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The synergistic and dynamic relationship between learning design and learning analytics

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The synergistic relationship between learning design and learning analytics has the potential for improving learning and teaching in near real-time. The potential for integrating the newly available and dynamic information from ongoing analysis into learning design requires new perspectives on learning and teaching data processing and analysis as well as advanced theories, methods, and tools for supporting dynamic learning design processes. Three perspectives of learning analytics design provide summative, real-time, and predictive insights. In a case study with 3,550 users, the navigation sequence and network graph analysis demonstrate the potential of learning analytics design. The study aims to demonstrate how the analysis of navigation patterns and network graph analysis could inform the learning design of self-guided digital learning experiences. Even with open-ended freedom, only 608 sequences were evidenced by learners out of a potential number of hundreds of millions of sequences. Advancements of learning analytics design have the potential for mapping the cognitive, social and even physical states of the learner and optimise their learning environment on the fly.

Introduction

One of the next frontiers in educational research may be a synergistic and dynamic relationship between learning design and learning analytics. These two perspectives – design and analytics - have heretofore primarily operated independent of each other, separated by time and space due to the complexity of dealing with interactional data in educational settings. However, now with the advent of near real time data and new ways of representing the decisions and actions of learners in digital learning environments, learning designers have new ways to use dynamic learning analytics information to evaluate learner characteristics, examine learning designs, analyse the effectiveness of learning materials and activities, adjust difficulty levels, and measure the impact of interventions and feedback. This new level of sophisticated information about learners, learning processes, and complex interactions within the learning environment has the potential to provide valuable insights for 'on the fly' educational planning and curricular decision-making fully integrated into the digital learning experience.

This paper reports on a case study demonstrating the synergetic relationship between learning design and learning analytics, with a focus on the application of navigation sequence and network graph analysis. Particularly, it illustrates how analytics may support the design of learning environments, which is followed by a discussion of implications and conclusion.

Learning design and analytics

Goodyear and Retalis (2010) emphasise that good educational design is the missing link between the learning sciences and the learning environments needed for success in the 21st century. Design patterns may offer a way of capturing design experience including (1) connecting recognisable problems with tested solutions, (2) relating design problems at any scale level (e.g., micro, meso, and macro), and connecting design solutions across scale levels, (3) supplementing design with research-based evidence, (4) balancing guidance with creativity, (5) having a wide application of designs but being customisable to meet specific needs, and (6) improving design performance while also educating the designer (Goodyear & Retalis, 2010). Dalziel et al. (2016) noted that:

> *The ultimate goal of Learning Design is to convey great teaching ideas among educators in order to improve student learning … successful sharing of good teaching ideas can lead not only to more effective teaching, but also to more efficient preparation for teaching*.

Learning design aims to provide a description of optimal designs for learning and teaching with a potential for reuse and adaptation of design, however, it does not offer

real-time insights how students are engaged and learn (Lockyer, Heathcote, & Dawson, 2013). Therefore, linking design for learning with learning analytics may provide actionable information for optimising learning environments in real-time. Hence, we propose that the next frontier in educational research may be a synergistic relationship between learning design and learning analytics.
Learning analytics use available information from various reactive and non-reactive educational sources including learner characteristics, learner behaviour, learner performance, as well as detailed information of the learning design (e.g., sequencing of events, task difficulty, learning outcomes) for supporting pedagogical interventions and re-designs of learning environments (Berland, Baker, & Bilkstein, 2014). Learning analytics are expected to provide the pedagogical and technological background for producing real-time interventions at all times during the learning process. Students benefit from learning analytics through optimised learning pathways, personalised interventions, and real-time scaffolds (Gašević, Dawson, & Siemens, 2015). Learning analytics provide facilitators detailed analysis and monitoring on the individual student level, allowing them to identify particularly instable factors, such as motivation or attention losses, before they occur (Gašević, Dawson, Rogers, & Gašević, 2016). However, ethical and privacy issues have been identified as a major concern with the adoption of learning analytics (Ifenthaler & Schumacher, 2016; Slade & Prinsloo, 2013). Learning analytics should be aligned with organisational principles and values as well as include a wide variety of stakeholders. In sum, learning analytics need to collect, use, and analyse data transparently and free of bias, and have multilevel relevance (Ifenthaler & Schumacher, 2016; Pardo & Siemens, 2014).

Learning analytics design is thus expected to generate valuable insights for planning and optimising of pedagogical designs, including adapting and optimising the sequencing of activities on the fly (Ifenthaler, 2017). The synergetic relationship between learning design and learning analytics is exemplifying the notion that teaching in higher education in the twenty-first century with ever changing cultural and technological changes has become a *design science* "because [teaching] uses what is known about teaching to attain the goal of student learning, and uses the implication of its designs to keep improving them (Laurillard, 2012, p. 1). Adaptation and optimisation of learning and teaching may occur, for example, based on educator-selected benchmarks that help to identify alignment or misalignment towards learning outcomes. In addition, detailed insights into pedagogical processes may facilitate micro interventions whenever the learner needs it (Bannert, 2009; Ifenthaler, 2012; van den Boom, Paas, van Merriënboer, & van Gog, 2004).

