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Belief Exploration in a Multiple-Media Open Learner Model for Basic Harmony

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Abstract. This paper focuses on whether learners of basic music theory may find a multiple-media independent open learner model useful to explore their knowledge of harmony concepts. Learners were given the option to explore example beliefs held in their learner model as music notation, audio or text, and shown how their beliefs compared to those of an expert. Results suggest users are both willing and make use of the open learner model, and show individual preferences for media format in which to view their beliefs. Participants mostly explored incorrect knowledge even though more correct knowledge was present in the model, and made greater use of the views specific to the music domain (music notation, audio) when their model showed "incorrect knowledge". Results indicate the potential to include multi-media information in open learner models in appropriate domains.

Keywords. Open Learner Models, Multiple Media, Basic Music Theory.

Introduction

Learner models exist in adaptive educational environments to allow the system to adapt to the current learning needs of the learner. Recent research has concerned *opening* learner models to the learner, presenting them with an external representation of their model for inspection. Open Learner Models (OLMs) have been found to be useful in domains ranging from computer programming [1] to second language acquisition [2]. Opening the learner model may bring additional benefits to the learner, allowing them to take charge of their own learning experience, for example prompting reflection through externalising representations of the learner model, encouraging self and formative assessment, and supporting planning and monitoring of learning, in addition to supporting learner metacognition [3].

Arguments have been made for making OLMs available to the learner independently of an Intelligent Tutoring System (ITS): independent open learner models (IOLMs). IOLMs, like ITSs, build the learner model based on user input, but tutoring is not provided: users identify their own learning requirements. This encourages responsibility and learner independence in learning [4]. Previous research in this area has explored showing misconceptions [4]; and considered how the presentation of the same knowledge in differing formats may be useful in learning [5]. Multiple views of the same learner model information is not thought to be confusing to the learner, although individual preferences are observed [5]. Even simple representations of the learner model are thought to have positive effects on the learning experience [1,6], though more complex representations may be more effective when learning relationships between concepts [7].

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The process of reflection and the fostering of learners' abilities to work independently have also been identified as important and necessary in music education provision [8,9,10,11]. It is thought that to achieve this learners of music need to be prompted think about what they know [11]. Whilst ITSs have previously been deployed in music education (e.g. *Musical-Score Learning (MSL)* [12], *Piano Tutor* [13], and *pianoFORTE* [14]), in each the learner model has remained closed to the learner, being used instead to influence the audio and multimedia which the learner observes. As stated above, IOLMs aim to stimulate these activities of reflection and independent learning [6]. We therefore raise the question of whether an IOLM might be useful for these purposes in music education, and whether students are willing to explore their open learner model and view examples of their beliefs, in appropriate forms.

In the tuition of music theory the basics are traditionally learnt through *drill and practice*, where a learner is repeatedly presented with material until able to recall the content at speed [15]. An IOLM presents an opportunity for learners to see the current state of their learning, through external representations of their learner model (views). OLM views often use text and graphical representations, with only a few other media being explored (e.g. a haptic OLM [16]; animation of concepts [17]). More common designs for model views range from simple skill meters [1,18,19] and text based views [20], through to more complex and graphical representations using concept maps [5,21], tree structures [5,22] and Bayesian models [23]. An IOLM for music theory requires additional domain-specific elements to externalise audio and music score components, previously not explored in OLM views. We raise the question of whether learners have a preference for a format in which to access their music learner model, and whether they have different preferences if shown how their beliefs compare to the domain.

In Section 1 we introduce MusicaLM (Musical Learner Model), in the domain of basic music theory. Section 2 presents results of investigations into the above questions.

1. MusicaLM

Through responding to a series of simple musical tasks, MusicaLM builds up a model of learner beliefs. The learner may then explore these inferred beliefs as text, music notation or audio representations, together with the confidence with which MusicaLM believes the inference to be an accurate depiction of the learner's current understanding. The learner model may be viewed at any point, including during a task.

