Individual and Peer Comparison Open Learner Model Visualisations to Identify What to Work On Next

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ABSTRACT

Open learner models (OLM) can support self-regulated learning, collaborative interaction, and navigation in adaptive educational systems. Previous research has found that learners have a range of preferences for learner model visualisation. However, research has focused mainly on visualisations that are available in a single system, meaning that not all visualisations have been compared to each other. We present a study using screen shots of OLM visualisations for individuals and for comparing one's own learner model to the models of other individuals or the group, to define visualisations that students would be able to use to identify their next steps, across a wider range of options.

1. INTRODUCTION

OLMs are learner models that are externalised to users in a human-understandable form [9]. We are here concerned with learner models that are open to the learner and to their peers. Reasons to open the learner model include prompting metacognitive activities such as self-monitoring and planning, as students reflect on their learning as they view the system's representations of their understanding or skills [8]; adaptive navigation support, as a range of materials may be accessed from within an OLM [3]; and promoting collaboration by allowing students to view the models of each other [11]. Benefits have been observed when students have access to OLMs, including significant improvements in self-assessment accuracy [21,27] and significant learning gains [4,25,30].

In some systems the learner model can be shown to the learner in different forms, and in such cases it has been found that, while some visualisations may be more popular, users do not all use the same visualisations, and will often use more than one [7,10,16,17,20,26]. To date, this research has compared use of visualisations within specific systems, and so not all visualisations have been compared against each other. We here introduce a study using screen shots from a range of successful systems, some with single, and some multiple model visualisations, to gain a more general picture of the visualisations that students expect to find useful to support their self-regulated learning.

Some systems show two sets of skills or beliefs to allow the learner to directly compare their own beliefs (e.g. from self-

their level of understanding to the expected level for the current stage of a course [10]. Some systems allow learners to view learner model information of others [4,6,11,14,15,23,29,31,32, 33] and/or an average or aggregate model of the group [3,4,6,11, 13,18,19,23,24,31,32]. The second part of the study showed screen shots of OLM visualisations allowing the learner to compare a learner model to that of other individuals or the group (in some cases with some editing to the screen shot). We also investigate whether participants would expect to find the same visualisations useful for inspecting their own learner model, as when

comparing their learner model to the learner models of others, and whether they would expect to use their individual or the comparison models when deciding what to work on next. This provides some insight into which visualisations to investigate further in systems with multiple or single visualisations, and which can be viewed on an individual and/or comparison basis.

2. LEARNER MODEL VISUALISATIONS

Figure 1 shows the comparison visualisations used in the study reported in Section 3. They variously use fill, colour, position or size to indicate the strength of understanding or skills. Because the participants were taking computing-related courses, each screen shot was taken from a system for a computing course, to provide some familiarity in the domain content. However, because the screen shots are from real systems, the domains are not identical – they were the same only when more than one visualisation was used from a multiple-view OLM.

The individual visualisations are similar to the comparison visualisations shown in Figure 1, but without the comparison features. For example, where the skill meters and graph show comparison of an individual model to the individual models of other students, or an overall group model or a specific individual peer, the individual versions lack the comparison components (e.g. showing the top 'my model' only, for Skill Meters 3 and Graph 2; the second 'my knowledge' column in Skill Meters 2 and Graph 1; or the top skill meter in each row for Skill Meters 1). Some of our examples are specifically for comparison to a range of individual other students, as each peer model is shown separately (Skill Meters 3, Graph 2, Bullets 2, Grid 2, Circle 2). The remainder could either represent a comparison to another individual peer's learner model, or a combined model of the group.

