Context-Appropriate Scaffolding Assemblages: A generative learning analytics platform for end-user development and participatory design

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ABSTRACT: There remains a significant tension in the development and use of learning analytics between course/unit or learning design specific models and generic, one-size fits all models. As learning analytics increases its focus on scalability there is a danger of erring toward the generic and limiting the ability to align learning analytics with the specific needs and expectations of users. This paper describes the origins, rationale, and use cases of a work in progress design-based research project attempting to develop a generative learning analytics platform. Such a platform encourages a broad audience to develop unfiltered and unanticipated changes to learning analytics. It is hoped that such a generative platform will enable the development and greater adoption of embedded and contextually specific learning analytics and subsequently improve learning and teaching. The paper questions which tools, social structures, and techniques from participatory design might inform the design and use of the platform, and asks whether or not participatory design might be more effective when partnered with generative technology?

Keywords: Contextually Appropriate Scaffolding Assemblages (CASA); generative platform; participatory design; DIY learning analytics

1 INTRODUCTION

One size does not fit all in learning analytics. There is no technological solution that will work for every teacher, every time (Mishra & Koehler, 2006). Context specific models improve teaching and learning, yield better results and improve the effectiveness of human action (Baker, 2016; Gašević, Dawson, Rogers, & Gasevic, 2016). Despite this, higher education institutions tend to adopt generalised approaches to learning analytics. Whilst this may be cost effective and efficient for the organisation (Gašević et al., 2016), the result is a generic approach that provides an inability to cater for the full diversity of learning and learners and shows "less variety than a low-end fast-food restaurant" (Dede, 2008).

Institutional implementation of learning analytics in terms of both practice and research remain limited to conceptual understandings and are empirically narrow or limited (Colvin, Dawson, Wade, & Gašević, 2017). In practice, learning analytics has suffered from a lack of human-centeredness (Liu, Bartimote-Aufflick, Pardo, & Bridgeman, 2017). Even when learning analytics tools are designed with the user in mind (e.g. Corrin et al., 2015), the resulting tools tend to be what Zittrain (2008) defines as non-generative or sterile. In particular, the adoption of such tools tends to require institutional support and subsequently leans toward the generic, rather than the specific. This perhaps provides at least part of the answer of why learning analytics dashboards are seldom used to intervene during the teaching of a course (Schmitz, Limbeek, van Greller, Sloep, & Drachsler, 2017) and leading us to the research question: How can the development of learning analytics better support the needs of specific contexts, drive adoption, and ongoing design and development? More broadly, we are interested in if and how learning analytics can encourage the adoption of practices that position teaching as design and subsequently improve learning experiences and outcomes (Goodyear, 2015) by supporting a greater focus on the do-it-with (DIW - participatory design) and do-it-yourself (DIY) design (where teachers are seen as designers), implementation, and application of learning analytics. This focus challenges the currently more common Do-It-To (DIT) and Do-It-For (DIF) approaches (Beer, Tickner & Jones, 2014).

This project seeks to explore learning analytics using a design-based research approach informed by a broader information systems design theory for e-learning (Jones, 2011), experience with Do-It-With (DIW) (Beer et al., 2014) and teacher Do-It-Yourself (DIY) learning analytics (Jones, Jones, Beer, & Lawson, 2017), and technologies associated with reproducible research to design and test a generative learning analytics platform. Zittrain (2008) defines a generative system as having the "capacity to produce unanticipated change through unfiltered contributions from broad and varied audiences" (p. 70). How generative a system is depends on five principal factors: (1) *leverage*; (2) *adaptation*; (3) ease of *mastery*; (4) *accessibility*; and (5) *transferability* (Zittrain, 2008). A focus for this project is in exploring how and if a generative learning analytics platform can act as a boundary object for the diverse stakeholders involved with the design, implementation and use of institutional learning analytics (Suthers & Verbert, 2013). Such an object broadens the range of people who can engage in creative acts of making learning analytics as a way to make sense of current and future learning and teaching practices and the contexts within which it occurs. The platform - named CASA, an acronym standing for Contextually Appropriate Scaffolding Assemblages - will be designed to enable all stakeholders alone or together to participate in decisions around the design, development, adoption and sharing of learning analytics tools. These tools will be created by combining, customising, and packaging existing analytics - either through participatory design (DIW) or end-user development (DIY) - to provide context-sensitive scaffolds that can be embedded within specific online learning environments..

