Learners Thrive Using Multi-faceted Open Social Learner Modeling

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An experimental study shows that, contrary to previous research, the richness and complexity of multifaceted open social learner modeling (OSLM) positively affects the learning experience in terms of the perceived effectiveness, efficiency, and satisfaction.

Social e-learning has recently been brought to the fore, affecting people's lives via formal and informal learning channels.[1] Such learning is rooted in the social constructivist learning theory,[2] which proposes that learners can acquire new knowledge through social interactions with peers. However, successful social e-learning requires novel tools to help learners,[3] especially with the rise of Massive Open Online Courses (MOOCs), which provide a variety of learning materials and diverse connections and interactions.

Adaptive Educational Hypermedia Systems (AEHSs) have a built-in component of learner modeling that maintains and updates information about each learner. Systems can thus adapt to individual learners, reducing the cognitive burden placed on learners when presented with a variety of accessible resources. Traditionally, systems have used learner models only internally, but recent studies argue in favor of exposing such models to the learners. This approach, coined *Open Learner Modeling* (OLM),[4] makes it possible for learners to observe their own progress, which can potentially promote metacognition, including self-reflection, self-direction, and transparency.[2]

To diminish the impact of isolation in e-learning, more recent studies propose letting learners observe peer models and group models.[5] This new social OLM approach, called *Open Social Learner Modeling* (OSLM), exploits both the metacognitive and social aspects of learning.[6] We furthered this research by conducting a study aimed at

- building on the younger generation learners' familiarity with social Web techniques and online games, and their ability to navigate with ease in complex social spaces;
- combining the visualization of learner performance with contributions to a learning community;
- adapting the visualization of the OSLM itself to the context of the learner;
- introducing and studying multiple axes of visualization context: *hierarchical,* based on the structure of the course; *topical,* based on the topics studied; and *social,* based on the learner interactions and contributions; and
- building a complex and rich OSLM based on these principles and evaluating its effectiveness, efficiency, and satisfaction, as perceived by learners.

In particular, our study explored multifaceted Open Social Learner Modeling (multifaceted OSLM) in a social personalized adaptive e-learning system. We targeted the following research questions: What social and personal features should be provided to learners via OSLM? What related interactive visualizations can we offer to enhance social e-learning systems and thus ensure that a high level of effectiveness, efficiency, and satisfaction is perceived by the learners?

Related Work

Here, we review related work, focusing on the limitations in comparison with the work we present here.

The Social E-Learning Context

Nowadays, learners—especially those of the younger generation—are familiar with social

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Web techniques; they use, navigate, and function in social spaces daily.[7] These learners have different patterns of attention and learning preferences. Systems must cater to these preferences to improve the user experience, making it user-friendly, engaging, and efficient.[3] Traditional e-learning approaches thus should be adapted to the needs of this new "social Web generation," offering support for social learning.

To date, many works have successfully used social Web techniques in educational settings.[1] Principles for designing a social experience—such as those related to identity, connectedness, and communication—are conforming to modern learning theories, such as connectivism and constructivism,[2] which argue that the learning process needs to be constructed by collaborative efforts of individual learners in groups.[5] Furthermore, in the social e-learning context, learners can be both content *consumers* and *producers*.[8] They often produce content in a collaborative and competitive manner. For example, a question asked by one learner might trigger answers from other learners, and learners can discuss and rate these answers to find the best one. This is in line with contribution-based pedagogies and competitive learning theories.[9]

However, this area has not been sufficiently studied to explore how popular social Web techniques can be directly applied to help learners create and maintain their own personal learning systems in a collaborative and interactive social e-learning context. Moreover, most experimental results reported focus on a single social Web technique, whereas a combination of these techniques might be more adequate for learning scenarios. Our study sought a more comprehensive approach to combine various social Web techniques and use the combination directly in social e-learning systems.

OLM Approaches

Learner models refer to models of learners' knowledge and other characteristics such as needs, goals, interests, preferences, and learning styles. The models are constructed from direct input or implicit observation of learning activities, and they're updated according to the learners' current understanding of the target learning contents. OLM[4] can support learners as they reflect on their own and their peers' learning processes, and can help explain the reasons behind a certain recommendation regarding what to do next and how to do it.[10] OLMs have been implemented using various modeling approaches, and the literature thoroughly discusses their educational benefits—such as increased self-awareness and self-regulation during the learning process.[11]

Building on OLM, OSLM helps further diversify learner modeling; offers richer visualization of and interaction with learner models[4]; and accumulates a variety of theories and techniques to create personalized, adaptive, and social e-learning systems.

