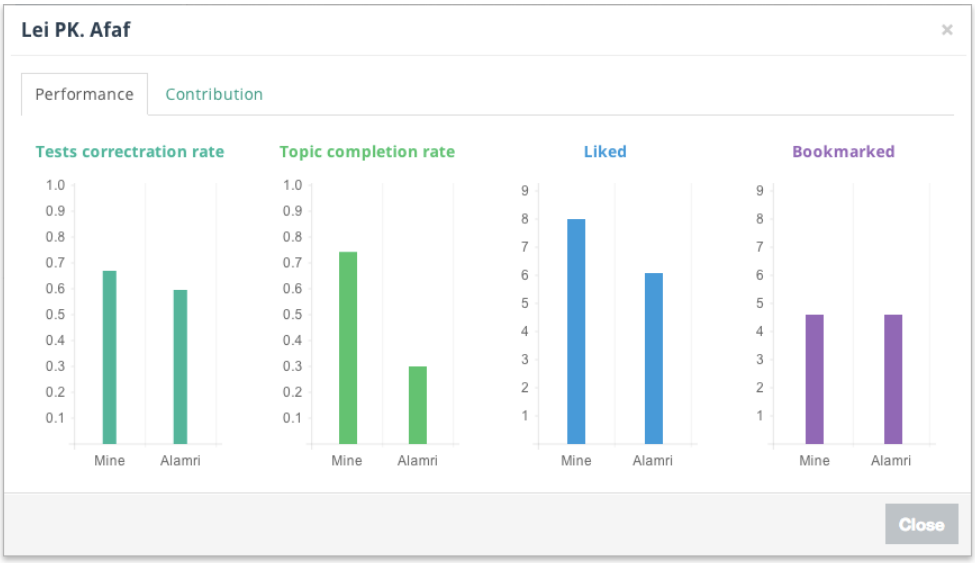

Figure 15 PK. – Performance (comparison)

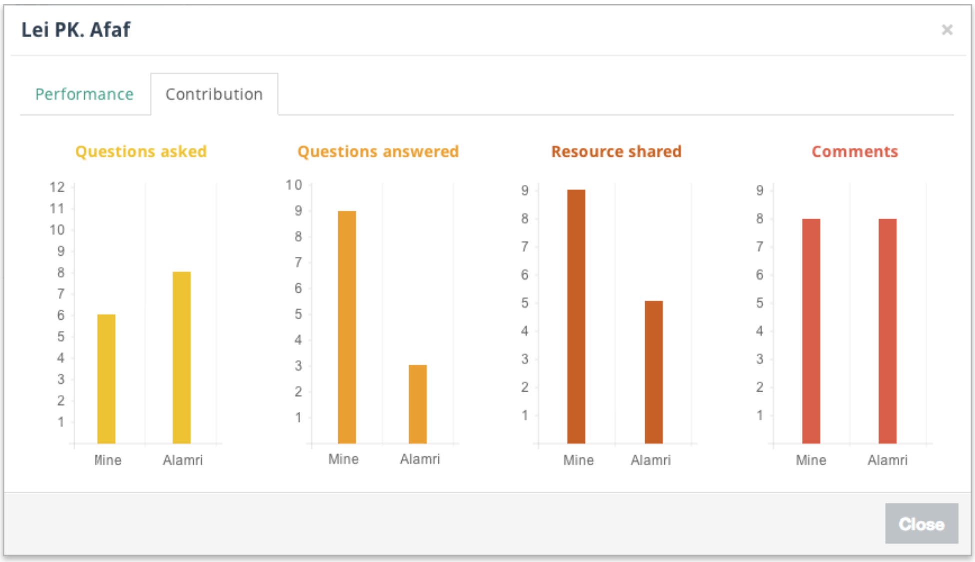

Figure 16 PK. – Contribution (comparison)