2 KNOW THY STUDENT – TEACHER DIY LEARNING ANALYTICS

Jones et al., (2017) uses a case of teacher DIY learning analytics to draw a set of questions and implications for the institutional implementation of learning analytics and the need for CASA. The spark for the teacher DIY learning analytics was the observation that it took more than 10 minutes, using two separate information systems including a number of poorly designed reports, to gather the information necessary to respond to an individual learner's query in a discussion forum. The teacher was able to design an embedded, ubiquitous and contextually specific learning analytics tool (Know Thy Student) that reduced the time taken to gather the necessary information to a single mouse click. The tool was used in four offerings of a third year teacher education unit across 2015 and 2016. Analysis of usage logs indicates that it was used 3,100 separate times to access information on 761 different students, representing 89.5% of the total enrolled students. This usage was spread across 666 days over the two years, representing 91% of the available days during this period. A significant usage level, especially given that most learning analytics dashboards are seldom used to intervene during the teaching of a course (Schmitz et al., 2017). Usage also went beyond responding to discussion forum questions. Since the tool was unintentionally available throughout the entire learning environment (embedded and ubiquitous) unplanned use of the tool developed contributing to improvements in the learner experience. This led to the implication that embedded, ubiquitous, contextual learning analytics encourages greater use and enables emergent practice (Jones et al., 2017). It provides *leverage* to make the difficult job of teaching a large enrolment, online course easier. However, the implementation of this tool required significant technical knowledge and hence is not easy to *master*, not *accessible*, nor easily *transferable*, Zittrain's (2008) remaining principles required for a generative platform. The questions now become: How to reduce this difficulty? *How to develop a generative learning analytics platform?*

3 CASA TECHNOLOGIES AND TECHNIQUES

To answer this question CASA will draw on a combination of common technologies associated with reproducible research including virtualisation, literate computing (e.g. Jupyter Notebooks), and version control systems (Sinha & Sudhish, 2016) combined with web augmentation (Díaz & Arellano, 2015) and scraping (Glez-Peña, Lourenço, López-Fernández, Reboiro-Jato, & Fdez-Riverola, 2014). Reproducible research technologies enable CASA to draw upon a large and growing collection of tools developed and used by the learning analytics and other research communities. Growth in the importance of reproducible research also means that there is a growing number of university teaching staff familiar with the technology. It also means that there is emerging research literature sharing insights and advice in supporting academics to develop the required skills (e.g. Wilson, 2016). Virtualisation allows CASA to be packed into a single image which allows individuals to easily download, install and execute within their own computing platforms. Web augmentation provides the ability to adapt existing web-based learning environments to embed learning analytics directly into the current common learning context. The combination of these technologies will be used to implement the CASA platform, enabling the broadest possible range of stakeholders to individually and collaboratively design and implement different CASA instances. Such instances can be mixed and matched to suit context-specific requirements and shared amongst a broader community. The following section provides a collection of CASA use case scenarios including explicit links to Zittrain's (2008) five principal factors of a generative platform.

4 CASA USE CASE SCENARIOS

A particular focus with the CASA platform is to enable individual teachers to adopt CASA instances while minimising the need to engage with institutional support services (*accessibility*). Consequently a common scenario would be where a teacher (Cara) observes another teacher (Daniel) using a CASA instance. It is obvious to Cara that this specific CASA instance makes a difficult job easier (*leverage*) and motivates her to trial it. Cara visits the CASA website and downloads and executes a virtual image (the CASA instance) on her computer, assuming she has local administrator rights. Cara configures CASA by visiting a URL to this new CASA instance and stepping through a configuration process that asks for some context specific information (e.g. the URL for Cara's course sites). Cara's CASA uses this to download basic clickstream and learner data from the LMS. Finally, Cara downloads the Tampermonkey browser extension and installs the CASA user script to her browser. Now when visiting any of her course websites Cara can access visualisations of basic clickstream data for each student.