Several other recent studies also relate to this work. IntrospectiveViews[12] provides parallel views of models of a learner and his or her peers. Learners can compare their learning progress (marked as "completed," "partially completed," "pending," or "following" [that is, the next task]) with either another peer's learning progress or the average progress of the entire learning group. However, the comparisons have a limited level of granularity when representing the learning content.

QuizMap[13] has a four-level hierarchical representation of a tree-map, and the information presented ranges from the entire class's performance (level 4) to the individual's performance on a single question (level 1). Learners can also compare their own performance with the rest of the class. However, QuizMap can't accommodate larger classes, because they generate too many cells.

ProgressiveZoom[6] is built on the Google-Maps paradigm and seeks to reduce information overload by enabling learners to zoom in or out in a multilayer fashion. However, it has limited ability to control comparisons between learners.

Progressor+[14] can visualize the sequence of content learned, the learner's identity, interactivity information, and comparisons with other learners, motivating students to spend more time learning the system. However, the visualization is relatively simple, and the features are somewhat limited.

Other Related Research

Cross-disciplinary work touches on many areas, and we were also inspired by the vast and growing areas of gamification[15] and learner analytics.[16] Gamification mechanisms of interest to us were ensuring a fast response and emphasizing visualization and competitions. We borrowed from learner analytics to determine how best to gather and analyze user data.

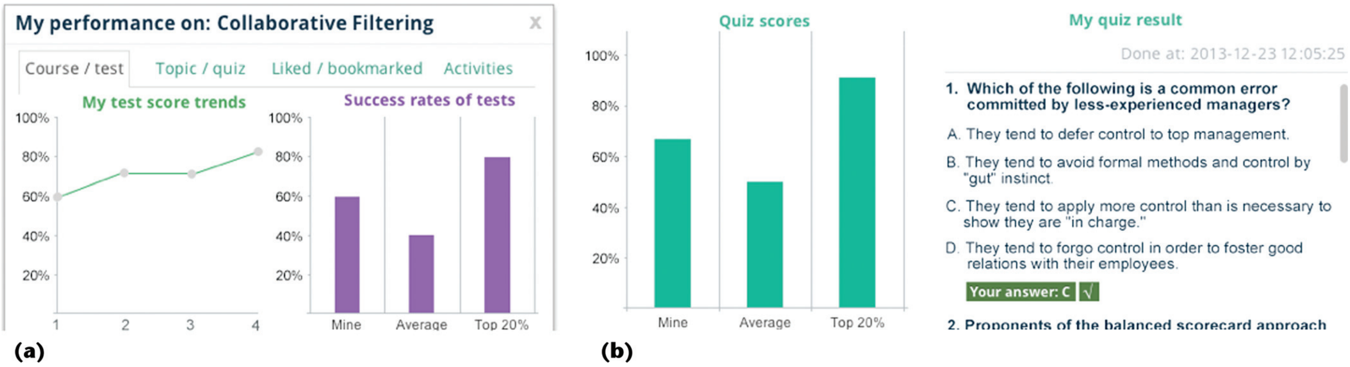

Figure 1. Performance visualization on a (a) course page and (b) topic page. Both exemplify comparisons between the current learner, the top 20 percent learners, and the entire class.

Multifaceted OSLM

We propose the new multifaceted OSLM approach, which is seamlessly integrated at all granularity levels—at the course level, topic level, resource level, and so on. This addresses the limited-level granularity learning content representations in IntrospectiveViews, and the concern of the overly crowded user interface in QuizMap. Moreover, multifaceted OSLM lets the learner compare his or her learning path, performance, and contribution to the "learning community" to individuals and groups, unlike in Progressive Zoom. Additionally, unlike other approaches, multifaceted OSLM is built with Facebook-like and popular game-like visualization, which potentially makes functionalities easier to use for today's learners.

Rationale

The proposed new OSLM approach is called "multifaceted" because learners can access their model and their peers' models ubiquitously, and the system can adapt visualizations to fit various contexts, corresponding to a classic hierarchy (with course, topic, resource, and profile pages). For example, in our approach, when viewing a learning content page, the multifaceted OSLM interface adapts to the content, so that the presentation of and comparison between learner models is in the context of this current learning content. This approach provides a finer, context-based granularity of the learner model visualization and reduces the learner's burden, because the process is automatic and doesn't require manual criteria selection to adjust the visualization.

Besides, this approach provides various comparison modes, such as between individuals or between an individual and a certain learner group or all other learners. These modes of multicontext and multicohort comparisons might lead to a greater engagement of learners by arousing their competitive instincts and thereby capturing their interest and increasing motivation, satisfaction, and fun.[9] This approach aims to introduce multiple functionalities without overwhelming users, instead of just opting for simplification, as in prior research.[15] Additionally, this approach visualizes a learner's performance and contributions, reflecting not only the learner's role as a knowledge consumer but also his or her role as a knowledge producer.

