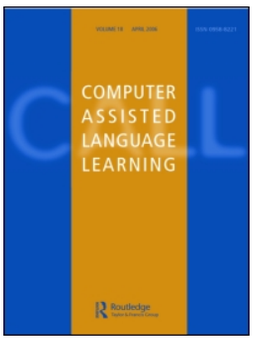

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Analytics in online and offline language learning environments: the role of learning design to understand student online engagement

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Analytics in online and offline language learning environments: the role of learning design to understand student online engagement

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ABSTRACT

Language education has a rich history of research and scholarship focusing on the effectiveness of learning activities and the impact these have on student behaviour and outcomes. One of the basic assumptions in foreign language pedagogy and CALL in particular is that learners want to be able to communicate effectively with native speakers of their chosen language. Combining principles of learning analytics and Big Data with learning design, this study used a student activity based taxonomy adopted by the Open University UK to inform module design. The learning designs of four introductory and intermediary language education modules and online engagement of 2111 learners were contrasted using weekly learning design data. In this study, we aimed to explore how learning design decisions made by language teachers influenced students' engagement in the VLE. Using fixed effect models, our findings indicated that 55% of variance of weekly online engagement in these four modules was explained by the way language teachers designed weekly learning design activities. Our learning analytics study highlights the potential affordances for CALL researchers to use the power of learning design and big data to explore and understand the complexities and dynamics of language learning for students and teachers.

KEYWORDS

Language learning; learning design; learning analytics

Introduction

As the demand for language education has increased in recent years, and adult learning is recognised as a vital component of the European Commission's life-long learning policy (EPALE, 2017), the role of technology, whether as Computer Assisted Language Learning (CALL), in combination with appropriate pedagogy can have a positive impact on foreign language (FL) learning

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(Abraham, 2008; Colpaert, 2006; Golonka, Bowles, Frank, Richardson, & Freynik, 2014; O'Dowd & Lewis, 2016).

In a review of 350 FL studies, Golonka et al. (2014) found strong support that technology can have a measurable and positive impact on FL learning when learners are supported by computer-assisted pronunciation training, in particular when so-called automatic speech recognition was used. At the same time, Golonka et al. (2014), p. 71) indicated that many CALL studies are primarily descriptive case-studies, with relatively small sample sizes, and often have 'poor choices of variables to be investigated … [and] lack of relevant data about participants.'.

In the emerging parallel field of learning analytics researchers are using principles of Big Data to measure, understand, and unpack the complexities of learning processes and learning outcomes. Learning analytics is defined as ' the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs' (Ferguson, 2012). Learning analytics provide institutions and language teachers with opportunities to support student progression and to enable personalised, rich learning (Allen, Perret, Likens, & McNamara, 2017; Bienkowski, Feng, & Means, 2012; Siemens & Long, 2011; Tempelaar, Rienties, & Giesbers, 2015). With the increased availability of large datasets, powerful analytics engines, and skilfully designed visualisations of analytics results (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013; Wolff, Zdrahal, Nikolov, & Pantucek, 2013), institutions like the Open University UK (OU), University of Michigan, and Arizona State University are already actively using past and current students' user behaviours and experience to create supportive, insightful models of primary (and perhaps real-time) learning processes (Allen et al., 2017; Allen, Snow, & McNamara, 2015; Herodotou et al., 2017; Koester, Fogel, Murdock, Grom, & McKay, 2017; Tempelaar et al., 2015).

Within CALL there is an emerging recognition that learning analytics may be important to understand the complexities of FL learning (Thomas, Reinders, & Gelan, 2017), as also highlighted by this special issue on 'language learning and learning analytics' and a keynote on learning analytics at EuroCALL 2014 conference in Groningen (Rienties, 2014). At the same time, two recent meta-analysis of the state of learning analytics research and policy (Ferguson & Clow, 2017; Ferguson et al., 2016) have warned that without a clear understanding of how learners learn (Golonka et al., 2014), how teachers design appropriate learning environments (Conole, 2012; Dalziel, 2016), and the respective context in which learning takes place (Thomas et al., 2017), the mere collecting of user engagement and clicking behaviour might have limited added-value.

Learning design, which is focussed on 'what students do' as part of their learning, rather than the 'teaching' which is focussed on the content that will be delivered, may provide an important bridge between pedagogy and learning analytics. Therefore, we suggest that an understanding of how language teachers

design their courses and linking learning design to actual student behaviour might advance our insights into how learning analytics can support CALL. Conole (2012, p. 121) describes *learning design* as 'a methodology for enabling teachers/designers to make more informed decisions in how they go about designing learning activities and interventions, which is pedagogically informed and makes effective use of appropriate resources and technologies.'

Within the OU, there is an increased recognition that learning design is an essential driver for learning (Conole, 2012; Conole et al., 2008). For example, Rienties and Toetenel (2016) linked 151 modules followed by 111,256 students at the OU with students' behaviour using multiple regression models and found that learning designs strongly predicted Virtual Learning Environment (VLE) behaviour and performance of students. The primary predictor of academic retention was the relative amount of communication activities (e.g., student to student interaction, student to teacher). Follow-up research by Nguyen, Rienties, Toetenel, Ferguson, and Whitelock (2017) unpacking longitudinal design decisions of 37 modules indicated that learning design activities per week made by teachers explained 58% of variance of students' VLE behaviour per week.

