Which Learning Visualisations to Offer Students?

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Abstract. Research on learning visualisations does not always consider open learner models (OLM), where visualisations support learner decision-making. A range of preferences has been found, but studies mostly compare visualisations within single systems, so some have not yet been contrasted. This paper: (i) offers OLM researchers further results based on screenshots that include a broader range of visualisations than previously; (ii) introduces OLM views for the attention of those in other e-learning fields, as these may be relevant to their context.

Keywords: Learning visualisations · Learner preferences
Open Learner Model

1 Introduction

There is a need to better integrate research on learning analytics dashboards (LAD) and open learner models (OLM) [1]. LADs aim to make data actionable, commonly using traditional bar charts, line graphs, tables, pie charts, network graphs [2]. Learner models are dynamic models of learning that allow personalisation; OLMs externalise this model to aid learner decision-making [3]. Whilst some OLMs use traditional visualisations, many use other methods: Fig. 1 outlines examples. *Skill Meters 1&2* show knowledge level in the filled part of the meter. *Bullets* use fill in the bullet. *Graph* has positive data on the right of the axis; problems on the left. *Grid* uses colour to show understanding. *Table 1* lists competencies in columns from weak to strong; a dot in a cell indicates strength of each competency. *Table 2* ranks understanding. *Radar Plot* portrays learning across a curriculum by fill and position. *Histogram* shows knowledge from weak to strong. *Word Clouds* have strong competencies in larger text on the left; weak competencies on the right. *Treemap 1* shows competency by size of the corresponding area; *Treemap 2* uses colour (size shows number of problems). *Circle* also uses colour. *Network* and *Hierarchical Tree* have hierarchical structures similar to that shown by indenting sub-topics in *Skill Meters 1, Table 1*, or zooming in *Treemaps 1&2*. *Pre-requisites* and *Concept Map* show corresponding relationships.

In multiple view OLMs, skill meters tend to be viewed more if they are an option, though all views are accessed [4, 5, 11]. Nevertheless, whilst skill meters were popular amongst Fig. 1 screens when considering 'what to work on next', pre-requisites and

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hierarchical tree were anticipated more useful for that purpose [12]; concept maps were more effective than skill meters to synthesise an overview in a controlled study [13]; and a simple ranked list was favoured over other views (including concept map, pre-requisites, hierarchical tree) in an experimental study [10]. Individuals may also use different views depending on reason for viewing [5]. This suggests a need to further investigate the relative usefulness of different views. Studies have typically been with single systems, so whilst several views have been compared, some have not yet been contrasted. As a first step, we follow approaches where screens were designed to gauge interest in options before deciding which to implement [14, 15], but we instead take visualisations from a range of *EXISTING* OLMs. These are from our own OLMs (for accessibility), but we use views that are similar to those commonly deployed.

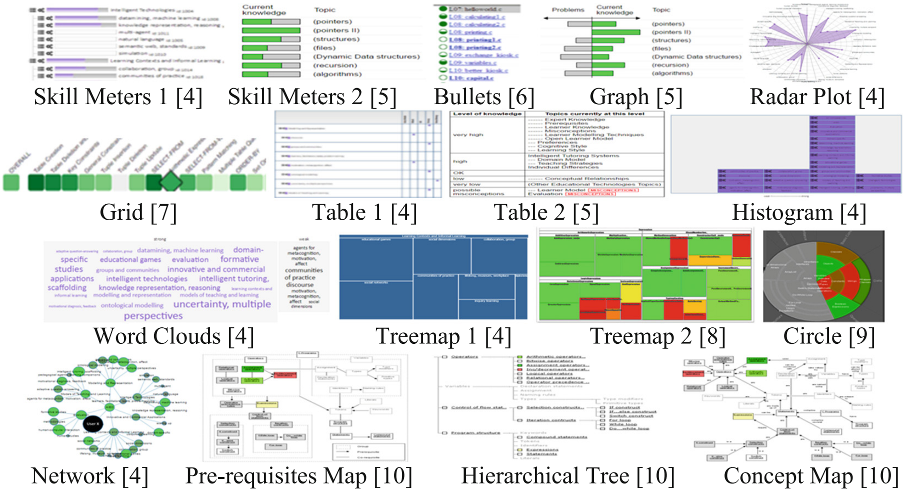

Fig. 1. Outline of layout of some common types of open learner model visualisation

2 Evaluation

38 students from School of Information Sciences, University of Pittsburgh, accepted an email invitation and were compensated $20. 16 had previously used *Grid*. The Fig. 1 screens were shown. Likert scale questionnaires (strongly agree 5-strongly disagree 1) included space for comments. Differences in learning data (concepts, skills, knowledge level, competencies) were not highlighted, to avoid responses based on this.