Visualization Type

Here, we briefly introduce five main *visualization types* of the multifaceted OSLM interface.

Performance visualization. This is one of the more common features in existing OSLM approaches,[13] and it's important because it can help motivate learners.[12] However, our performance visualization also introduces a timeline that presents test score trends (a less common feature in other approaches) and comparison features (such as a comparison of test success rates between learners). Figure 1 shows examples of performance visualization for tests, which includes a time chart and quizzes, for both a course page (Figure 1a) and a topic page (Figure 1b).

Both exemplify comparisons between the current learner, the top 20 percent of learners, and the entire class. Although these two examples show the performance visualization in different formats, both are triggered by clicking on the "My Performance" button, located in the same place on the two webpages. This exemplifies

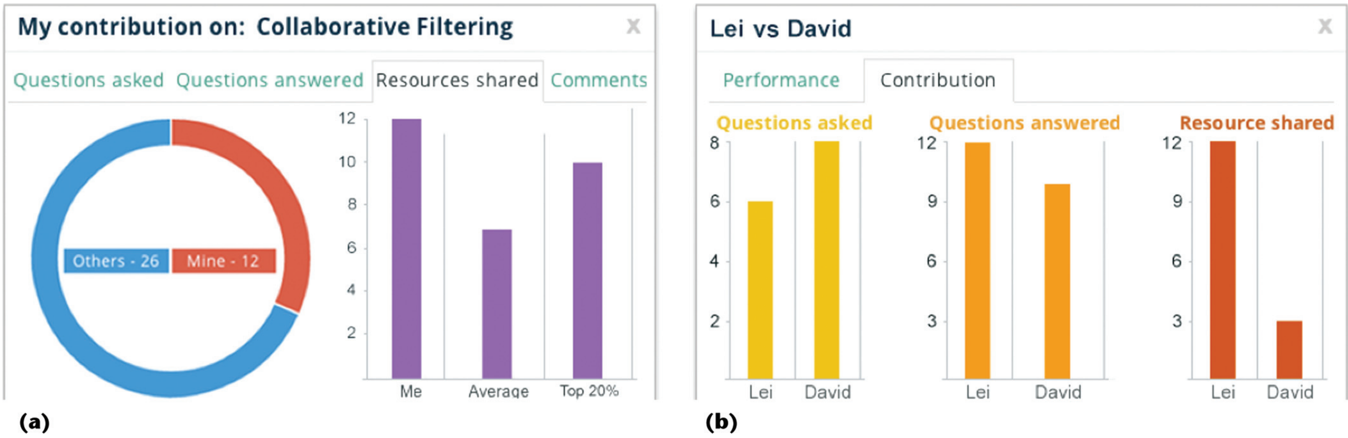

Figure 2. Contribution visualization: (a) the learner's contributions are compared to others and (b) the "vs" mode: a one-to-one comparison of contributions.

mechanisms introduced to reduce the learners' burden.

Contribution visualization. In social e-learning systems, learners become more than just passive recipients; they become authors of the learning content as well. They contribute by sharing, commenting, asking, and answering (see Figure 2a). Here, we support the notion that visualizing learners' contributions can encourage them to contribute more and become active members of the learning community, because seeing each other's contributions can stimulate imitation, collaboration, and competition.

Comparison visualization. This approach visualizes a direct comparison of the current learner's performance or contribution and the profile page's owner. For example, Figure 2b compares the contribution of Lei, the current learner, to David, another learner. Contributions include the number of questions asked and answered and resources shared. Performances include the number of tests with a passing grade, topic completion rates, and the number of shared resources that others have "liked" or bookmarked.

We implemented comparison visualization based on the competition-based learning theory and gamification,[15] which have shown that comparisons can help increase performance, enjoyment, and motivation.[9] We also wanted to visualize comparisons because of younger learners' familiarity with online games, where they are used to competing against each other on a one-to-one basis via avatars. (Privacy concerns raised by the disclosure of the learner model to others are not the main purpose of this study, so we don't directly address these concerns here.)

Learning path visualization. A learning path is visualized as a hierarchical tree, representing the entire course structure and the learner's progress. Figure 3a shows structured topics within the course: a hollow circle shows that the learner has not learned the topic; a solid circle shows that the learner has learned the topic; an unlocked lock shows that the learner is ready to learn this topic; a locked lock shows that the learner should finish learning all the prerequisite topics before starting to learn this topic; and the highlighted text, "up next," recommends the next most appropriate topic to learn. This gives the learner an overview of his or her progress.