To further customise her CASA instance Cara uploads additional data to provide more contextual and pedagogical detail (*adaptation*). The ability to do this is sign-posted and scaffolded from within the CASA tool (*mastery*). To expand the learner data Cara sources a CSV file from her institution's student records system. Once uploaded to CASA all the additional information about each student appears in her CASA and Cara can choose to further hide, reveal, or re-order this information (*adaptation*). To associate important course events (Corrin et al., 2015) with the clickstream data Cara uses a calendar application to create an iCalendar file with important dates (e.g assignment due dates, weekly lecture times). This is uploaded or connected to CASA and the events are subsequently integrated into the clickstream analytics. At this stage, Cara has used CASA to add embedded, ubiquitous and contextually specific learning analytics about individual students into her course site. At no stage has Cara gained access to new information. CASA has simply made it easier for Cara to access this information, increasing her efficiency (*leverage*). This positive experience encourages Cara to consider what more is possible.

Cara engages in a discussion with Helen, a local educational designer. The discussion explores the purpose for using learning analytics and how it relates to intended learning outcomes. This leads to questions about exactly how and when Cara is engaging in the learning environment. This leads them to engage in various forms of participatory design with Chuck (a software developer). Chuck demonstrates how the student clickstream notebook form Cara's existing instance can be copied and modified to visualise staff activity (*mastery*). Chuck also demonstrates how this new instance can be shared back to the CASA repository and how this process will eventually allow Daniel to choose to adopt this new instance (*transferability*). These discussions may also reveal insights into other factors such as limitations in Cara's conceptions and practices of learning and teaching, or institutional factors and limitations (e.g. limited quality or variety of available data).

5 CONCLUSIONS AND QUESTIONS

This paper has described the rationale, origins, theoretical principles, planned technical implementation and possible use cases for CASA. CASA is a generative learning analytics platform which acts as a boundary object. An object that engages diverse stakeholders more effectively in creative acts of making to help make sense of and respond to the diversity and complexity inherent in learning and teaching in contemporary higher education. By allowing both DIW (participatory design) and DIY (end-user development) approaches to the implementation of learning analytics we think CASA can enable the development of embedded, ubiquitous and contextually specific applications of learning analytics, better position teaching as design, and subsequently improve learning experiences and outcomes. As novices to the practice of participatory design we are looking for assistance in examining how insights from participatory design can inform the design and use of CASA. For us, there appear to be three areas of design activity where participatory design can help and a possibility where the addition of generative technology might help strengthen participatory design.

First, the design of the CASA platform itself could benefit from participatory design. A particular challenge to implementation within higher education institutions is that as a generative platform CASA embodies a different mindset. A generative mindset invites open participation and assumes open participation provides significant advantage, especially in terms of achieving contextually appropriate applications. It sees users as partners and co-designers. An institutional mindset tends to see users as the subject of design and due to concerns about privacy, security, and deficit models seek to significantly limit participation in design. Second, the DIW interaction between Cara, Helen and Chuck in the use case section is a potential example of using participatory design and the CASA platform to co-design and co-create contextually specific CASA instances. What methods, tools and techniques from participatory design could help these interactions? Is there benefit in embedding support for some of these within the CASA platform? Lastly, the CASA approach also seeks to enable individual teachers to engage in DIY development. According to Zittrain (2008) the easier we can make it for teachers to develop their own CASA instances (*mastery*) the more generative the platform will be. What insights from participatory design might help increase CASA's generative nature? Can CASA be seen as an example of a generative toolkit (Sanders & Strappers, 2014)? Or, does the DIY focus move into the post-design stage (Sanders & Strappers, 2014)? Does it move beyond participatory design? Is the combination of participatory design and generative technology something different and more effective than participatory design alone? If it is separate, then how can the insights generated by DIY making with CASA be fed back into the on-going participatory design of the CASA platform, other CASA instances, and sense-making about the broader institutional context?

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Contextual Inquiry, Participatory Design, and Learning Analytics: An Example

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ABSTRACT: The methods used in learning analytics for early specification of design requirements are still generally grounded in prior research, theoretical frameworks, and the existing body of practice. These traditional methods provide a strong background for development, but adapting them to a wide range of user needs is challenging. Participatory design and contextual inquiry can address this challenge. These user-centred design methods help extend theoretical principles into real-world applications. As such, we propose field-based contextual inquiry and participatory design methods to elicit design requirements for learning analytics features and present an exemplar study as a starting point for future exploration and validation of these approaches.