Building on this large-scale research, in this study we will unpack whether the principles developed for learning design at the OU are also applicable in a CALL context, and to what extent the way in which module teams designed four introductory and intermediate modules in French and Spanish influenced how 2111 students were engaging in the VLE on a weekly basis. First, we will describe how the OU uses learning design principles to map the learning activities of students, after which we will critically evaluate whether (or not) these principles are applicable for FL. Second, we will empirically test and verify whether the learning design decisions made by FL teachers influenced students' online engagement. Finally, we will critically review how learning analytics approaches might advance our insights into CALL, and provide practical and policy recommendations.

Learning analytics and learning design in CALL

CALL and FL at a distance

Language learning is often a long-term undertaking, which learners will need to combine with other priorities in their life, thus giving many learners a key reason to choose online and distance learning rather than a classroom provision (Abraham, 2008; Chang & Windeatt, 2016; O'Dowd & Lewis, 2016; Rosell-Aguilar, 2005; Sockett & Toffoli, 2012). Distance Language Learning (DLL) is clearly an extremely powerful learning approach, enabling learners to engage in an authentic language learning experience at a distance, often from the comfort of their home or workplace, with an opportunity for speaking and listening practice as well as to provide an immersive experience of the culture of the target language.

There are both similarities and significant differences between CALL and DLL. While CALL has long since moved away from the behaviourist paradigm

which informed many of its early instantiations, distance learning, for its part has largely shed the 'lockstep' approach which held sway until the final decades of the last century. Both shifts owe something to the same source: the advent of global networked computing, which rendered such approaches obsolete. However, while in CALL, it is increasingly rare for software to act as a surrogate tutor, rather than offering a platform for communication, in distance language learning, the delivery of resources, which in turn enables learning activities, continues to lie with technology, frequently in the shape of a Virtual Learning Environment (VLE). Traditional distance learning methods and approaches have evolved in waves to the real-time, authentic models of CALL we have today (Chang & Windeatt, 2016; O'Dowd & Lewis, 2016; Toetenel, 2013). Language teaching in particular has seen many debates about the form and function of instruction, possibly more than any other subjects. Examples are the 'Great Debate' around Grammar teaching in the nineties (Rose, 1996; Skretta, 1996; Vavra, 1996) and more recently the use of social networking sites in language learning (Toetenel, 2013).

One abiding difference between CALL and DLL seems to be that distance learners tend predominantly to be studying on their own, rather than in cohesive groups or classes. For some, this is a matter of personal choice, for others (e.g. offender learners, or those with severe disabilities) solitary learning is inevitable. It is hard to apply popular frameworks, such as sociocultural theory, situated learning theory, or even the concept of community of inquiry to such learners.

At the same time, the interconnection and the boundaries between formal and informal language learning have become blurred recently with the advancements of technology, and smart phone learning in particular (Sharples et al., 2016). For example, the use of social networking sites for language learning, such as Duo Lingo, Busuu and Language Exchange as well as one-to-one tools such as Skype have 'disrupted' some of the traditional classroom and ODL based provision (Chen, Shih, & Liu, 2015; Golonka et al., 2014; Toetenel, 2013). In relation to English, it has actually been argued that more learners are now learning the language informally by gaming, using fan sites or watching streamed video than are attending formal tuition (Sockett & Toffoli, 2012). This is beginning to transform the language learning landscape and ODL in particular.

Numerous hardware tools, such as Ipad and smart phones; and software applications such as podcasts, blogs, wikis and learning management systems, have been used in distance and online instruction and have proved to be useful in facilitating individual learning (Chen et al., 2015; Finger, Sun, & Jamieson-Proctor, 2010; van Doremalen, Boves, Colpaert, Cucchiarini, & Strik, 2016), as well as generating educational data on an unprecedented scale, thus opening up the field of learning analytics. One of the main challenges for learning analytics research is to deliver actionable feedback in both formal and informal learning contexts (Bienkowski et al., 2012; Ferguson et al., 2016; Sharples et al., 2016;

Tempelaar et al., 2015), which might be achieved by taking into account the context in which the learning data is situated.

Learning design and FL learning

In the past fifteen years several educational initiatives have been undertaken across the globe to gain better insights how teachers design and implement courses. These initiatives can be bundled under the umbrella term of learning design, and include among others the Australian Universities Teaching Council LD project (AUTCLearningDesign, 2002), the Educational Modelling Language project (Koper & Manderveld, 2004), the Learning Activity Management System (Dalziel, 2003), LdShake (Hernández-Leo, Moreno, Chacón, & Blat, 2014), the Open University Learning Design Initiative (Conole et al., 2008), and the SoURCE project (Laurillard & McAndrew, 2001).

Although we acknowledge that substantial progress has been made at various institutions how learning design can help to inform teachers and learners (Colpaert, 2006; Dalziel, 2016; Mor, Ferguson, & Wasson, 2015), few institutions (with the notable exception of the OU) have captured and updated these data in order to reflect on how these modules are delivered to students. Recent research and practical experience at the OU indicates that learning design has a fundamental influence on our students' learning behaviour, their satisfaction of the module, and most importantly pass-rates (Conole, 2012; Nguyen et al., 2017; Rienties & Toetenel, 2016; Toetenel & Rienties, 2016).