This is made possible by combining content-based recommendation and learner modeling. Our approach differs from others, in which learners can access only recommended and previously seen material, by letting learners access locked topics. However, a confirmation-request step lowers the possibility of inadvertently accessing inappropriate topics while improving the adaptability, controllability, and accessibility of the system.

Learning activity visualization. The proposed approach exposes learners to their activity logs, as in another approach,[16] but it adds a social layer, in which learners can "like" or comment on each other's activity logs. This feature is designed based on our expectation that observing activity logs of learners and their

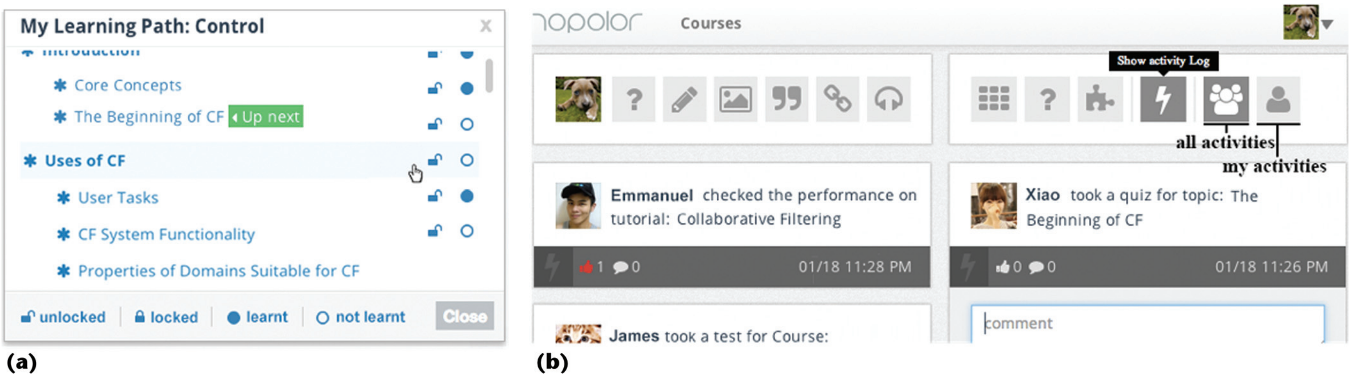

Figure 3. Learning path and learning activity visualization: (a) learning path visualization and (b) learning activity visualization on the home page.

peers' can stimulate interactions and better engage learners.

Furthermore, based on one of our design principles—allowing multiple ways of accessing functionality—the system provides two ways to view a learner's activity logs. One is on the main system page (Figure 3b), where a learner can filter to view his or her own activity logs or all learners' activity logs; the other is on a learner profile page, where a learner can view the profile owner's activity logs, including his or her own activity log, to allow various paths to information. As evident in Figure 3b, we use a Facebook-like appearance to build on the younger generation learners' familiarity with social Web techniques.

Use Case

The use case presented here demonstrates how a learner could use various multifaceted OSLM functionalities.

John is a postgraduate student taking an online course on collaborative filtering at the university. He has learned 16 out of 20 topics in the course using the system. He is taking a break and browsing randomly through the system. He arrives on the course page. He clicks on the "My Performance" button and a pop-up view appears. He then clicks on the "Topic/Quiz" tab, which compares his topic completion rate to that of all students and the top 20 percent students. He realizes that his topic completion rate (80 percent) is higher than the average (65 percent), but lower than the top 20 percent (90 percent). He believes he can reach the top 20 percent students and decides to start learning a new topic.

He clicks on the "Learning Path" button. He finds four new topics left to study, two of which are unlocked. Although the system recommends next studying "evaluation of accuracy," he is more interested in the locked topic "social navigation." Clicking on this topic title, the system reminds him that this topic is locked and asks for confirmation to start studying. He clicks on the "Yes" button and is then directed to this topic page.

After reading a few resources shared by other students, he notices that one student, Emilia, shares the most often. He is curious about Emilia's learning progress, so he clicks on her avatar. The system presents a pop-up view with options to send a message to Emilia or go to her profile page. John chooses the latter. Now he is on Emilia's profile page, which lists what she has done so far. The list shows recently asked questions, recently shared resources, and current topics she's learning.

John clicks on the "vs" button and a pop-up view compares his performance with Emilia's, including test scores, contributions, and comments. Indeed, Emilia has shared many resources and has asked many questions. John closes this view and goes to Emilia's questions list. At the top of the list a question regarding "collaborative filtering in the Python implementation," which has received the most "likes" and "bookmarks." John reads several answers from other students and then writes down his answer.