The Skill Meters (1 [7]; 2,3 [10]) show level of understanding by the proportion of the meter that is filled; the Graph views [10] show this with the positive knowledge on the right of the axis, and areas of difficulty on the left. (Skill Meters 2 and Graph 1 actually show the learner's current knowledge alongside the instructor's stated expected levels for the stage of the course, but were edited for this study to indicate peer knowledge; and Skill Meters 1 show data from different sources, but are used here to indicate peer competencies). The Bullets [5] indicate level of knowledge by the amount of fill in the bullet. [...] ation has only one column [...] lited to add extra columns to show peer knowledge.) The Grids [4] use colour to indicate level of understanding, with Grid 1 comparing against the group (or, for this study, also a single individual); and Grid 2 comparing against a ranked list of individuals. Table 1 [7] lists the competencies in the first column, with the remaining columns ranging from weak to strong, with a dot in the cell indicating the strength of the competency in each case. (The actual comparison visualisation shows data from different sources, but is used here to indicate peer competencies. The corresponding individual table has only one dot per row.) Table 2 [10] ranks topics from
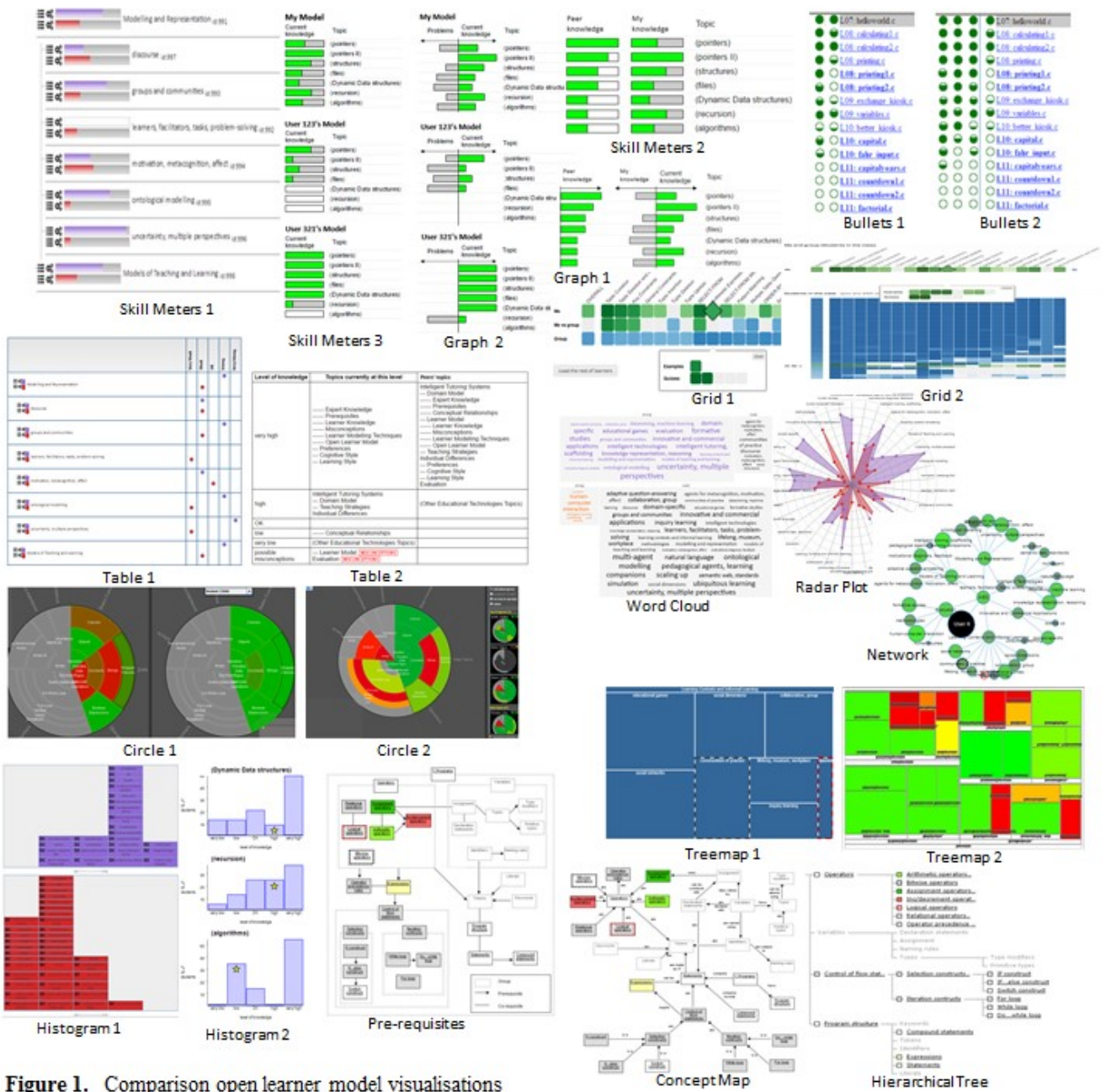
Figure 1. Comparison open learner model visualisations