At the beginning of the 21st Century, several researchers at the OU started to focus on conceptually mapping and understanding how teachers were making decisions about what and how to teach at a distance. After a range of small pilots and conceptual experiments (Conole et al., 2008; Laurillard & McAndrew, 2001), the Open University Learning Design Initiative (OULDI) was introduced at the OU in consultation with eight other Higher Education institutions (Cross, Galley, Brasher, & Weller, 2012). All modules at the OU (and in most fully online learning providers) are developed collaboratively across a range of stakeholders. One of the main challenges identified with this collaborative design approach is the need to develop a shared vision (Albashiry, Voogt, & Pieters, 2015), which led to the introduction of a taxonomy through which practitioners make informed design decisions with a pedagogical focus using activity representations. The implementation of Learning Design included the introduction of a range of descriptors to categorise learning activities, and the OULDI taxonomy identifies seven types of learning activity as indicated in Table 1: assimilative; finding and handling information; communicative; productive; experiential; interactive; and assessment.

As described by Conole (2012) and elaborated upon by Rienties, Nguyen, Holmes, and Reedy (2018), a*ssimilative activities* are tasks in which language learners attend to language-specific information. This includes reading text

Table 1. Learning design taxonomy in language learning context.

Learning type	Original definition	Languages definition
Assimilative	Students read, listen, view information in materials and resources.	Students read listen, view information in materials and resources. Students use receptive skills.
Finding and Handling Information	Students are actively and critically engaged in gathering and manipulating information (e.g. list, analyse, collate, plot)	Students are actively and critically engaged in gathering and manipulating information in either L1 or L2.
Communication	Students discuss theories and concepts with at least one other person.	Students discuss theories, concepts or elements of their learning with at least one other person, moving towards communication in the target language. For example, students communicate about the course, specific tasks, and activities on the forum or in a face-to-face setting.
Productive	Students apply their knowledge and skills together or alone in order to create an artefact. This could be a list, a piece of narrative text which answers a question, a reflective account, a report, a video or a presentation etc.	Students apply their knowledge and skills together or alone in order to create an artefact. This could be a list, a piece of narrative text which answers a question, a reflective account, a report, a video or a presentation etc., usually in the target language.
Experiential	Students are required to apply their skills, knowledge and understanding in a real-world setting.	Students communicate in the target language with native speakers of the target language, who are not also students, in a real-world scenario. If students are asked then asked to discuss or reflect the experience this becomes meta-communication.
Interactive/adaptive	Students are required to apply their skills, knowledge and understanding in a simulated setting, receive immediate feedback and are then given the opportunity to adapt their approach.	Students communicate with other students (social rather than cognitive) in the target language in order to practice that language in a simulated setting. This could be a role play or on any created scenario. Adaptive communication.
Assessment	Students are assessed on their learning.	Students are assessed on their learning.

online (in case of language learning, while in other discipline some materials are still provided offline), watching and listening to videos, or listening to an audio file. *Finding and handling information* activities (which might involve information sources such as the Internet or Youtube) are those which focus on skills development and encourage language learners to take more responsibility for their learning, and to identify authentic language learning clips. *Communicative activities* are those in which language students communicate with another students or the teacher about module content. *Productive activities* are those in which language learners build and co-construct new artefacts. This could be a list, a piece of narrative text which answers a question, a reflective account, a report, a video or a presentation. *Experiential activities* provide language learners with the opportunity to apply their learning to a real-life setting. The key here is that language students receive real-life feedback on the activity (for example, from native speakers) and have an opportunity to reflect in context. *Interactive / adaptive activities* do a similar thing but in a pedagogically or practically safe

setting, such as those provided by simulations. Activities falling into this category might include role-play, problem-based scenarios, simulated case studies or simulated experiments. Finally, *assessment activities* encompass all activities focused on assessment, whether formative (to monitor and feedback on progress, peer review or self-assessment) or summative (for measurement and qualifications).

However, the use of such a taxonomy raises questions in relation to language learning, since in this context all activities relate to communication in the target language and the categories may not be neatly applied to learning design activities (Conole, 2012). For example, when students are actively and critically engaged in gathering and manipulating information, this would usually be categorised as *finding and handling information*, but if it is done in the target language, it could also be defined as language output, or in OULDI jargon *communication*. Similarly, *interactive activities* might refer specifically to social (and linguistic) interaction, usually with speakers of the target language and also with peers. In purely linguistic terms, it could be argued that *assimilative activities* can serve to expand the lexical repertoire of learners. However, for lexis to become part of a learner's active vocabulary, uptake and use are required. This is best ensured by engaging in interaction with others (whether peers or FL experts) and eventual production, though how these two types of activity can be best sequenced remains moot. An excess of assimilative activity may lead to boredom. Inadequately prepared and unsupported production may be experienced as wearisome, while interaction may induce stress in less confident learners. The result of either might be demotivation—a major barrier to retention and ultimate success in distance learning.

Therefore, for the development, review or redesign of modules, the OU uses a process of so-called 'module mapping.' Beginning with a stakeholders' workshop, in which the various possible learning activities are discussed in the context of the module being designed, the module's initially intended learning design is analysed and subsequently presented back to the module team as a combination of graphics and text (by means of the OU's Activity Planner visualisation tool). The aim is to make explicit the module teams' otherwise tacit learning design decisions so that they might consider whether amendments to their learning design might enhance the quality of their module.