Experimental Study

To evaluate the proposed multifaceted OSLM approach, we conducted two experiments during two real-world university courses.

Methodology

The first experiment was conducted at the University of Warwick, UK, where 15 postgraduates were learning a course on collaborative filtering using Topolor 2.[17] The experiment included four stages:

- two time-controlled one-hour learning stages (students sat in a classroom);
- one flexible (nontime-controlled) learning stage (students accessed Topolor 2 at their preferred time and location); and
- the survey stage (coordinator-led optional questionnaire answering—the coordinated asked questions functionality by functionality, ensuring students understood the functionality to which the question referred).

Students were explicitly told that their participation in the survey had no impact on course results. Ten students submitted questionnaires.

The second experiment was conducted at the Department of Economics, Sarajevo School of Science and Technology, Bosnia and Herzegovina, where 20 undergraduates, two observers, and one course instructor participated in the 1.5-hour online learning session, using Topolor 2 to teach/learn a course on control (management). After the online learning session, students were encouraged to further use Topolor 2 to revise the learning materials for two weeks (allowing for a longitudinal study). Then, students were asked to complete an optional online survey. Fifteen students completed the same online survey as in the first experiment. In total, 25 questionnaires were collected from the two experiments.

Traditionally, e-learning system evaluation has mainly relied on the accuracy of content recommendation and learners' performance—that is, on test scores. This evaluates the perceived learning impact. However, over the years, researchers have reached a consensus on the necessity of taking into consideration cognitive aspects, such as learners' perception of system usage, including effectiveness, efficiency, and satisfaction. ISO 9241-11 defines effectiveness as "the accuracy and completeness with which specified users can achieve specified goals in particular environments."[18] It defines efficiency as "the resources expended in relation to the accuracy and completeness of goals achieved," and defines satisfaction as "the comfort and acceptability of the work system to its users and other people affected by its use."[18]

Our work evaluated learners'

- perceived effectiveness, asking if the multifaceted OSLM functionalities were useful (for their goals);
- perceived efficiency, asking if the functionalities were easy to use (effort required); and
- satisfaction, asking learners to score a set of statements.

To determine which functionalities should be provided, it is important to evaluate both their perceived usefulness and ease of use. This helps determine if a certain functionality is important, needs better implementation, or should be removed.

Effectiveness and Efficiency

Forty-eight multifaceted OSLM functionalities (shown in Tables 1 and 2) were individually evaluated on a five-point Likert scale, ranging from –2 (very useless/hard to use) to 2 (very useful/easy to use). Table 1 lists functionalities that appear on the homepage and course page, while Table 2 lists functionalities that appear on the topic, resource, and profile pages. Tables 1 and 2 also include the means, medians, and standard deviations (SDs) for the evaluation results.

The results indicate that the proposed multifaceted OSLM approach positively affects the learner's perceived effectiveness, given that the means are greater than the neutral response (0), ranging from 0.56 to 1.76, with medians between 1 and 2 and an SD between 0.37 and 0.76.

Similarly, the approach is perceived as leading to an even higher degree of efficiency, with means between 1.70 and 1.76, medians between 1 and 2, and an SD between 0.37 and 0.60. This is encouraging, because it could further support our hypothesis that using a Facebook-like appearance and a game-inspired paradigm can quickly transform learners into expert users of the system. Moreover, the results are reliable, as indicated by Cronbach's alpha for usefulness (.85) and ease of use (0.8).

In analyzing the extreme means, results show that functionality 45, "statistics for the profile's owner," received the highest mean for usefulness. This indicates that learners are very interested in seeing overviews of their own activities and comparing them to their peers' activities. This might also indicate the success

Table 1. Multifaceted OSLM functionalities appearing on the homepage and course page, and the evaluation results. The minimum and maximum values appear in bold.