1.1. Building the Learner Model

Domains for music systems are generally very narrow, specialised, and based upon specific concepts, allowing the learning activity to be focussed [24]. MusicaLM takes basic harmony as its domain (combinations of simultaneous notes). Harmony contains some of the basic building blocks of music theory which are a music student's primary focus throughout their initial transition to the world of music theory [25]. Four topics are included in MusicaLM, these build upon each other and increase in relative level of difficulty (*accidentals, common intervals, rare intervals* and *triad chords*). The learner is required to respond to musical tasks on a topic of their choice to maintain the model, providing input using a virtual keyboard or interactive music stave, as shown in Figure 1a (task – Chords – The pitch of 'A' is shown. Enter two other notes to form a

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diminished chord). As multiple notes are required to be entered simultaneously, both of these input methods ignore timing aspects of the music, acting as if frozen in time.

A learner's response to a musical task, a sequence of notes, is compared to the domain content, and using pattern matching of note sequences and the context of the task, musical beliefs are inferred (e.g. in Figure 1a, the notes *A*, *C* and *Eb* demonstrate a *diminished triad chord*). Using a library, common misconceptions are identified (for example, "black keys are the only accidentals").

The learner model is quite simple. An entry exists for each concept, formed from the three most recent pieces of inferred evidence, comprising the *concept tested, concept demonstrated* by the learner and any *misconceptions* potentially present in this combination. Evidence is weighted depending on age, the most recent contributing 50% to the overall understanding, decreasing to 30% and then 20% with age. These three pieces of evidence may contain conflicting beliefs. When externalising the model, MusicaLM compares each belief in turn, combining the weightings of those that match. The belief selected for display is the one with the greatest weighting, or the most recent understanding where there is conflict between two beliefs of equal weighting.

1.2. Externalising the Learner Model

The learner may explore their inferred beliefs through an abstract representation of the learner model, shown in Figure 1b. The left hand portion of the screen introduces concepts held in the learner model using a tabbed structure, which dynamically updates as the learner uses MusicaLM. Each entry presents icon-based hyperlinks to each of the (equally accessible) learner model views associated with the concept. Selection of a hyperlink will display in the scrolling log, on the right hand side of Figure 1b, an example of the understanding held for that concept (a learner model view).

The first entry in the scrolling log on the right of Figure 1b is the *music notation view,* the second the *text view*, and the third the *audio view.* In each view the concept is introduced with a title and contains the percentage certainty with which MusicaLM believes the information is an accurate representation of the learner's belief.

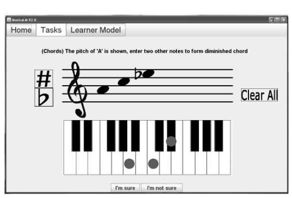

Figure 1a. Task Interface

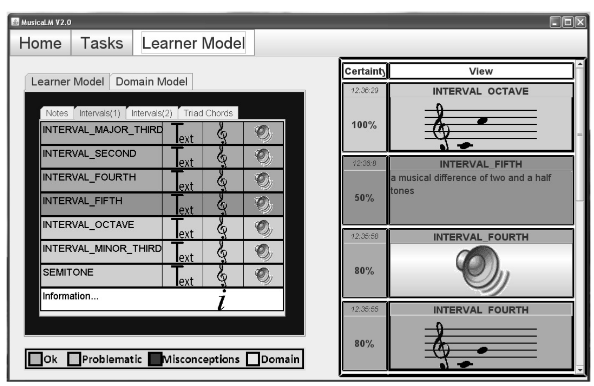

Figure 1b. The Open Learner Model.