Keywords: Contextual Inquiry, Participatory Design, Learning Analytics, Learning Dashboards

1 INTRODUCTION

Participatory design (PD) integrates users into the technology creation process through a variety of methods (e.g., interviews, observations, or design activities; Muller, 1993, 2003) to elicit requirements from the early stages of the design process. Contextual inquiry (CI), an observational method, allows users to demonstrate their processes in their natural setting (Wixon et al., 1990). Like in PD, a key component of CI is the partnership between the researcher and participant where the researcher acts as apprentice to the participant who is a master of his/her process (Holtzblatt & Beyer, 2012). CI is a method that draws significantly from ethnographic studies and can be applied as part of the task analysis stage of any software development process. In such stages, the researcher aims to uncover users' existing practices, processes, beliefs, or use of artefacts to identify opportunities to improve upon existing tasks or to specify requirements for new technology that are better grounded in user needs. This gives researchers an accurate and thorough understanding of the activity, including important details that may be overlooked when other methods are used. PD and CI can also reveal hidden elements of user's mental models that result from the difficulty associated with verbalizing one's process. Moreover, they can empower students to take ownership over their learning (Birch & Demmans Epp, 2015), which is atypical when other methods are used.

Current educational technology contexts reinforce existing power structures, which can contribute to adverse consequences (Avison, Baskerville, & Myers, 2001) that include the ignoring of provided analytics (Ferguson et al., 2016) or their misinterpretation and misuse (Demmans Epp & Bull, 2015). At present, CI and PD are rarely used despite their potential to inform design by better understanding learners and their environments. This potential along with a need to make learner decision-making processes explicit makes these methods crucial for designing better analytics, streamlining the design process, generating novel insights, and increasing learning analytics adoption in ways that traditional methods have not. This paper presents an exemplar study that takes these first steps.

2 CURRENT STUDY

Adult English Language Learners (ELLs) require strong writing skills to improve their work and social opportunities. In traditional classrooms, resource constraints make it a challenge to consistently provide timely and personalized feedback that support writing development. We are building a mobile application to support the writing development of mature ELLs (Age: M = 40.1, $SD = 9.2$). This study applies CI and PD guidelines to the task of designing an application that addresses the unique needs and challenges of this group of learners. We have designed and conducted a field study with 15 mature ELLs who are recent immigrants to Canada. In the first two sessions, participants completed writing samples, peer-reviewed other participants' writing samples, and participated in a one-on-one interview that explored their writing challenges and needs. The third and final session is currently underway. It consists of focus groups where ELLs actively engage in application design to generate guidelines and feature ideas for the tool through discussion, scenario-based prompts and sketching activities facilitated by the researcher. Instruments, like the Motivated Strategies for Learning Questionnaire (MSLQ), provided insight into participants' goal orientations, motivations, and beliefs. Observations of participants' writing tasks and interviews provided complementary information.

Below, we outline the advantages of CI and PD as we enacted them within this study. We explore how involving learners throughout the design process generated context-relevant insights that supplemented the results obtained through traditional methods. Some of the observations from the first two sessions are shared. We then discuss how the early incorporation of CI methods shaped the design of the focus group and the PD activities that occurred during the third session.

2.1 Advantage one: Provides context to empirical findings

Prior work stresses the importance of completing CI observations before introducing the idea of new technology (Axtell & Munteanu, 2017). This prevents participants from fixating on technology limitations or wondering how their performance will affect its design, and it helps prevent imposing pre-defined structures on analytic design. The first research objective was to study writing practices. Once these practices were understood, the next objective was to design a tool that supported natural writing flow. The CI used consisted of direct observations of participants' writing tasks and their use of help tools as well as questioning them about their workflow (when appropriate as to not disturb writing flow).

When performing peer-review activities, four ELLs were seen using their phones to translate words. When questioned, most said something similar to "I can improve my vocabulary because for the first one I think some of his words I even don't know. And I look up in my dictionary. I think it's better for me to improve the vocabulary." While ELLs understood the objective of peer-review was to provide feedback, they also viewed it as an opportunity for advancing their own learning. High MSLQ scores for both intrinsic goal orientation (M = 6, SD = 0.6 out of 7; how motivated learners are by internal factors) and task value (*M* = 6, *SD* = 0.8; importance of mastering a learning activity) were consistent with this participant claim. Observing ELLs as they performed learning activities allowed us to capture how their beliefs and motivations manifested into practice, which informed the tool's design. For instance, we could provide features to support ELL learning of unfamiliar words to expand their own knowledge as they engage in peer-review.