	Multifaceted OSLM functionality	Usefulness (effectiveness)			Ease of use (efficiency)		
Visualization type	**Homepage**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**
Learning activity	1. Filter by everyone's activities	1.20	1	0.58	1.12	1	0.44
	2. Filter by my activities	**1.40**	1	0.50	**1.00**	1	0.50
	Course page						
Learning path	3. Learning path—tree view*	1.20	1	0.58	1.48	2	0.59
Performance	4. Performance—pop-up view*	1.12	1	0.67	1.32	1	0.48
	5. Score trends—line chart*	0.84	1	0.75	**1.68**	2	0.48
Contribution	6. Contribution—pop-up view*	1.08	1	0.64	1.44	1	0.51
Performance and comparison	7. Test success rates—bar chart†	1.00	1	0.58	1.24	1	0.52
Performance	8. Average quiz score—bar chart†	1.08	1	0.49	1.12	1	0.60
	9. Topic completion—bar chart†	0.92	1	0.40	1.16	1	0.47
Learning activity	10. Number of activities—bar chart†	0.92	1	0.57	1.32	1	0.56
Performance	11. Bookmarked—bar chart†	0.80	1	0.58	1.48	1	0.51
Contribution and comparison	12. Questions asked—bar chart†	0.92	1	0.49	1.36	1	0.49
Performance	13. "Liked"—bar chart†	1.00	1	0.41	1.28	1	0.54
Contribution	14. Questions answered—bar chart†	1.08	1	0.64	1.52	2	0.51
Performance and learning activity	15. Activity types—radar chart*	0.84	1	0.69	1.52	2	0.51
Contribution and comparison	16. Questions asked—donut chart‡	0.84	1	0.69	1.60	2	0.50
	17. Resources shared—bar chart†	0.88	1	0.53	1.24	1	0.52
	18. Questions answered—donut chart‡	**0.76**	1	0.52	1.36	1	0.57
	19. Comments—bar chart†	1.00	1	0.65	1.40	1	0.50
	20. Resources shared—donut chart‡	0.88	1	0.67	1.16	1	0.55
	21. Comments—donut chart‡	0.88	1	0.53	1.44	1	0.51

*Current student's data
†Comparison between current student, the whole class, and the top 20**%** of the class.
‡Comparison between current student and rest of the class

of our approach in exposing learner data and supporting various comparisons.

Interestingly, functionality 46, "waterfall list of activity logs," received the highest mean for ease of use, but the lowest (while still high) mean for usefulness, suggesting that this functionality might need to be removed or improved. For example, perhaps a future system could also suggest further actions that learners could perform, which might increase the functionality's usefulness. Similarly, a moderate mean was received by functionality 18, "questions answered," which indicates that students might need more encouragement to help their peers and answer their questions. Longitudinal follow-up studies are planned to clarify this.

Students were also not enthusiastic about functionality 11, "bookmarked," but they might not have fully understood the benefit of having their own bookmarks, especially given that the system would "remember" what they would need to read next.

Table 3 aggregates the results according to visualization type. The averages in this table are computed as a mean of all multifaceted OSLM functionalities created for that particular type of visualization, as shown in the first two columns of Tables 1 and 2.

Table 3 shows, in a more compact way, that while both the usefulness and ease of use categories were highly rated, the tool's ease of use, for all visualization types, is higher. This specifically supports our visualization approach. From the usefulness viewpoint, the learning path visualization was most appreciated—possibly because it is the most well-known. Learners also liked

Table 2. Multifaceted OSLM functionalities appearing on the topic, resource, and profile pages (see Table 1 for functionalities 1–21), and the evaluation results. The minimum and maximum values appear in bold.

	Multifaceted OSLM functionality	Usefulness (effectiveness)			Ease of use (efficiency)		
Visualization type	**Topic page**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**
Learning path	22. Learning path—tree view*	1.56	2	0.51	1.64	2	0.49
Performance	23. Performance—pop-up view*	1.32	1	0.48	1.64	2	0.49
Contribution	24. Contribution—pop-up view*	1.36	1	0.70	1.60	2	0.50
Contribution and Comparison	25. Questions asked—donut chart‡	1.24	1	0.60	1.52	2	0.59
	26. Questions asked—bar chart†	1.16	1	0.55	1.40	1	0.58
	27. Questions answered—donut chart‡	1.24	1	0.60	1.64	2	0.49
	28. Resources shared—bar chart†	0.96	1	0.45	1.24	1	0.52
	29. Questions answered—bar chart†	0.96	1	0.54	1.48	1	0.51
	30. Comments—bar chart*	0.96	1	0.54	1.20	1	0.50
	31. Resources shared—donut chart‡	1.20	1	0.50	**1.08**	1	0.40
	32. Comments—donut chart‡	1.16	1	0.37	1.72	2	0.46
Performance	33. My quiz results—pop-up view*	1.60	2	0.50	1.56	2	0.51
	34. View quiz scores—bar chart†	1.24	1	0.44	1.56	2	0.51
	Resource page						
Learning activity	35. Author's name and stats	1.04	1	0.54	1.16	1	0.55
	Profile page						
Performance	36. Check my performance	1.60	2	0.50	1.64	2	0.49
Contribution and Comparison	37. Check my contribution	1.12	1	0.53	1.64	2	0.49
Comparison	38. "vs" compare me with another	1.24	1	0.44	1.28	1	0.54
Contribution and Comparison/ learning activity	39. List of resources shared	1.48	1	0.51	1.16	1	0.37
	40. List of questions asked	1.52	2	0.51	1.56	2	0.51
	41. List of questions answered	1.28	1	0.54	1.20	1	0.41
Performance and learning path/ learning activity	42. List of courses learned	1.48	2	0.59	1.32	1	0.48
	43. List of topics learned	1.44	1	0.58	1.20	1	0.50
	44. List of topics learned	1.36	1	0.64	1.44	1	0.58
Performance	45. Statistics for the profile's owner	**1.76**	2	0.44	1.20	1	0.41
Learning activity	46. Waterfall list of activity logs	**0.56**	1	0.71	**1.76**	2	0.44
	47. Like an activity log	1.00	1	0.76	1.52	2	0.59
	48. Comment on an activity log	1.20	1	0.65	1.24	1	0.44