The text view contains a written description of the musical belief. This is a simple adaptation of systems that use text as an alternative to novel open learner model interfaces (haptic [16], animation [17). In contrast to the text, both the audio and music

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notation views make use of a sequence of notes to describe a musical belief. The music notation displays these notes on a music stave, spaced apart to provide clarity, and the audio view allows the same notes to be heard as if played on a piano. In the audio view notes are heard first in ascending order to demonstrate the intervals and then simultaneously to demonstrate the full harmonic content. Notes are heard instantly on selecting the view, and can be replayed as the user wishes. Only the initial 'viewing' (per model access) is included in the logs so that this data is equivalent to that of the other views, as the other representations remain on screen during a single model access.

Colour is used throughout the screen to indicate how the learner model compares to the domain model, and is adapted from OLMlets [6]; logical relationships between colours and what they represent have already been found to be successful in navigation support [18] and in IOLMs [4]. Green is used for *confirmed* knowledge, grey for *problematic* knowledge (not related to specific misconceptions) and red for *misconceptions.* In Figure 1b (the open learner model) colour is present on the concepts in the tabbed structure and also in the beliefs detailed in the scrolling log on the right.

2. Use of an IOLM for Basic Music Theory

This section addresses the following questions: are learners of basic music theory willing to access their open learner model; do they explore example beliefs; are there any view preferences where multiple formats are available for the example beliefs (text, music notation and audio); and how is the format of an example belief affected by its knowledge category (understanding as compared to an expert's knowledge: *correct, problematic* or a *misconception*)?

2.1. Participants, Materials and Methods

Participants were 12 adult volunteers (aged 18-65), who were learning basic music theory, but not taking part in formal music tuition. Each was pursuing their chosen instrument through personal interest, and they had varying backgrounds, including: keyboard, voice, guitar, flute, cello and trombone, and wished to improve their understanding of harmony. Each of the participants first completed a short test on music theory elements which would be encountered in manipulating the task interface – the prerequisites of using the system.

Participants were then given an individual introduction to MusicaLM involving a demonstration and explanation of functionality. Participants made use of MusicaLM for several minutes to familiarise themselves with the environment, being prompted to explore each of the features for themselves and given the opportunity to ask questions.

Participants were then invited to make use of MusicaLM for a period of time they defined and were asked to attempt some of the questions, and were reminded that they could make use of the open learner model at any point. Particpants' period of usage ranged from 25 minutes to 1½ hours. All interactions were logged.

2.2. Results

Each participant made use of their open learner model on more than one occasion and chose to explore example beliefs they held on more than one occasion (in the scrolling log, right of Figure 1b). Participants used more than one view to explore beliefs, each showing individual preferences towards a combination, of which they made regular use.

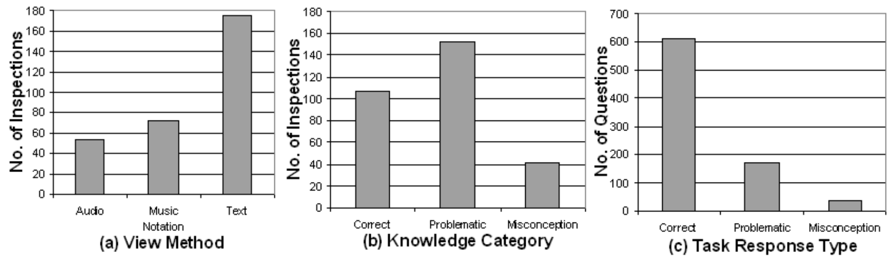

Figure 2. Belief Inspections by View Method **(a)** and Knowledge Category **(b)**. Task Correctness **(c)**

The most frequently used view, as shown in Figure 2a, was the text, accounting for 175 (58%) of the belief inspections, with music notation accounting for 72 (24%) and audio 53 (18%). Figure 2b shows the state of the belief at the time of the exploration, which may match the domain (correct), oppose the domain (problematic), or oppose the domain and reveal a misconception (misconception): the knowledge category. Amongst participants, problematic knowledge (153 inspections; 51%) was most frequently explored, followed by correct knowledge (107 inspections; 35%) and misconceptions (41 inspections; 14%), however only 7 participants had misconceptions in their learner model at some point. Figure 2c indicates the "correctness" of responses to tasks, which influenced the knowledge category of beliefs in the learner model. 611 answers were correct (75%) whilst 170 were problematic (21%) and 36 demonstrated likely misconceptions (4%). Participants viewed more incorrect than correct beliefs, even though there were many more correct beliefs in the model.