The mapping process is comprehensive, but labour-intensive – typically taking between three and five days for a single module, depending on the module's number of credits, its structure, and quantity of learning resources. A team of learning design specialists reviews all the available learning materials, classifies the types of activity, and quantifies the time that students are expected to spend on each activity. As indicated by Rienties and Toetenel (2016), classifying learner activity can be subjective but consistency is important when comparing module designs across disciplines in the institution. Therefore, the learning design team holds regular meetings, involving respective module team members,

to improve the consistency. The meetings enable a form of moderation (informal 'inter-rater reliability') to take place. For example, learning design team members map the same week of a specific module, following which they share their findings, differences are discussed and a common approach is agreed. Finally, the learning design team manager reviews the module and its respective learning activities. In other words, each mapping is commonly reviewed by at least three people. This shared understanding leads to greater consistency of approach, and enhances the reliability and robustness of the data. It also feeds into guidance and support provided by the learning design team for faculty staff (e.g., via regular training courses for curriculum managers), to build their skills and confidence in the mapping process. Increasingly, following the training, faculty-based module teams are also mapping the modules themselves in order to compare initial and implemented learning design and also to facilitate further iterative development during module production or review.

Main research question

Within the School of Languages and Applied Linguistics module teams are strongly encouraged to align their modules across the students' journey. Building on previous large-scale research on the impact of learning design on students' engagement, in which we found that a balance of activities with a greater focus on communicative and productive engagement rather than assimilative tasks improved student outcomes (Rienties & Toetenel, 2016), in this study we aim to explore to what extent the learning design decisions made in these four introductory and intermediate modules in French and Spanish influenced how 2111 students were engaging in the VLE. In line with recent research (Nguyen, Rienties, & Toetenel, 2017), we are particularly keen to move beyond 'aggregate' learning design decisions made across an entire language module and unpack how "dynamic' learning decisions made on a week by week basis by language teachers influenced actual student engagement (Chen et al., 2015). Therefore, our overall research questions is: How are learning design decisions influencing language students' engagement in the VLE over time?

Method

Setting and participants

This study took place at the OU, a distance-learning institution with an open-entry policy and the largest university in the UK. In order to provide meaningful comparisons of learning design in CALL, we selected four foreign language modules with identical study intensity (30 credits), level of study (undergraduate), study length (30+ weeks), comparable size (448–567 students), and the same subjects (French, Spanish) with different levels of difficulty (Beginner, Intermediate).

These four modules are part of a curriculum which comprises four European languages. These are structured around the Common European Framework of Reference for Languages. Completion of the Beginners' module is said to take learners to level A2 of the CEFR, while the Intermediate module is claimed to raise proficiency levels to B1. Together these four modules amount to 50% of a Certificate in Higher Education. Linguistically, the modules are relatively conservative in conception, focusing firmly on the development of basic language knowledge and skills (e.g. lexical and phonological competence). In addition to language proficiency, they are claimed to develop learners' digital and information literacy, employability and transferable professional skills. The intermediate modules aim to introduce learners to a range of non-metropolitan language varieties. Learning outcomes are measured in terms of specific 'can-do' statements, rather than in terms of one or two global competences. Module resources are delivered using a Moodle-based Virtual Learning Environment. Synchronous tutorials take place in a modified version of Blackboard Collaborate, badged as OU-Live.

In total, 2111 students were enrolled in these four modules. There were on average more female students (68.56%) than male students (31.44%) studying these 4 modules. Most students were from the UK (92.73%) and declared their ethnicity to be 'white' (88.10%). Students varied considerably in age, with 19.65% under 25 years old, 37.58% aged 25–39, 32.38% aged 40–59, and 10.58% aged 60 and over.

39.85% of participants were working full-time, while 23.48% were working part-time, 13.28% were not in paid work, 7.13% were retired, 7.88% were unemployed and looking for a job, and the employment status of 8.43% was unknown. There are no formal academic entry requirements at undergraduate level at the OU or for the language modules in particular. In this study, 34.93% of the students had A levels or equivalent (suggesting they had two or more years of post-compulsory schooling), 25.53% had no A levels (suggesting they had not progressed beyond compulsory schooling), 24.10% had higher education degrees, 8.28% had a postgraduate qualification, and 1.78% with no formal qualifications. On average, 17% of the students had a reported disability.

Instruments

Learning design at the Open University

To develop a consistent approach to quantifying student workload, the seven types of learning activity were measured in terms of the duration in hours that was allocated for each type of activity. This was determined through a detailed and comprehensive mapping process between learning designers and instructors as described above, with measurements captured at an aggregate and weekly level. In order to 'benchmark' these four language modules, we included also average learning design scores of 56 other undergraduate modules across the OU as a reference point.

VLE engagement

In line with Tempelaar et al. (2015), two different types of data were gathered for each module from the university's Moodle VLE: average time spent on the VLE per week (in minutes); and average time spent per session on the VLE (in minutes). Subsequent derivatives of these were recorded from week − 3 until week 40 (data streams typically start three weeks before the official start of the module). More fine-grained tracking data were available for the four modules, providing information about types of content, materials and ICT tools (such as wikis, videoconference and discussion forums). At present these rich data are inconsistently captured at the OU (e.g., videoconference logs only contain attendance but not what students do and for how long), and extracting meaningful behavioural data from Moodle is complex. Furthermore, as is previously found (Bienkowski et al., 2012; Ferguson et al., 2016; Sharples et al., 2016) students behavioural engagement in distance learning can only be followed when learners are working online on the VLE and their behaviour is tracked. Several weekly tasks in these modules could be completed by working offline using print-based materials, so the measured VLE engagement will most likely be an underrepresentation of total learner engagement in a week.