Case study

This case study aims to demonstrate how the analysis of navigation patterns and network graph analysis could inform the learning design of self-guided digital learning experiences. In particular, two research questions were addressed: 1. Can navigation patterns identify individual user paths and contribute to optimised learning design? 2. Do visualisations of network graphs help to understand user patterns within a digital learning environment? Ethics approval for the case study has been obtained.

Context

The Curtin Challenge digital learning platform (http://challenge.curtin.edu.au) supports individual and team-based learning via gamified, challenge-based, open-ended, inquiry-based learning experiences that integrate automated feedback and rubric-driven assessment capabilities. The Challenge platform is an integral component of Curtin University's digital learning environment along with the Blackboard learning management system and the edX MOOCs platform. The Challenge development team at the Curtin Learning and Teaching are working towards an integrated authoring system across all three digital learning environments with the view to create reusable and extensible digital learning experiences.

Curtin Challenge includes three sets of content modules: Leadership, Careers and English Language Challenge. Over 2,600 badges have been awarded for the completion of a challenge. This case study includes analysis from the Careers Challenge, which has 12 modules each of which can normally be completed in 60 minutes or less. The design features of each module contain approximately five activities designed to include one to three different interactions.

The module "Who am I" in the Careers Challenge is a collection of five web pages (called 'activities') containing interactions, such as choosing from among options, writing a short response to a prompt, spinning a wheel to create random prompts, creating, organising and listing ideas, matching items, and so forth. The average time to complete the 'Who am I' module is 1.4 hours. The five activities in the module are 1. Why is self-awareness important for your career, 2. Career values, 3. Self-awareness in action, 4. Employability skills, 5. Final thoughts.

Analytics snapshot of the case study

Analytics data for the presented case study includes 2,753,142 database rows. Overall, 3,550 unique users registered and completed a total of 14,587 navigation events. Figure 1 provides an overview of modules started (M = 3,427, SD = 2,880) and completed (M = 2,903, SD = 2,303) for the Careers Challenge. The average completion rate for the Careers Challenge was 87%. The most frequently started module was “Who am I?” (10,461) followed by the module “Resumes” (7,996). The module “Workplace Rights and Responsibilities” showed the highest completion rate of 96% followed by the module “Interviews” (92%). A total of 60 activities were included in the analysis of the twelve modules of the Careers Challenge. The average completion rate for the 60 activities was 89% (M = 580, SD = 476). The most frequently started activity was “Why is Self-awareness Important for your Career?” (3,225) which is part of the “Who am I?” module. The activity “How do People see You?” within the module “Interviews” showed the highest completion rate of 99%.

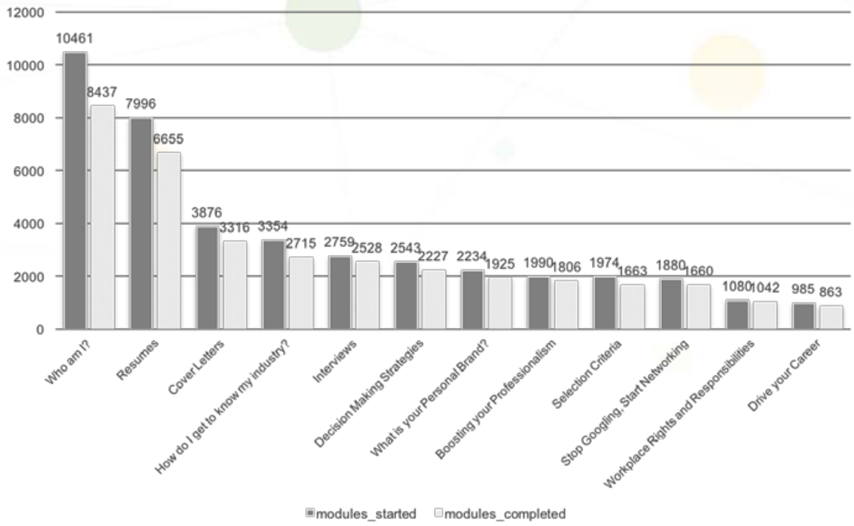

Figure 1: Module completion of Careers Challenge

Activity network graph analysis

The network analysis identifies user paths within the learning environment and visualises them as a network graph on the fly. The dashboard visualisations help the learning designer to identify specific patterns of learners and can reveal potentially problematic learning instances, such as learner disengagement. The nodes of the network graph represent individual interactions. The edges of the network graph represent directed paths from one interaction to another. The indicator on the edges represents the frequency of learners taking the path from one interaction to another and in parenthesis the percentage of learners who took the path. An aggregated network graph shows the overall navigation patterns of all learners. A network graph can be created for each individual learner, for selected groups of learners (e.g., with specific characteristics), or for all learners of the learning environment. Updates of the network graph are generated in near real-time. This has the potential to help the learning designer to identify people who require further help within the learning environment. In addition, the learning designer may identify learning materials or activities that do not contribute to an optimal learning experience. A learning design dashboard (in preparation) will enable the learning designer to zoom into specific learning events of individual learners or of specific groups of learners.