The interviews also revealed that many ELLs had minimal instruction on writing. For almost half, neither early schooling nor their English classes emphasized writing, as one participant shared:

> They didn't say about how to write the essay. Just our teachers said: 'You have to write three paragraphs, one paragraph about your opinion. The second paragraph it means the body, and the last paragraph you have to describe the conclusion.'

This finding was validated by an ELL instructor hired to grade the essays, who found the participants had little understanding of essay structure. In this case, combining existing practices (skill assessment) with interviews provided deeper understanding of barriers faced by ELLs, namely a systemic lack of instruction on core writing fundamentals.

2.2 Advantage two: Shines light on hidden assumptions

When asked what makes a "good" teacher, ELLs emphasized the value of praise. As one said, "It's positive. It is like the motive to continue writing because you're receiving a good feedback. Someone is praising you." Others felt unwarranted praise should not be given: "My teacher was saying all the time for me: 'oh you're doing well'. I will say: 'No, that's bad look at how many mistake' … the moment he starts saying to me 'good' that was like saying 'very bad'." This variability highlights the importance of involving learners in the design process and avoiding letting "common sense" guide design. This variability in learner personalities cannot always be captured with traditional, empirical methods. When designing technologies for real-world adoption, it is important to design for the spectrum of learners, not the average.

Beyond this, our ELLs had strong beliefs about what comprised good feedback. They had many follow-up questions on feedback they received. Their ability to articulate the feedback they wanted prompted us to reflect on our app's structure. In the initial design, writers had no direct communication with their peer-reviewer. The peer-reviewer communicated through predefined rubrics. ELLs' clarity suggested they may benefit from more direct communication with reviewers. One design to help learners access this feedback is to allow them to submit questions to guide their reviewer's assessment.

As seen here, combining results from CI with traditional assessments can provide additional insight. One major advantage of integrating both approaches is that it provides both an objective view of the learning context and the learner's perception of it. This can highlight surprising (in)consistencies between the two. Another advantage of CI is that it can help generate design ideas.

2.3 Advantage three: Identifies limitations of existing technology

Initially, a desktop app was envisioned, like most learning-to-write technologies (Schunn, Godley & DiMartino, 2016). However, interviews with the learners revealed several assumptions made by these applications that did not apply to these learners and that were not captured by the psychometric scales. First, these apps assume an instructor will manage the writing task. However, in the weeks between the first and second sessions, almost all ELLs stopped attending classes, and so, had no instructor. Second, many of these tools expect learners to compose essays, making a desktop-based application appropriate. However, most of our ELLs were job hunting or had full-time jobs and personal commitments that made regularly writing essays unfeasible. During the second session, we realized our participants required a tool that would allow them to complete short, consistent writing exercises and get feedback for improvement without instructor involvement. Thus, we began envisioning a mobile app where networks of learners provided feedback to one another on quick, daily writing exercises in a self-sustained system. Through these interviews, we constructed an understanding of the complexities in our mature ELLs' learning environments, putting us in a stronger position to start designing technology that could be integrated into learners' real-world work flow, thus addressing imbalances in their access to learning opportunities.

2.4 Advantage four: Brings theory into the real world

The final phase consists of a PD session. We drew on PD guidelines (Birch & Epp, 2015), while ensuring design decisions were supported by educational research. Participants worked in groups of three to complete sketching activities around the design of a low-fidelity user interface prototype on paper, augmented with additional props such as sticky notes. We chose this process because PD can extend theoretical principles into practical findings which can be incorporated into the development of real-world, usable technologies, provided the PD is well-grounded in theory from the start.

One important design decision for learning analytics is the information type and granularity to include (Bull & Kay, 2007). Too little information may not support a well-informed decision-making process, while too much may distract. Applying this decision in real-life contexts is challenging as it is not always clear what "too little" or "too much" looks like. One objective of our PD session is to find this balance. For instance, one feature participants design is the analytics they will receive as they complete a writing task. We have created mock-ups of several possible prompts, each of which requires different levels of learner reflection. These prompts range from short writing tips (low), to a post-writing checklist (medium), to self-assessment (high). Our goals are to have these prompts springboard design ideas that support meaningful revision without overloading the learner.

3 CONCLUSION

Though CI and PD are rarely used in educational contexts, incorporating these methods can help researchers gain a more holistic understanding of learners and the learning context, as illustrated by our study. We found the psychometric scales, synthesized with CI methods, helped provide a comprehensive and holistic understanding of both the challenges and needs of ELLs learning to write. CI and PD complement existing practices, most importantly, they can guide researchers in drawing theory into practice. Preliminary analyses, including the designs generated from PD, challenges and suggestions for future directions will be discussed at the workshop.