Results: Each view had some expecting to use it, and some not. All anticipated using multiple views (mean 8.5; median 8; range 3–14). Table 1 shows *Skill Meters 1&2, Tables 1&2, Treemaps 1&2, Bullets, Graph, Pre-requisites Map* most easily understood: at least 30 claiming ‘I understand the purpose of [VIEW]’ (agree/strongly agree); then *Grid, Histogram, Network, Hierarchical Tree*, *Concept Map*, with 27–29. ‘In a system with many visualisations I would use [VIEW]’ had *Skill Meters 1&2* as most

Table 1. Understand/would use view; easily identify well known/not well known.

View	C	**Understand**/Would use				**Identify well known/**not well known			
		n. agree	mean	median	range	n. agree	mean	median	range
Skill M 1	+	**33**/28	**4.5**/4.1	**5**/4	**3–5**/2–5	**34**/30	**4.5**/4.2	**5**/5	**2–5**/2–5
Skill M 2	+	**31**/27	**4.6**/4.0	**5**/4	**3–5**/2–5	**36**/32	**4.6**/4.4	**5**/5	**2–5**/2–5
Bullets	+/-	**34**/17	**4.4**/2.4	**5**/3	**2–5**/1–5	**28**/27	**4.2**/4.1	**5**/5	**2–5**/2–5
Graph	+	**32**/23	**4.2**/3.8	**4**/4	**2–5**/1–5	**25**/28	**4.1**/4.1	**4**/4.5	**2–5**/2–5
Grid	+/-	**29**/21	**4.1**/3.7	**4**/4	**2–5**/2–5	**29**/30	**4.1**/3.8	**4**/4	**1–5**/1–5
Table 1	+/-	**33**/14	**4.4**/3.1	**4.5**/3.5	**3–5**/1–5	**26**/26	**4.0**/4.0	**4**/4	**1–5**/2–5
Table 2	+/-	**32**/21	**4.3**/3.6	**5**/4	**2–5**/2–5	**32**/27	**4.2**/4.0	**4.5**/4.5	**2–5**/2–5
Radar Plot	+/-	**23**/18	**3.8**/3.5	**4**/3	**2–5**/1–5	**21**/22	**3.7**/3.7	**4**/4	**1–5**/1–5
Histogram	–	**27**/15	**4.0**/3.1	**4**/3	**2–5**/1–5	**24**/24	**3.8**/3.7	**4**/4	**2–5**/2–5
Word Cl	–	**17**/12	**3.5**/2.8	**3**/3	**2–5**/1–5	**19**/12	**3.3**/3.0	**3.5**/3	**1–5**/1–5
Treemap 1	–	**30**/17	**4.0**/3.1	**4**/3	**2–5**/1–5	**23**/24	**3.6**/3.7	**4**/4	**1–5**/1–5
Treemap 2	–	**31**/12	**4.1**/3.9	**4**/3	**2–5**/1–5	**23**/16	**3.6**/3.3	**4**/3	**1–5**/2–5
Circle	+/-	**24**/17	**3.8**/3.2	**4**/3	**2–5**/1–5	**21**/23	**3.7**/3.6	**4**/4	**2–5**/1–5
Network	+/-	**29**/19	**4.2**/3.5	**4.5**/3.5	**2–5**/1–5	**19**/21	**3.6**/3.0	**3.5**/4	**1–5**/1–5
Pre-req M	+/-	**31**/22	**4.1**/3.6	**4**/4	**2–5**/1–5	**26**/24	**4.0**/3.7	**4**/4	**2–5**/1–5
Hier Tree	+/-	**29**/25	**4.2**/3.7	**4**/4	**2–5**/1–5	**23**/26	**3.9**/4.0	**4**/4	**2–5**/1–5
C Map	+/-	**28***/19	**4.1**/3.4	**4**/3.5	**2–5**/1–5	**20**/22	**3.6**/3.5	**4**/4	**1–5**/1–5