Data analysis

In preparation for the panel analysis of 4 language modules and 34 modules with weekly longitudinal data, a Hausman test was used to differentiate between a fixed effects and a random effects model. This test checks whether the coefficients estimated by the random effects estimator are the same as the ones estimated by the consistent fixed effects estimator (Hausman, 1978). Our result supported the assumption of correlation between observation errors and predictors. For this reason, a fixed effects model was used as it removes the effect of time-invariant characteristics to assess the net effect of the predictors on the outcome.

Variance inflation factor (VIF) was computed using Stata 13 after each model to check for multicollinearity. All VIFs for the predictors were smaller than 2.00, indicating there was no significant correlation among the independent variables. In other words, there was little overlap of measurements among seven types of learning activity. In addition to visualising the longitudinal learning design decisions in Tableau 10.1.4 we used Social Network Analysis (UCINET 6.627) to study the relationships among learning activities, as this technique enables us to quantify and visualise the interactions and connections between the seven learning activities (Hora & Ferrare, 2013; Nguyen et al., 2017).

Results

In order to illustrate the complexity of categorising student activities but also to demonstrate how this can enable detailed and useful analysis of student online

behaviour, we compared the learning designs of our four language modules over time. An example of learning design activity in Beginners' French is illustrated in Figure 1, whereby most activities were labelled as assimilative, followed by productive and assessment.

The content provided to learners and the time expected to be spent on assessment across the four language modules were broadly similar when looking at an aggregate level (see Figure 2). For the intermediate Spanish module there was a stronger focus on assimilative activities, while for the Beginners' French module there was a slightly lower focus on assimilative activities, and more time devoted to productive activities. The difference in time spent on assimilative activities was largely due to the addition of an introductory guide for the Spanish module. This was in response to student feedback about the complexity of the module materials and aimed to guide students through the first few weeks in a more structured way. As might be expected, both modules offered a range of activities to teach a topic**.** Assimilative and productive activities within the module book were combined with self-assessment and interactive activities in the audio-visual materials on the website and longer text or dictionary practice in the reading and writing skills book. These activities are all part of the same topic and offer the student a variety of ways to learn the language.

As illustrated in Figure 2, in comparison with 56 other OU modules Beginners' French and Beginners' Spanish had considerably higher amounts of time allocated for communication activities (10% in both compared to 3% for language modules and 4% for 56 modules). Furthermore, while Intermediate French and Intermediate Spanish had lower time allocated for communication activities, they were allocated more time on experiential activities compared to other OU modules. The mapping on an aggregate level did demonstrate strong similarities in module designs giving students a comparable learning experience across the four language modules.

As previously highlighted, novice FL learners may require more assimilative content because there is a lot for them to learn before they can begin to convert declarative knowledge into procedural knowledge. Novice FL learners may not have attained the degree of proficiency which would enable extended interaction in the target language. They might also require more structured support when communicating in the target language, an activity that will be very different depending on whether a student is communicating with their tutor and the whole class in an online tutorial; with another student who shares the same first language or with a native speaker of a second language. Although the description of the tasks was slightly different, the assessment strategy was consistent, situated in a real-life context and with a clear focus on vocabulary and grammar development (see Figure 3). This is also illustrated in Figure 4 when learning the future tense in Spanish, students had the opportunity to read, write and speak.

Linking learning design to language learners' online engagement

When we introduced an analysis of student behaviour in the VLE for these modules, we were able to quantify how long students on average spent on different online activities. Assimilative and productive activities accounted for the majority of the total workload in the initial weeks of all modules. A closer look at Beginners' Spanish, and Beginners' French revealed some similarities in the design of both modules, which allocated 4.5 h for communication activities at the beginning in combination with some readings. At the same time, the visualisations per week in Figure 5 did highlight some subtle differences across the four modules, in how students were expected to work across the first six weeks. For example, from week 1 onwards in the Beginners' Spanish module experiential activities were planned, while only from week 4 onwards these activities were planned for the Beginners' French module. Similarly, in both intermediate modules there was (continuous) assessment from the beginning of the module, while in the beginners modules the first assessment was introduced in week 3. This could be a conscious decision from the module designers to ease beginning, novice students into language learning, while for intermediate modules students may want to have immediate feedback on their language usage.

As indicated by the red lines in Figure 5, the average time spent on VLE per week remained relatively constant over time for Beginners' French (M = 79.48, SD = 116.96) and for Beginners' Spanish (M = 76.34, SD = 117.13), while there were opposing peaks in Intermediate French and Spanish in week 5. This reflected the learning designs of the respective modules, whereby a substantial piece of assessment was planned in week 4 for the introductory modules, while this was planned in week 5 for the intermediate modules. In our four language modules, the time spent on the VLE tended to increase in an assessment week, as might be expected. Again these findings support our earlier findings (Nguyen et al., 2017; Nguyen et al., 2017) that in order to understand the peaks and troughs of learning analytics data it is important to know the respective learning design activities.