high to low, with the comparison shown in a separate column. The Word Clouds show strong competencies in larger text on the left, and weak competencies in larger text on the right; and comparison has to be made between the upper (individual's) learner model in this case, and the lower word clouds. On the Radar Plot, the comparison data is overlaid, with the competencies listed around the rim (The Word Clouds and Radar Plot also actually show a comparison of data from different sources, but are used here to illustrate peer comparison). Treemap 1 [7] shows the individual's level of competency by the size of the corresponding square, and has been edited by adding dashed lines around two competencies – in grey if the learner has a higher level than the comparison peer(s), and red if their own

competency level is lower; and Treemap 2 [2] uses colour to show level of understanding (size relates to the number of problems related to the skill). We used the visualisation in its original way for the individual part of the study, and informed participants in the comparison part of the study that colour represented the individual's understanding in comparison to that of others – an individual or the group – with green showing they had stronger understanding than others, and red, weaker. Both Treemaps are zoomable, allowing users to access the next layers in the hierarchical structure. The Circles [19] also use colour to indicate strength of knowledge, with Circle 1 comparing against an individual or the group; and Circle 2 showing multiple peer OLMs. Histogram 1 [7] shows data from different sources in the

two examples given, but here we advised students that the comparison was between the individual and a single other peer or the group. Histogram 2 [10] indicates the learner's own level of knowledge for each topic by a star, on the scale of weak to strong, with other students' knowledge distributed along the scale as appropriate. The remaining visualisations are more obviously structured. While Skill Meters 1 and Table 1 do show the hierarchical structure by indenting sub-competencies, in the Pre-requisites [26], Concept Map [26], Hierarchical Tree [26] and Network [7], the layout of the visualisation makes this more apparent. Each of these has been edited with dashed lines around nodes (as Treemap 1), to show comparison information.

3. EVALUATION

The study presented here investigates the perceived utility of a range of visualisations from existing OLMs, to determine preferences for visualisations of one's own learning and for comparison of their learning to that of individual peers or a combined model of the group, to make decisions about their learning.

3.1 Participants, Materials and Methods

Participants were 33 volunteers who responded to an email invitation to students studying in the School of Information Sciences, University of Pittsburgh. They attended one of two 1.5 hour sessions, and were compensated 20USD for their participation. Participants were shown 17 examples of OLM screen shots relating to an individual's learner model, and the main features of each were explained. Participants were able to ask questions at any point. They then received the first questionnaire about their perceptions of the individual learner model visualisations, which required responses on a five-point scale: strongly agree (5), agree (4), neutral (3), disagree (2), strongly disagree (1). They also received paper copies of the screen shots as a reminder, but could also ask for the screen shots to be projected again, while they completed the questionnaire. The procedure was then repeated using 23 comparison visualisations. There are more comparison visualisations because some show comparisons to a single peer or the group, while some show comparisons to multiple other individuals. Participants were instructed to interpret the visualisations comparing to just one other, or the group, as being applicable to both cases.

3.2 Results

Table 1 gives results from the questionnaire item asking whether students could easily identify what to work on next for each of the 17 individual visualisations, and Table 2 shows results for the same item for the 23 comparison visualisations. For both types of visualisation, the range of responses is similar. Each visualisation has some people claiming it to be easy to use to identify what to work on next, and some claiming not to be able to use it easily for this purpose. However, in most cases, there are more people agreeing with the statement than disagreeing. Those that stand out as more towards the negative for the individual visualisations are Table 1, Word Cloud, Treemap 1, Treemap 2, Circle and Network, where the means and medians are in the neutral range; and Bullets (marginally), Grid, Table 2, Radar Plot, Histogram and Concept Map, where although the medians are 4 (agree), there is a higher proportion of participants responding neutrally and/or negatively. Particularly strong are the responses for the Pre-requisites and Hierarchical Tree visualisations. The remaining three visualisations had mostly positive responses (Skill Meters 1, Skill Meters 2, Graph).