*underlined: at least half agree/strongly agree. *one missing answer for questionnaire item.*

likely (>70%); and at least half chose *Graph, Grid, Table 2, Network, Pre-requisites Map, Hierarchical Tree*, *Concept Map*. For the two items 'I could easily identify topics I know well/do not know well using [VIEW]': at least half responded positively for well known topics for all views; only *Word Clouds* and *Tree map 2* had less than half for topics not known well. *Skill Meters 1&2* scored especially high for both.

Most views attracted positive (+) and negative (–) comments (C). Table 2 provides typical examples, often indicating the positive uses of detail as well as negative perceptions of too much detail. As domains often use a hierarchical structure, to further highlight individual differences in preferences, Table 3 shows the hierarchical views chosen by the ten students expecting to use the least views (3–6) overall (mean 1; median 1; range 0–2). The most popular, *Skill Meters 1*, was selected by only half; *Hierarchical Tree*, by three; a *Treemap*, by two. Three participants anticipated using no hierarchical view, but each of these selected *Table 2*, which *CAN* show structure in topic labels (e.g. dashes before sub-topics, as in the screen in the study). The other 28 students (7 or more views) chose at least one hierarchical view (mean 3.7; median 4; range 1–6). A combination of *Skill Meters 1*, *Hierarchical Tree* and *Network* would cover these participants' preferences; omitting any one of these would leave only one student with no preferred hierarchical structure. (Considering all participants together, values for expecting to use hierarchical views were: mean 3; median 3.5; range 0–6.)

Discussion: OLMs use not only traditional methods of information visualisation often found in LADs (see [2]), but also other options, from simple displays for a quick overview, to highly structured views that include information about relationships. This paper identified that, *APART FROM* *Radar Plot*, *Word Clouds* and *Circle*, all views were claimed to be understood by at least two thirds (and only *Word Clouds* by less than half). For a multiple-view OLM, over 70% of participants anticipated using *Skill Meters 1&2*; and at least half, *Graph*, *Grid*, *Table 2*, *Network*, *Pre-requisites Map*, *Hierarchical Tree, Concept Map*. These nine visualisations were also considered easily usable to identify well known and less known topics by at least half of the students.

Table 2. Typical responses for some of the visualisations claimed as most likely to be used.

View	Positive (+)	Negative (–)
Table 2	It has topics of similar knowledge level blocked together	I don't like reading too much words while they are not clearly categorized
Pre-req M	Can help me to make a study plan to know what I need to learn step by step	Too much information in it
Hier Tree	The hierarchy helps to navigate to particular topic I want to go	So much information […] tedious to find out what is being told
C Map	Can help me specify the relationship between knowledge	Way too confusing

Skill Meters 1&2 were the top views for all four questionnaire items. This echoes findings that skill meters are used frequently in practice when amongst the options available [4, 5, 11]. However, initial results looking at the same views to identify 'what to work on next' revealed different preferences (*Pre-requisites Map*, *Hierarchical Tree*) [12], compared to findings here for well known/less known topics (*Skill Meters 1&2*), though over half also stated they would use *Pre-requisites Map* and/or *Hierarchical Tree* in a multiple-view OLM. Furthermore, of those who expected to use fewer views overall, only half anticipated using the hierarchical *Skill Meters 1*. We therefore recommend considering providing each of the above (*Pre-requisites Map*, *Hierarchical Tree,* one of *Skill Meters 1&2)* to the extent that the domain structure allows.

Table 3. Hierarchical views expected to be used by those using the fewest views overall (3–6).