*Current student's data
†Comparison between current student, the whole class, and the top 20% of the class.
‡Comparison between current student and rest of the class

knowing about their own performance and that of others, showing that the openness of the learner model, together with its visualization techniques, was highly regarded. Contribution and comparison, although considered very easy to use, were considered only moderately useful.

Given that these are novel features, some initial reluctance in the acceptance is to be expected. Having passed the difficult and important hurdle of usability, it is clear that more work is needed to better analyze these functionalities. Our planned longitudinal studies can bring more insight, because the usefulness of peer interactions is likely only evident in longer-term use (due to known issues—such as the "cold start" problem). Such studies will show if more or different motivational elements are needed to induce peers to contribute more often while still keeping in place or extending mechanisms for quality-of-contribution checks. As this study suggests, the complexity of the functionality offered—a major issue in any new system, but especially in e-learning systems—should be balanced with good visualization techniques based on familiar paradigms. This can open up avenues for further research, focusing on functionality optimization.

Table 3. Results per visualization type.

	Usefulness (effectiveness)			Ease of use (efficiency)		
Visualization type	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**
Performance	1.21	1.18	0.31	1.40	1.44	0.18
Contribution	1.09	1.08	0.21	1.40	1.40	0.18
Comparison	1.08	1.00	0.21	1.38	1.38	0.18
Learning path	1.41	1.44	0.14	1.42	1.44	0.17
Learning activity	1.19	1.24	0.29	1.32	1.28	0.21

Table 4. Statements in the satisfaction questionnaire and the results. The minimum and maximum values appear in bold.

#	Statement	Mean	Median	SD
S01	Topolor helped me to learn more topics.	0.64	1	0.71
S02	Topolor helped me to learn more profoundly.	0.92	1	0.81
S03	Topolor helped me to identify my weak points.	0.72	1	0.61
S04	Topolor helped me to plan my classwork.	**0.52**	1	0.51
S05	Topolor increased my learning interests.	**1.52**	2	0.51
S06	Topolor increased my learning confidence.	**0.52**	1	0.51
S07	Topolor increased my learning outcome.	0.76	1	0.60
S08	It was easy to use Topolor.	1	1	0.65
S09	It was easy to learn how to use Topolor.	1.24	1	0.66
S10	It was easy to remember how to use Topolor.	1.08	1	0.70
S11	It was easy to discuss with peers.	0.80	1	0.58
S12	It was easy to share content with peers.	1	1	0.58
S13	It was easy to access the content shared by peers.	1	1	0.50
S14	It was easy to tell peers what I liked/disliked.	1.12	1	0.67
S15	The statistical numbers (mine & peers') engaged me to learn more.	1	1	0.65
S16	Topolor helped me engaged in interacting with peers.	1.2	1	0.50

Satisfaction and Learning Impact

Table 4 shows 16 statements (S01–S16) designed to evaluate the learners' satisfaction—in particular, their perceived learning impact (S01–S07). These statements were measured on a five-point Likert scale, ranging from –2 (strongly disagree) to 2 (strongly agree). The table also shows that the means are greater than the neutral response (0), ranging from 0.52 to 1.52, and the medians are between 1 and 2, with an SD between 0.51 and 0.81. In this case, Cronbach's alpha of 0.80 indicates a good level of reliability.

These results indicate that the learners were generally satisfied with the multifaceted OSLM functionalities, and that the perceived learning impact was positive—even very high in some areas. For example, statement S05, "Topolor increased my learning interests," received the highest mean (1.52). This is encouraging, because motivating the new generation of learners was an important aspect of our approach. Nevertheless, statement S04, "Topolor helped me to plan my classwork," and S06, "Topolor increased my learning confidence," received the lowest (while still high) scores. These results suggested we need to further enhance the approach. For example, in the future, we could allow learners to manipulate their classwork plan based on system recommendations.