The results for the comparison visualisations in Table 2 are generally lower than for the individual visualisations. Those that scored less on the individual visualisations also scored lower for the comparison (Table 1, Word Cloud, Treemap 1, Circle 2, Network). In contrast, the Prerequisites and Hierarchical Tree, that had the strongest results in the individual visualisations, were not so strong for comparison purposes, with the means and medians both being lower. However, these were not out of line with other comparison visualisations. The other Treemap (2) and Circle (1), while having medians of 4 (higher than for the corresponding individual visualisations), each had a mean of 3.6 reflecting a greater tendency for neutral/negative responses than for some of the other visualisations. Both Graph comparisons have lower means than the individual Graph visualisation. The

Table 1. Questionnaire responses: individual visualisations

Visualisation	Responses	Mean	Median	Range
Skill Meters 1 / 2	32 / 33	4.1 / 4.0	4 / 4	2-5
Bullets	33	3.9	4	2-5
Graph	33	4.1	4	2-5
Grid	33	3.8	4	2-5
Table 1 / 2	33 / 33	3.4 / 3.8	3 / 4	1-5
Radar Plot	33	3.4	4	1-5
Histogram	32	3.4	4	1-5
Word Cloud	33	3.1	3	1-5
Treemap 1 / 2	33 / 33	2.7 / 3.3	3 / 3	1-5
Circle	32	3.3	3.5	1-5
Pre-requisites	33	4.4	5	2-5
Hierarchical Tree	33	4.1	5	2-5
Concept Map	33	3.8	4	2-5
Network	33	3.4	3	2-5

Table 2. Questionnaire responses: comparison visualisations

Visualisation	Responses	Mean	Median	Range
Skill Meters 1 / 2	33 / 33	4.4 / 4.1	4 / 4	2-5
Skill Meters 3	33	3.5	4	1-5
Bullets 1 / 2	33 / 33	4.0 / 3.9	4 / 4	2-5
Graph 1 / 2	33 / 32	3.4 / 3.5	4 / 4	1-5
Grid 1 / 2	33 / 33	3.7 / 3.7	4 / 4	1-5
Table 1 / 2	33 / 33	3.5 / 3.8	3 / 4	1-5
Radar Plot	33	3.5	4	1-5
Histogram 1 / 2	33 / 33	3.6 / 3.8	4 / 4	1-5
Word Cloud	33	2.6	2	1-5
Treemap 1 / 2	33 / 33	2.9 / 3.6	3 / 4	1-5
Circle 1	33	3.6	4	2-5
Circle 2	33	3.5	3	2-5
Pre-requisites	33	3.8	4	1-5
Hierarchical Tree	33	3.6	4	1-5
Concept Map	33	3.5	4	1-5
Network	33	3.2	3	1-5
Concept Map	33	3.5	4	1-5
Network	33	3.2	3	1-5

Bullets, Grids, Radar Plot, Histograms and Concept Map comparisons are similar to the corresponding individual results. Skill Meters 1 and 2, while high for the individual visualisations, scored highest for comparison. Skill Meters 3 was lower.

Ranking the visualisations for ease of identifying what to work on next, we obtain the order in Table 3. The 'structure' columns relate to whether the structure of the domain is represented within the visualisation. For example, the highly structured visualisations are the Pre-requisites, Concept Map, Hierarchical Tree and Network, which all display relationships between nodes. Those labelled medium indicate some structure, but this is less obvious from looking at the screen shot. For example, the Treemaps are zoomable to the next level in the hierarchy, but relationships between different parts of the tree are not shown simultaneously; the Circles show concepts grouped in segments, but the relationships are not obvious; and Skill Meters 1 and Table 1 indent sub-competencies, but this hierarchical structure is not as clear as in the visualisations defined as highly structured. Indeed, these require scrolling to see all competencies when there are a large number. The 'sing/mult' column for the comparison visualisations indicates whether the corresponding visualisation was for comparison to a single other individual or the combined group; or for multiple individual peer models.