	P1(3)	P2(4)	P3(4)	P4(5)	P5(5)	P6(5)	P7(5)	P8(6)	P9(6)	P10(6)
Skill M 1	X	X					X		X	X
Table 1										
Trm 1&2			X							X
Network										
Hier Tree						X	X		X	

A controlled study found a concept map more effective than skill meters for synthesis of an overview [13]; a ranked list was used more often than other views in an experimental study [10]. Our *Concept Map* had three quarters claiming it understandable, and half stated they would use it in a multiple-view OLM. *Table 2* positions topics on five levels, similar to a ranked list, and is considered understandable by as many as for *Skill Meters 1&2*, and over half stated they would use it. We therefore further propose considering *Table 2* and *Concept Map*. However, we also had participants finding the above views difficult. Comments revealed perceptions of too much detail; others found detail useful for specific purposes: identify knowledge (*Table 2*) or conceptual relationships (*Concept Map*), form a study plan (*Pre-requisites Map*), navigation (*Hierarchical Tree*). This supports multiple views for different users, or individuals for different goals. Students can explain why they use different views at different times [5], indicating they understand the relative benefits and limitations *FOR THEM*; and consistent with OLMs where other views are used as well as skill meters [4, 5, 11]. Whilst we largely support using multiple views, when an OLM has a specific purpose, we suggest a view similar to one of the above (e.g. concept map for an overview of understanding of conceptual relationships; pre-requisites to plan activities).

Since the range values show most views had some students expecting to not use them, we also consider alternatives from the remaining views that had at least half anticipating using them and stating they would be able to identify known and less known topics: *Graph*, *Grid* and *Network*. We do not suggest *Network* or *Graph* if only one view is to be employed, since these were not the most used views in their respective deployed OLMs [4, 5]; and *Network* shares the structure of *Hierarchical Tree*, with *Graph* very similar to *Skill Meters 2* - both already recommended above (with higher scores). However, these may be useful as additional views to provide greater choice. Thus, we propose the above 8 visualisations be considered as options in a multiple-view OLM. *Grid* is more difficult to compare, since 16 participants were already familiar with it. This may have inflated the values, but *Grid* has been successfully used in practice in a single-view OLM [7], and may be helpful when space in an interface is limited (e.g. where the OLM is displayed together with course content). *Bullets* are an interesting case: they were claimed to be more easily understandable than any other visualisation, scored well for identification of known/less known topics, but had less than half expecting to use them. For this reason, we suggest *Bullets* for cases where space is especially restricted as they will likely be understood, and offer information in a similar manner to *Skill Meters 2*. However, we would not propose *Bullets* as a replacement where *Skill Meters 2* (or *1*) can be used. Finally, *Treemap 1* could be considered for a large, many-layered hierarchical domain, also to efficiently use available space. (These three views may also be useful as additional options in a multiple-view OLM.) Table 4 summarises our initial suggestions, to be supplemented with any additional visualisations appropriate for the specific context.

Because domains are often structured hierarchically, we further consider responses relating to these views. The median for anticipated use of hierarchical views was 3.5. *Skill Meters 1*, *Hierarchical Tree* and *Network* together would satisfy all 28 participants anticipating using at least 7 views; removing any would leave only one person with no preferred option. However, amongst the ten choosing only 3–6 views overall, four would have no favoured hierarchical view. Three of these expected not to use any of the hierarchical views, but these all opted for *Table 2*, which CAN be configured to show hierarchy levels - albeit not within the hierarchical structure (as (sub-)topics are simply ranked). Nevertheless, including *Table 2* may raise awareness of the hierarchal structure, and lead to a better understanding of the full hierarchical view(s). In this case, only one student (who chose a *Treemap*) would have no preferred view.

Participants predicting use of a feature does not necessarily mean they will use it in practice [16], but offering visualisations that students can anticipate easily using may lead them to try to interpret the information in context. This paper therefore offers a *STARTING POINT* for OLM and LAD designers who are selecting learning visualisations to incorporate. Further research into these combinations in use can then be undertaken.

Table 4. Visualisations suggested for consideration for single and multiple-view OLMs.

Views	SM1&2	Bullets	Graph	Grid	T2	TM1	Net	Pre-r	HT	CM
Single view	X				X			X	X	X
Single/restricted		X		X		X				
Main mult views	X				X			X	X	X
Additional views		(X)	X	(X)		(X)	X			

3 Summary

Building on findings that students may use different views when there are multiple options in an OLM, we studied reactions to typical OLMs to explore relative benefits and drawbacks of view combinations. The screenshots were largely judged understandable, though there were differences in expected use. Combining views designed to fit the purpose of viewing with ones previously successfully used, also taking into account our findings here, is a step towards providing useful alternatives in future e-learning systems, as well as for considering options when only one view is preferred.

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