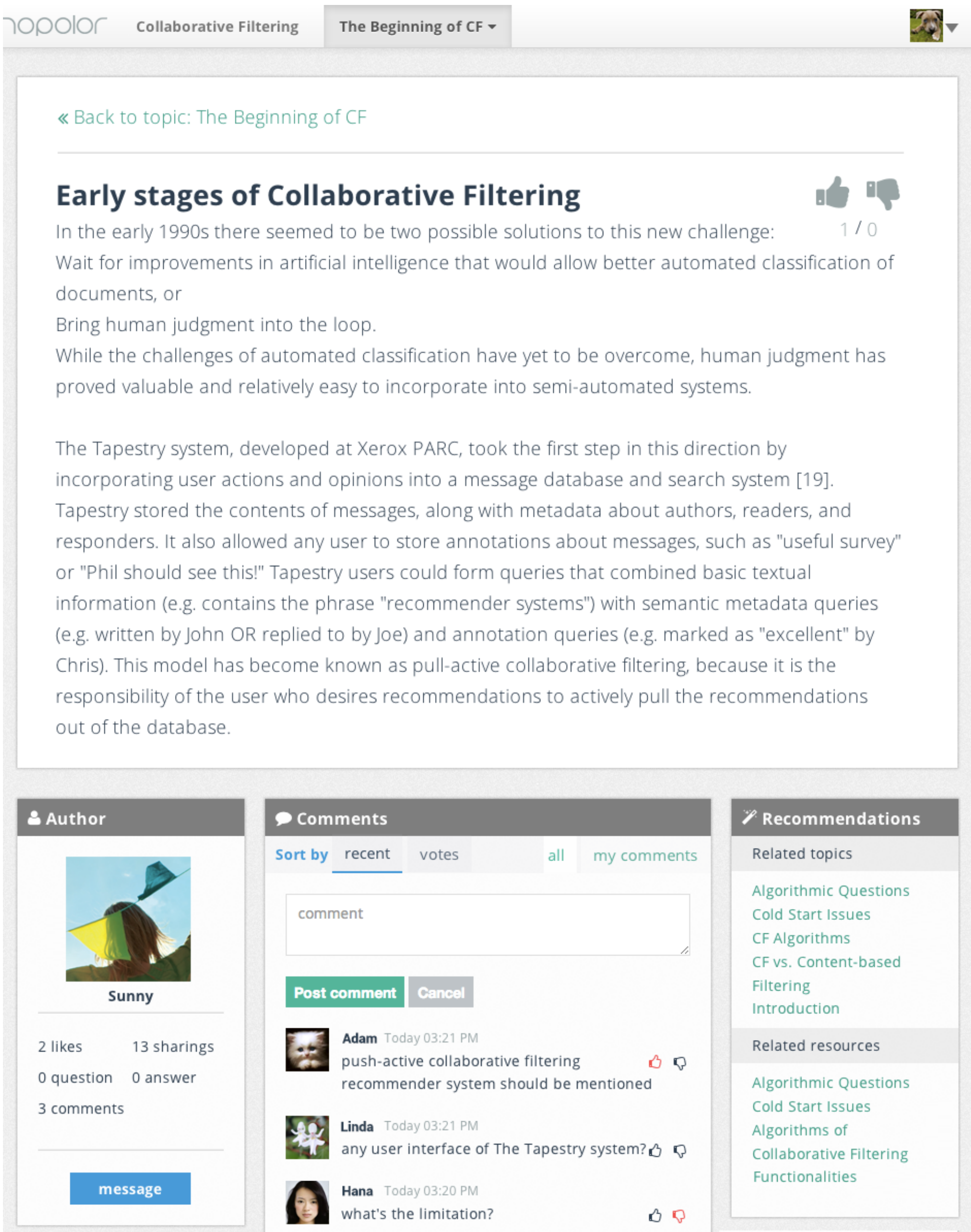

Figure 17 Resource Page

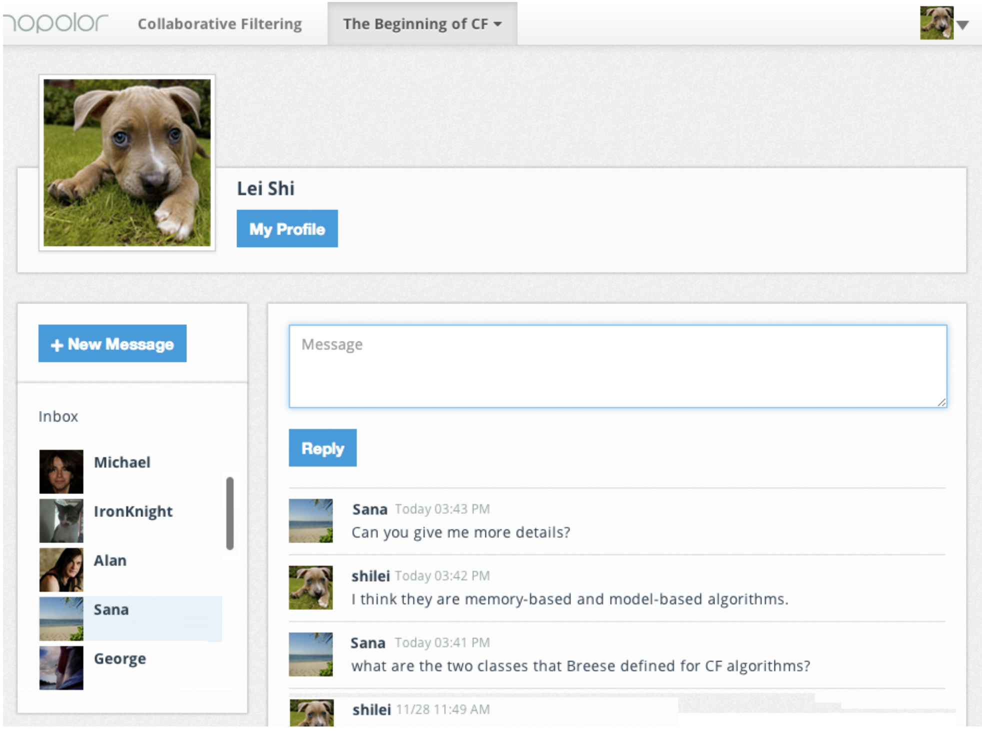

Figure 18 Message Page