Discussion and Future Studies

To reduce bias, we conducted two experiments involving students from different disciplines: computer science and economics. Computer science students (participating in the first experiment) might have a better understanding of system development, so their responses might not purely reflect perceptions about the learning process. The two different student groups, despite potential advantages, could have introduced additional problems, such as variety in data, not allowing for a coherent combined analysis. However, the settings of the two experiments were similar to prevent such problems. For example, both contained time-controlled and nontime-controlled learning processes, and both used the same questionnaire. Indeed, the separate pilot analysis on the data showed that both sets of results were very similar.

The results might appear counterintuitive, because you would think that the high number of functionalities would be complex for learners. However, using a Facebook-like appearance and a game-inspired paradigm quickly transformed learners into expert users of the system. Due to the low number of learners, no definite conclusions can be drawn, and the results are illustrative. However, because the learners individually scored these functionalities, we were able to receive initial feedback for individual functionalities and some measure of their relative importance. This suggests answers for the research question of what features and visualizations should be provided via OSLM—such as functionality 45, "statistics for the profile's owner." Follow-up longitudinal experiments are already running at Jordan University and Pittsburgh University to further delve into what features are important and why. Overall, evaluation results have revealed the potential benefits of applying the proposed multifaceted OSLM approach in social personalized adaptive e-learning. The high means and medians of the Likert-scale questionnaire survey results, along with the high reliability scores, suggest that this approach is promising.

In this experimental study, because the system was new to learners, we found that students performed many exploratory activities. For example, some of them tried various functionalities in a relatively short period of time. This did not demonstrate a focused learning process. However, such behaviors might also occur when learners are familiar with the system—such as when they are bored or lost, thereby randomly checking out various functionalities. Therefore, we've planned further longitudinal studies to analyze any changes in behavior with learners who are more familiar with the system. Nevertheless, these exploratory behaviors did not obstruct the importance of the results and lessons learned, because students' exploration allowed them to consider and provide feedback on various types of individual functionality.

Moreover, it's important to understand learner performance when evaluating an e-learning system. Topolor 2 lets students store various quiz and test results and maintain a learning record status of what's "known," "unknown," or "being learned." These learning records are similar to those appearing in traditional user modeling approaches in adaptive educational hypermedia. However, the exploratory behaviors kept learners from taking a sufficient amount of quizzes and tests, so we couldn't evaluate objective learning outcomes and performances. Although the focus of the study was to investigate subjective perception of effectiveness, efficiency, and satisfaction, this has been a limitation. However, we asked students specific questions about their perceived learning impact, and current outcomes are positive. Moreover, the follow-up experiments in Jordan and Pittsburgh should help address these limitations. We have also planned more controlled experiments, in which we will collect more quiz and test scores from students.

Furthermore, although most visualizations of comparisons between learners and their learning group—such as the top 20 percent of class learners—hide other learners' data, the "vs" mode does not, which might raise ethical and privacy issues. However, establishing the best practices for the private handling of data was not the purpose of this work, and there are other studies directly applicable to this approach. Further work will look into introducing privacy management mechanisms based on previous studies, to let learners expose data to different groups in different ways. Potential solutions are disclosure on a voluntary basis (like in Facebook, sharing different parts of the private information with different users). Moreover, none of the students in any of the studies presented here, or the follow-up studies, raised privacy concerns—possibly as their performance in the system didn't affect any grades and was entirely voluntary.

In addition to the quantitative results from the questionnaire survey, some qualitative feedback was also received from the course instructor, observers, and students. It was generally consistent with the quantitative results. A number of participants made positive remarks and expressed interest in further using Topolor 2.

Yet some students using smartphones to access Topolor 2 complained that it was not obvious what they should do next. This indicated that device types might influence the user experience. Although Topolor 2 was designed mainly for laptop and desktop use, it is clear that nowadays the ability to adapt to the hardware context is essential, given the widespread use of mobile devices. Therefore, adapting the learner data visualization to different hardware context is part of our follow-up research agenda.

This work suggests considering the proposed multifaceted OSLM approach when developing or improving a social e-learning system. More specifically, it shows that interactive multifaceted visualization of learners' performance, contributions, comparisons, learning path, and learning activity, rooted in learning theories such as connectivism, constructivism, and competitive learning,[2,9] can enhance social e-learning systems. Multifaceted visualization can thus provide a high level of effectiveness, efficiency, and satisfaction perceived by the learners, as long as it is based on social media visualization principles. **MM**

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