The aggregation of all individual network graphs provides detailed insights into the navigation patterns of all learners. Figure 2 shows the aggregated network graph network including paths taken by all 3,550 learners showing 14,587 navigation events. The five modules are highlighted using different colours. This example of a network graph can assist the learning designer to optimise the current design as well as reflect on the planning of future learning designs. Accordingly, such a network graph can also function as an instrument for professional development of learning designers.

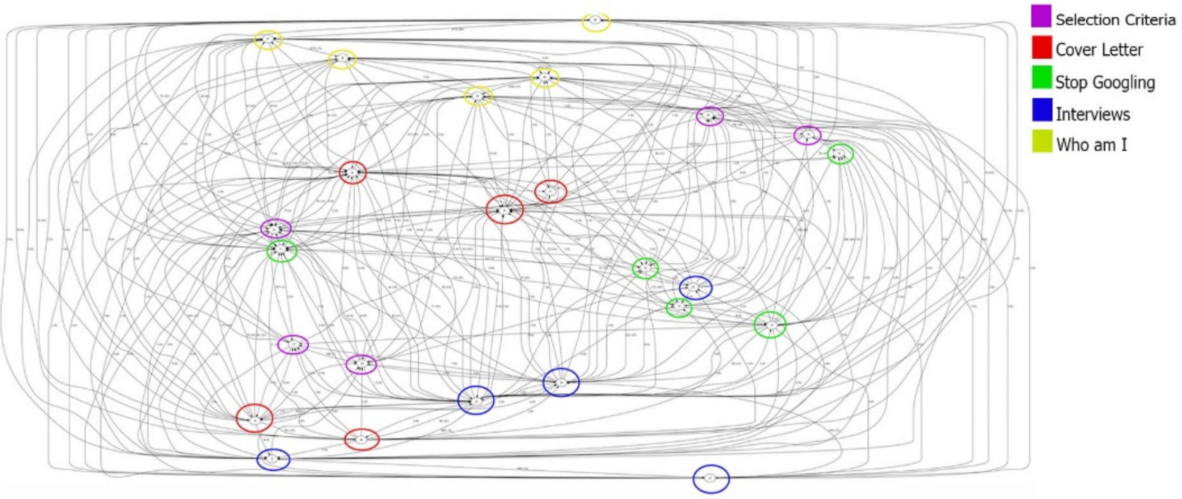

Figure 2: Aggregated network graph

Discussion and conclusion

The learning designers of the example case could have directed users to flow through the modules of Careers Challenge in a particular order, or in some small subset of orders of the modules, but instead chose to leave the entire set of modules open at all times to all users. This design decision resulted in Figure 2 that shows a few preferred paths (the thicker lines), but on the whole, a wide variety of paths. However, even with open-ended freedom, only 608 sequences were evidenced by learners out of a potential number of hundreds of millions of sequences (e.g., the combination of sequences of 5 interactions in any order out of 50 is (50*49*48*47*46) = over 254 million sequences). Of the 608 sequences created by users, far fewer have large percentages of the population traversing the same paths. For example, 17% of the total population gave one activity a try and then left the Challenge; another 16% engaged with a sequence of only four interactions and then exited. With the extremely small subspace traversed by users, it is perhaps understandable to think that there is meaning in that pattern (e.g., why are there not more sequences evidenced and why these particular sequences?).

The initial authored content in the Careers Challenge represents an incremental step from typical online content – where the learner reads content and then answers some questions, or perhaps creates lists of ideas when prompted. The advance in the Careers Challenge learning design took place at the interaction level rather than the activity path level. For example, fourteen new learner interactions were mapped, including drag and drop, spinning wheels for randomising content, list construction, list item creation, priority ranking of items, and more. The analysis of these interactions is a level deeper than tracking which activity page someone lands on; it might be a starting point for mapping how a crowd of learners utilises the learning resources within an activity, and is closer to a cognitive analysis than simple landing page analysis.

Using analytics data to support learning design decisions requires a deep understanding about the meaning of the network graph and underlying algorithms. This is a new challenge for future learning designers but also a new opportunity to reflect on design decisions in near-real time and thus, optimise learning environments on-the-fly.

To sum up, the integration of analytics data into the design of learning environments is a promising approach. Learning design may offer the right set of theoretical foundations for planning optimal design and reuse of cross-platform learning and teaching sequences. Learning analytics in turn is able to offer detailed insights into individual and collective learning processes and evidence for validating assumptions about the effects of learning designs in various contexts. Accordingly, the synergistic relationship between learning design and learning analytics, i.e., *learning analytics design* (Ifenthaler, 2017), opens up a bright future for the design of personalised and adaptive learning. It is up to educators-as-designers to make the links between learning design and learning analytics operational and use learning analytics design to further advance the educational arena.

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