This was also confirmed by a fixed effect regression model (Adj-R2 = 55.33%, not illustrated), which indicated that assessment activities were positively associated with time spent on the VLE. Based upon the behaviour of 2111 students in

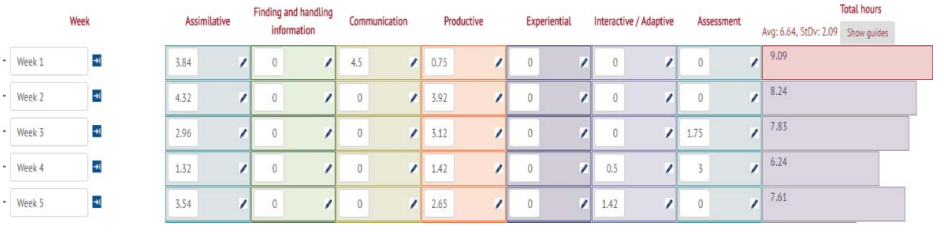

Figure 1. Beginners' French categorised by activity type (on weekly level).

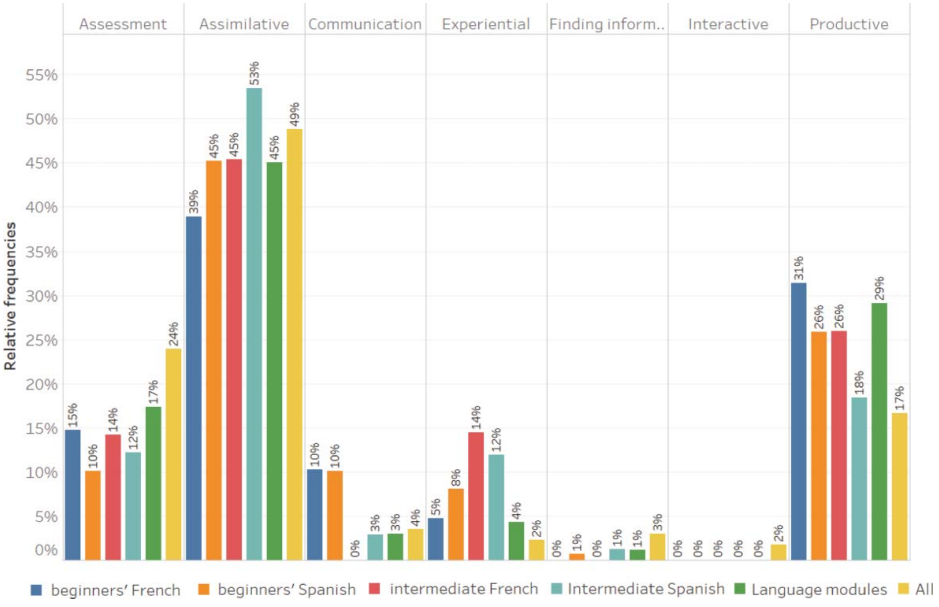

Figure 2. Comparison of four module designs (aggregate level).

these four modules, it was found that the weekly learning design activities could explain up to 55% of the variance in student behaviour in VLE. In plain English, this means that a substantial amount of time that students spent on language learning on a weekly basis is directly influenced by how language teachers design their respective courses. At the same time, as highlighted by the subtle differences between the four modules in terms of learning design and VLE engagement language teachers can pro-activity design courses with strong interaction and engagement.

Building on previous work (Hora & Ferrare, 2013; Nguyen et al., 2017), we used social network analysis to further unpack the complexity of the four learning designs, especially how the seven different types of learning activities interconnect. In Figure 6, the thickness of the links represents the associated strength between two co-occurring types of learning activities. With these example sections from beginners level modules, assimilative and productive activities were

Figure 3. Activity instruction in French and Spanish *intermediate modules*.