Table 3. Visualisations ranked according to stated ease of identifying what to work on next (adjacent =,=*,=⁺=^: same ranking)

Individual Visualisations	Struc-ture	Comparison Visualisations	Struc-ture	Sing/ Mult
Pre-requisites	high	Skill Meters 1	med	single
Hierarch. Tree	high	Skill Meters 2	none	single
= Skill Meters 1	med	Bullets 1	none	single
= Graph	none	Bullets 2	none	multiple
Skill Meters 2	none	= Table 2	none	single
Bullets	none	= Histogram 2	none	single
= Grid	none	= Pre-requisites	high	single
= Table 2	none	=* Grid 1	none	single
= Concept Map	high	=* Grid 2	none	multiple
Radar Plot	none	=⁺ Histogram 1	none	single
Histogram	none	=⁺ Treemap 2	med	single
= Table 1	med	=⁺ Circle 1	med	single
= Network	high	=⁺ Hierarch. Tree	high	single
Circle	med	=^ Skill Meters 3	none	multiple
Treemap 2	med	=^ Graph 2	none	multiple
Word Cloud	none	=^ Radar Plot	none	single
Treemap 1	med	=^ Concept Map	high	single
		Graph 1	none	single
		= Table 1	med	single
		= Circle 2	med	multiple
		Network	high	single
		Treemap 1	med	single
		Word Cloud	none	single

As indicated above, the rankings of the visualisations for ease of identifying what to work on next, were not consistent across individual and comparison views. While the most popular individual visualisations were highly structured, this is not the sole reason for their choice, since other structured visualisations are lower on the ranked list. In the comparison visualisations, the highly structured visualisations are spread throughout the list.

There is no clear difference between whether participants can identify what to work on next from visualisations with a single other comparison (individual peer or group), or where many individual peer models are available.

Table 4 shows the frequency with which participants claimed that they would use individual and comparison visualisations to decide what to work on next; and whether they would expect to use the same or different visualisations for this purpose, assuming that multiple options were available in a system.

Table 4. Anticipated use of individual and comparison views

Anticipated Visualisation Use	Mean	Median	Range
Use individual / what to work on next	3.9	4	1-5
Use comparison / what to work on next	3.6	4	2-5
Use same visualisation to view own learner model and comparison model	3.4	3	1-5

The medians are high (agreeing with the statement) for anticipated use of individual and comparison views for identifying what to work on next, but with a greater tendency towards neutral or negative responses for the comparison visualisations. Some participants stated that they expected to use the same, and some that they expected to use different visualisations to monitor their own learning and to compare to others. The relative rankings of individual and corresponding comparison visualisations was generally reflected in responses about whether participants could use each to identify what to work on next. The top ranked visualisation pairings were: Individual Skill Meters 1 / Comparison Skill Meters 1; Individual Skill Meters 2 / Comparison Skill Meters 2; Individual Pre-requisites Map / Comparison Pre-requisites Map; Individual Hierarchical Tree / Comparison Hierarchical Tree. The bottom ranked pairs were: Individual Table 1 / Comparison Table 1; Individual Network / Comparison Network; Individual Word Cloud / Comparison Word Cloud; Individual Treemap 1 / Comparison Treemap 1.

3.3 Discussion

Table 1 showed that the individual Prerequisites and Hierarchical Tree had particularly strong responses. These visualisations are more obviously highly structured than most of the others; and the structure can be easily seen at a glance. However, it is probably not simply the existence of structure that appeals, since the Concept Map is also highly structured, also uses colour of nodes to show level of understanding, but scored lower despite being from the same system as the two visualisations that had the very strong responses. It may be that the particular relationships shown in the Hierarchical Tree (topics and subtopics) and Pre-requisites (pre-requisite relationships) were easier to understand than the conceptual relationships portrayed in the Concept Map, or in the circular display of hierarchical links in the Network. At this stage, therefore, we tentatively propose that it is the nature of the relationships and/or familiarity of the layout that makes the difference for these participants, and such relationships might be usefully included in OLM visualisations. For simpler (less or unstructured) visualisations, Skill Meters and similar (Graph, Bullets), are generally claimed to be the most useful. Skill Meters are also used relatively often in practice in systems that have multiple visualisations, where skill

meters are amongst the options available [7,10,17]. Therefore these or similar might also be usefully considered as options in a system – unless it is important in a particular context to include the domain structure in the display. In that case, the hierarchical Skill Meters 1 might be useful if it is the hierarchical structure that is important.