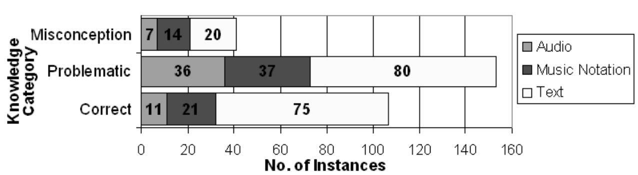

Figure 3. Usage by Knowledge Category broken down by View Method.

Figure 3 breaks down the belief explorations in each knowledge category by view type. When exploring beliefs which are identified as correct the text view is used in 75 cases (70%), with more limited use being made of the music notation (21 instances; 20%) and audio (11 instances; 10%). Whilst use of the text view is highest for each of the three knowledge categories, the audio and music notation views receive a higher proportion of usage when knowledge opposes the domain (47% when problematic and 51% when a misconception, versus 30% when correct). When knowledge is problematic both the audio and music notation views receive approximately the same level of usage (37 and 36 instances, respectively), whilst when misconceptions are explored the music notation is used twice as often as the audio (14 and 7 instances respectively). Each view is used more frequently to explore problematic concepts than either of the other categories and the heaviest usage amongst the views is of the text view to explore problematic and correct knowledge (80 and 75 instances respectively).

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Table 1. Interaction Logs: View Usage

	Tasks Answered					Belief Inspections Made									
						Audio			Music Notation			Text			
Participant	**Correct**	**Problematic**	**Misconception**	**Total**	**OLM Accesses**	**Correct**	**Problematic**	**Misconception**	**Correct**	**Problematic**	**Misconception**	**Correct**	**Problematic**	**Misconception**	**Total**
S1	118	14	6	138	54	-	-	-	7	5	3	33	9	4	61
S2	39	15	3	57	10	-	3	-	-	4	-	1	6	1	15
S3	50	13	-	63	4	-	8	x	2	7	x	2	6	x	25
S4	41	9	1	51	30	-	3	-	-	-	-	4	12	1	20
S5	46	3	-	49	8	2	2	x	2	2	x	-	2	x	10
S6	86	46	17	149	30	-	2	1	5	5	6	6	9	4	38
S7	59	8	-	67	10	1	4	x	-	-	x	5	7	x	16
S8	13	7	5	25	28	1	-	3	2	2	2	10	8	7	35
S9	43	19	-	62	28	5	7	x	1	4	x	7	5	x	29
S10	29	11	3	43	12	1	2	2	2	4	2	4	10	2	29
S11	35	11	-	46	7	1	2	x	-	2	x	1	2	x	8
S12	52	14	1	67	11	-	3	1	-	2	1	2	4	1	14
Total	611	170	36	817	232	11	36	7	21	37	14	75	80	20	300
Mean	50.9	14.2	3.0	68.0	19.3	0.9	3.0	0.6	1.8	3.1	1.2	6.3	6.7	1.7	25.0
Median	44.5	12	1	59.5	11.5	0.5	2.5	0	1.5	3	0	4	6.5	1	22.5
Range	13-118	3-46	0-17	25-149	4-54	0-5	0-8	0-3	0-7	0-7	0-6	0-33	2-12	0-7	8-61

Table 1 breaks down each belief inspection by participant and by the knowledge category of the belief at the time it was viewed, and summarises the knowledge category of each task responded to by each participant. Participants attempted between 25 and 149 tasks (mean 68.0; median 59.5). In the case of each participant a greater number of these tasks were answered correctly than incorrectly, although when inspecting beliefs 11 of the 12 participants made more inspections of incorrect knowledge than correct knowledge.