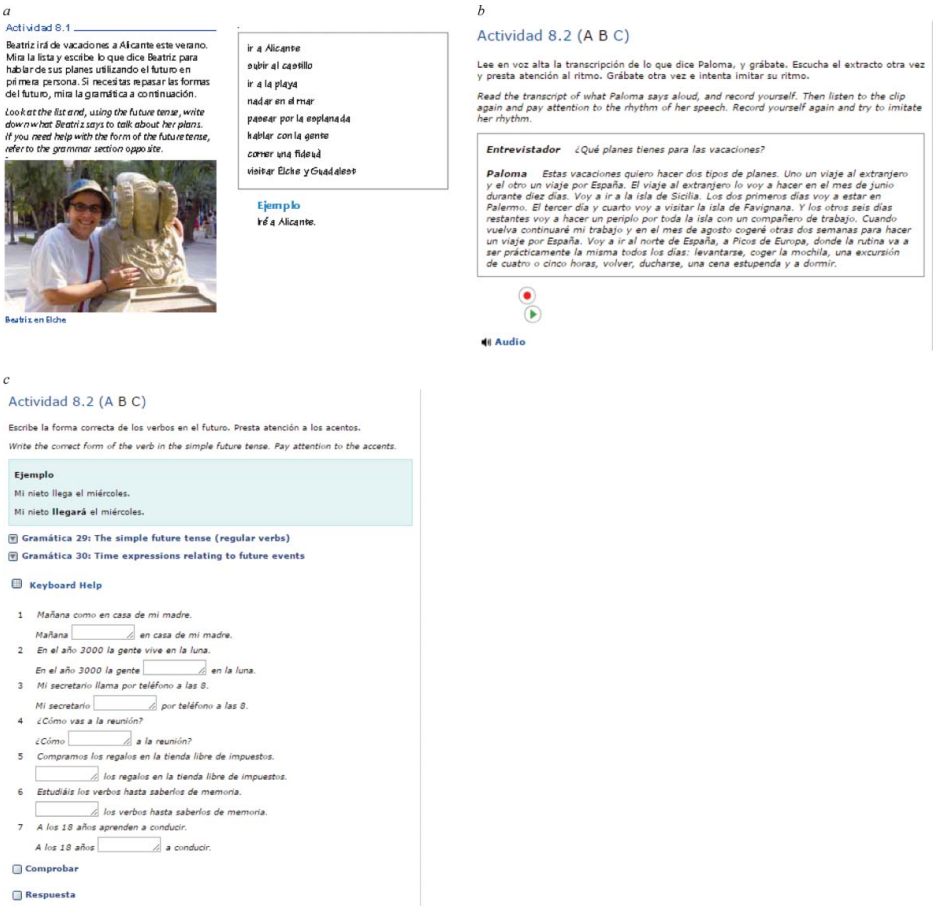

Figure 4. (a) Assimilative activities in the book. (b) Speaking activities. (c) Self-assessment activities.

strongly connected, showing that language educators often combined text with questions to reflect on the materials (Figure 6(a,b)). The visualisations also nicely illustrate a strong and common link across all four modules between assimilative and productive activities. At the same time, in the two intermediary modules a relatively stronger focus on assessment and assimilative learning activities is present in comparison to the beginners' modules. Furthermore, the SNA visualisations also illustrate which learning design activities were not used (e.g., interactive activities in Beginners' Spanish, information, communication and interaction in Intermediate Spanish).

Discussion

The role of technology to support Computer Assisted Language Learning (CALL) has a rich and diverse impact on how our students are learning over time. In line with a call by Golonka et al. (2014) to provide more robust

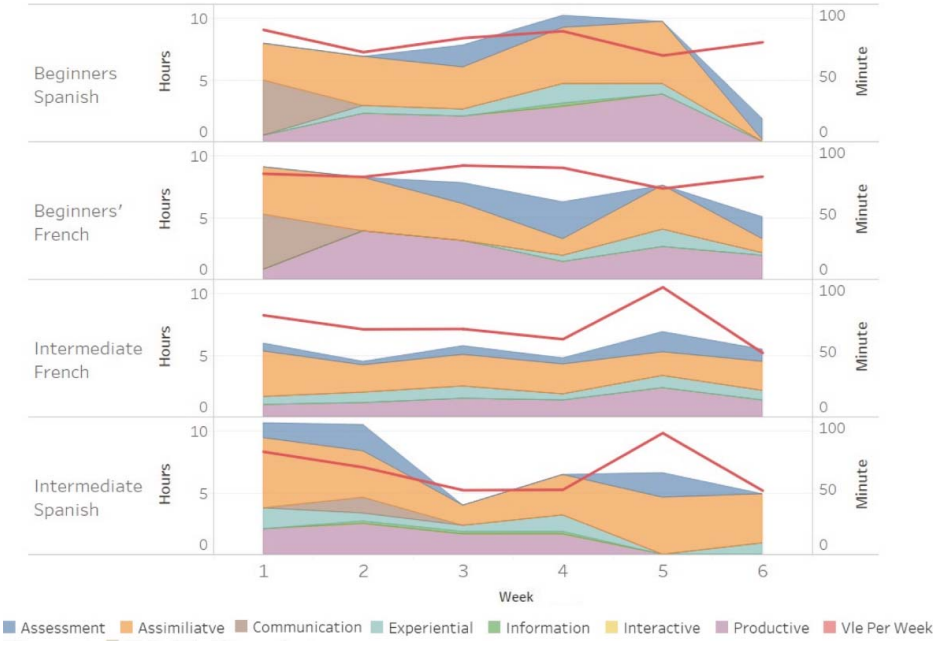

Figure 5. Longitudinal visualisations of learning design and time spent on Virtual Learning Environment.

empirical and evidence-based research on the impact of FL on how language students are actually learning in large scale settings, using learning analytics data this study explored how language teachers designed four beginners and intermediate modules in French and Spanish and how this influenced actual student behaviour.

In terms our overall research question (i.e., How are learning design decisions influencing language students' engagement in the VLE over time?) we found strong support that the way language teachers design their modules directly predicts students' online behaviour. Up to 55% of variation in what students were doing on a week-by-week basis was explained by the specific learning design activities that language teachers designed, in particular when these were related to assessment and productive activities. This highlights a need for CALL module authors to be fully conversant with learning design principles and for course delivery patterns to be sufficiently flexible to accommodate iterative modifications in response to findings derived from learning analytics (Dalziel, 2016; Hernández-Leo et al., 2014).

Given these preliminary findings that learning design plays an important role in terms of what language learners are actually doing, the collection and analysis of VLE data in real time may offer opportunities for language educators to respond to student behaviour and to offer support and intervention in a way which has not previously been available in distance education (Tempelaar et al., 2015; Tempelaar, Rienties, & Nguyen, 2017). Traditionally students have

provided feedback at the end of a module enabling amendments to be made to materials for the next cohort of students, but not typically benefiting those students who provided the feedback (Li, Marsh, Rienties, & Whitelock, 2017). However, a major advantage of learning analytics is the ability to capture and analyse big trend data as well as fine-grained data such as the time spent on key learning activities, and the frequency of visits (Wolff et al., 2013). Combining these data with demographics and performance history allows language educators to both make personalised interventions in relation to each student, as well as to adjust the module according to overall trends evident in the student cohort (Ferguson et al., 2016; Thomas et al., 2017; Verbert et al., 2013).