We believe that the lower ranking for the Prerequisites and Hierarchical Tree in the comparison visualisations is because the dashed outlines are harder to see easily and/or the comparison of being behind or ahead of others is harder to interpret. However, because these are strong for the individual visualisations, and fare well when individual and comparison visualisation preferences are considered together, we suggest it useful to retain these in systems. Visualisations using enclosed areas to show skills (Treemaps, Circle) are not generally considered as useful for individual or comparison models, and Word Cloud is also thought hard to use to identify what to work on next. Although some would expect to use these, it is likely less useful to include them in a system if there is to be only one visualisation.

Visualisations that here showed only one comparison, could also be used to display more individual peer models. For example, the visualisations that in reality show data from different sources (Skill Meters 1, Table 1, Radar plot, Word Cloud, Treemap 1, Histogram 1, Network), can actually show more than just two sources. Therefore, they could also have been used to show multiple individual models – Skill Meters 1 and Table 1 can show several sets of data in each row; the Radar plot can have multiple overlays of data; and the Word Cloud, Treemap 1, Histogram 1 and Network can show multiple models in separate displays. We did not investigate the latter here, as we anticipated that such repetition would be difficult to use in practice. However, future work could usefully investigate the extent to which Skill Meters 1 in particular, could support comparison to multiple peers, given their popularity for all cases studied.

As the screen shots were taken from existing systems, while they all related to computing, the domains were still different. Furthermore, some learner models comprised many concepts, while others were more limited, and levels of understanding of topics were consistent only in cases where more than one visualisation of a learner model was used from a multiple-view OLM. This therefore limits our findings. Conversely, because we used a range of existing OLMs that have been used successfully in practice, the advantage is that we are comparing a wider range of real visualisations. This is clearly a trade-off that needs to be kept in mind when interpreting the results. Ongoing studies (such as [22]) may complement this, as new combinations of visualisations are implemented to compare the same data; and this could also be extended to include comparison models.

Another limitation is that participants were not aware of the comparison visualisations until after they had responded to the questionnaire on the individual visualisations. This was done to avoid the comparison visualisations having an effect on the choices for individual visualisations. Thus, the results for individual visualisations may be used more easily for making decisions about what to include in a system, or for further study, if not also considering comparisons. However, when considering both, our results provide a starting point for further investigation. Even though some participants considered that they would use different visualisations to monitor their own learning and to compare themselves to others, when using a system in practice, if using both individual and comparison visualisations they

might find it easier to routinely use the same one(s). This needs further investigation.

Asking participants what they would expect to do before they actually do it has limitations – there is no guarantee that they will actually behave in the way they predicted [28]. However, the alternative is to implement a prototype containing many individual and comparison visualisations, and then have students use it. Our current work aims to help reduce the space of choices before such a study is undertaken. Those visualisations at the bottom of the ranked lists might be reasonably omitted, while those at the top might be especially useful to include. Given that all the visualisations used in the study were taken from (or adapted from) visualisations that have been used in systems in practice, they have, at some stage, been considered useful by the system designers.

4. SUMMARY

This paper has introduced a range of visualisations previously used in OLMs, and presented a study comparing responses to questionnaire items about whether the visualisations would help participants identify what to work on next, with reference to: (i) an individual learner model; (ii) comparing an individual model to that of another student or the group; and (iii) comparing an individual model to the models of several individual peers. It was found that some of the highly structured visualisations are perceived useful for this task when it comes to the individual model, and that skill meters and similar visualisations are considered easy to use for this purpose especially in comparison visualisations. While there are individual differences, the above-mentioned visualisation types also do well when considering individual and comparison visualisations together. Based on our results, and following previous research showing that multiple visualisations will be used in practice, we recommend offering several options in systems that open the learner model to the learner. Our ranked lists aim to help designers of future studies, and system developers, to select those most appropriate to their context (individual, comparison or both).

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