All but 1 of the participants made use of the audio feature, 5 for only exploring beliefs which opposed the domain, and the remaining 6, whilst also exploring correct concepts with audio, made greater use of the audio feature for concepts opposing the domain. All participants made more explorations of incorrect beliefs than correct beliefs, using the audio view. The same is also true for the music notation view with 4 participants making use of the music notation view solely for information which opposed the domain and 6 making greater use for beliefs opposing the domain above correct beliefs (1 participant did not use the music notation, and 1 showed equal usage levels). None of the participants made more explorations of correct beliefs than incorrect beliefs using the music notation view. The text view was used by all participants, and in all but the case of S5 was the most frequently accessed view. Again, in the case of 10 participants more explorations of beliefs which oppose the domain were made, whilst 2 participants made more explorations of correct beliefs.

In total 232 navigations to the open learner model were made (mean 19.3; median 11.5; range 4-54) and 300 beliefs were inspected (mean 25.0; median 22.5; range 8-61). Individual preferences for the format used to explore a given belief are observed, with several participants choosing not to use a particular model view (e.g. S1, audio; S4 music notation). Several participants showed bias towards using one view over another (e.g. S1, text) whilst others had a secondary preference (e.g. S6, primary: text, secondary: music notation) and some showed little overall preference (e.g. S3, S11).

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2.3. Discussion

Participants showed individual preferences as to which views to use to explore beliefs in their learner model. This is consistent with earlier studies with structured [5] and simple [6] graphical and text-based models. The music notation and audio views of the learner model in MusicaLM are specific to the domain of music theory, and designed to present harmony concepts. However the text is more limiting, confining the harmonic description to words. Nevertheless, learners showed a preference for text, a non-music-based view. This could be attributed to the lack of musical experience of the participants as compared to their experience with interpreting text; or users might have been trying to understand the less familiar views by comparing them to the text. Further research could investigate the influence of familiarity, and its effect over time. It does seem that music notation and audio were useful to some, and particularly when exploring misconceptions and problematic knowledge.

For problematic concepts the overall number of belief inspections was greater than for correct knowledge, despite there being more correct knowledge in the learner model of each participant. This suggests that learners seemed to recognise where they had problems and probably desired more information about their incorrect beliefs, or thought the identification of incorrect knowledge to be part of a problem solving activity (though they were not instructed to do this). Alternatively it could be that users found it harder to identify the information required when problems were encountered, and so explored the OLM more intensively. Further work is required to verify this.

The exploration of misconceptions using audio was limited, potentially indicating audio representations of misconceptions to be too abstract for learners of basic music theory to interpret. Further work will investigate this with more advanced musicians.

Within this small sample group it is shown that learners are both willing and make use of their OLM representations, the question initially raised. Further work should investigate this outcome with a larger sample size, and with more advanced learners. Additional research could help identify what motivates learners to make use of domain-specific features of their open learner model and whether they desire more information when exploring their beliefs. Additional issues to consider include precisely *when* learners wish to explore their beliefs during learning and whether comparison to an expert's model of beliefs is useful to learners of basic harmony.

The results indicate there is potential in including multi-media information in open learner models in the domain of basic music theory. The question is raised as to whether open learner models in other domains could also benefit from multi-media content; and how this may be incorporated into more complex open learner models.

3. Summary

A small scale study has been conducted involving 12 learners of basic music theory using an independent open learner modelling system, MusicaLM. The results suggest that learners are both willing and make use of their open learner model and show individual preferences for the media format in which they view their beliefs. Participants explored predominantly incorrect knowledge even though more correct knowledge was present in the model. Although the text view was used the most, learners made greater use of the views specific to the domain of music (music notation and audio) when their learner model showed "incorrect knowledge".

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