Our findings seem to indicate that the safest prescription for effective FL learning design is consequently for a balanced regime of all seven types of activity identified by learning design. There is clearly some way to go before OU language modules will be able to boast this. The way forward lies in ever closer cooperation between specialists in learning design and learning analytics, applied linguists and foreign language module writers. In the design of online language learning, as in so much else, the future is interdisciplinary.

A key challenge for CALL, indeed for all DLL, is keeping up with developments in technology when developing and implementing courses and modules in particular (Finger et al., 2010; Sockett & Toffoli, 2012; Toetenel & Rienties, 2016). This is a particular obstacle at the OU, where often, given the large scale of production, modules have a life span of 8–10 years. The foreign language modules described in this study are nearing the end of their life span and are due to be replaced, which allows a redesign of the materials and teaching

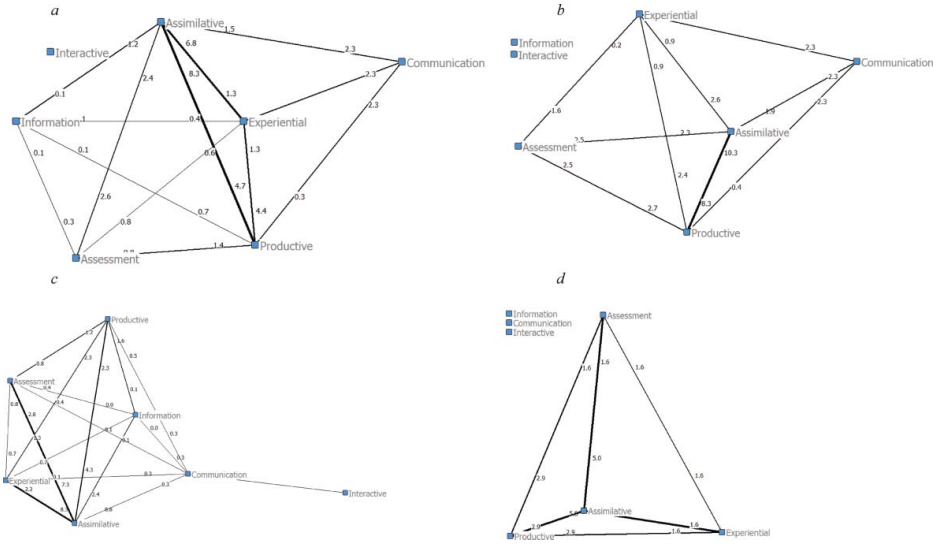

Figure 6. (a) Network analysis of Beginners' Spanish learning design. (b): Network analysis of Beginners' French learning design. (c) Network analysis of Intermediate Spanish learning design (d) Network analysis of Intermediate Spanish learning design.

approach. Applying the adapted OULDI taxonomy and making use of detailed learning analytics will ensure a sound pedagogic approach (and vice-versa of course) to the development of module materials, and offers an opportunity to carefully consider the structure of the module, the range of student activities, and whether or not we need to alter our learning design and learning analytics approach.

Module teams are currently reconsidering which activity types lend themselves best to online learning and which can be done offline (but on-screen) – for example communicative forum activities require online connection, while reading material or videos can be downloaded for later use. This preparation has led to more detailed planning of related activities to avoid the need for students to switch frequently between media types and is likely to be reflected in the updated network analysis. These activities all reflect the collaborative approach of learning design leading to an improved student experience, but the key benefit is in the potential to better understand how students engage with different activities and how this contributes towards their success in learning.

Limitations and ways forward

One obvious limitation of our research is that we did not include more micro level fine-grained analyses of actual student behaviour on the various FL tasks, such as those done by Chen et al. (2015). Given the size of its student population, the OU is currently only able to keep fine-grained data for the modules on which predictive analytics engines are being piloted instead of individual student data (Wolff et al., 2013). A second limitation is that we did not include models predicting whether the learning designs led to improved retention and satisfaction. Given the relatively small sample of four modules, in the near future more language modules will be linked, on implementation, with actual student outcomes to determine the long-term impact of subtle differences in learning design. Finally, although the learning design categories have been shown to be significant predictors of student engagement on VLE, satisfaction, and pass rates (Rienties & Toetenel, 2016), there are several caveats in the current approach. On one hand, learning activities could overlap between two or more categories (i.e., students exchanging dialogue on discussion forums also produce artefacts). The OULDI mapping approach does allow learning to be categorised across more than one activity type, for example students might produce a resource (productive) which they then share for peer review (communicative). On the other hand, learning design categories could be further contextualised to different disciplines and instructional approach (i.e., assessment activities could be either formative or summative).

The analytic capabilities of CALL open up immense opportunities to analyse language learning at scale (see e.g., Allen et al., 2015, 2017), to bridge the gap between language learners and language practitioners, to inform practice using

evidence (Ferguson & Clow, 2017; Ferguson et al., 2016), and to begin to understand how learners really interact with learning materials. We hope that our learning analytics study will encourage other CALL researchers to embrace the power of learning design and big data to unpack the complexities of language learning.

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