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Collaborative Personas for Crafting Learners Stories for Learning Analytics Design

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ABSTRACT: Learning analytics innovations are attracting the attention of researchers and designers for providing personalized learning experiences, tracking improvement and better understanding the social aspects of learning. However, current design practices often neglect learners' involvement causing a misalignment with learners' intentions and representations of learners. In this paper, we explore the role of current user modeling tools such as Persona Profile in a collaborative setting to enhance representations of learners This illustrative case study describes the main finding when designing representation with current students in the Bachelor of Nursing program.

Keywords: Learning Analytics, User Modeling, Participatory Design

1 INTRODUCTION AND RELATED WORK

Design for Learning analytics (LA) is a new field where often interdisciplinary teams work together including designers, tutors and researchers. When it comes to define who is the main beneficiary, designers often find that representing learners is an elaborated task that requires lots of effort. In particular for learning analytics, researchers are starting to bring students along the design process including this particular steep that consists of stablishing roles and using this information further down the co-design process (Jisc, 2016) (McGregor, 2016a).

User representations became popular as a design object when researchers from marketing areas tried to enhance classic segmentation(Cooper, Reimann, Cronin, & Noessel, 2014), in terms of learning, researchers and designers may benefit from bringing this into LA adapting the original application to learning scenarios. In design for learning, practitioners use representations to describe what a learner is. With a traditional implementation, we still find misalignment on what constitutes a learner from the designers' perspective and how learners see themselves in the design for learning ecosystem (McGregor, 2016a)

The structure of this papers starts with a brief description of how a widely used tool from design practices like Personas can be used in a participatory setting to enhance representations of learners The following sections describe an illustrative study involving students from the Bachelor of Nursingz` program, the process followed during the participatory design sessions and a preliminary analysis on resulting data used for crafting User Stories.

2 PERSONA PROFILE AS LEARNERS REPRESENTATIONS

In the current field of design, we find some practical tools that help designers to create user representations from different sources of data. Designers used general characteristics to generate a first profile including age, gender, occupation and familiarity with technology (Junior & Filgueiras, 2005). Establishing what characteristics are most descriptive can be problematic and in learning settings, students may be subject for profiling and false assumptions (Goodwin, 2005).

Personas have proven to be useful when it comes to practical representations. There are few examples of how Persona representations are being used as practical objects aligning users' expectations with their goals and needs (Junior & Filgueiras, 2005). Still, there are some challenges when LA designers put together learners' characteristics from available information without falling into a biased confirmation for our profile (Marsden & Haag, 2016).

Collaborative design methods for crafting representations are starting to be an interesting approach to address the current challenges. Regardless of the field, collaboration is helping designers shape better Personas as pointed by (Nielsen & Hansen, 2014) and (LeRouge, Ma, Sneha, & Tolle, 2013). However, in education related areas such as Learning analytics, Learning design and Educational Data Mining there is still some work to do when it comes to representations in collaborative settings (Bodker, Christiansen, & Nyvang, 2012; McGregor, 2016b). Involving students in design sessions can bring an additional layer of data that can be enhanced with tutors and designers perspectives (Sciences, 2016) (IIDC, 2015). When designing learning innovations, these representations can be useful for generating a unified vision of who the educational technology will provide support to and how learners expect the product to align with their personal interests and goals (Gladys Castillo, Joao Gama, & Breda, 2006) (Pruitt & Adlin, 2005).

3 ILLUSTRATIVE STUDY

3.1 Learning analytics design context

During the Bachelor of Nursing program, students require to attend a series of practice-oriented courses involving simulations while using representative tools such as manikins, professional equipment and support machinery. The learning objective is to provide accurate scenarios where different skills are developed including communication (with patients and peers), problem solving and leadership. When learning a new procedure (examples Cardiopulmonary resuscitation (CPR), life support, stroke) students require to read/watch the relevant material provided by tutors, demonstrate in group work how to conduct this new practice and then reflect on what can be improve.

The challenge for us is to design an automated feedback tool to provide learners with useful insights on their practice. Using learning analytics tools, it is possible to track different sorts of activity around the classroom. In this initial part of the study, it is important to understanding how learners can help to create better representations in this scenario and what other problems may find benefit from using a data intensive approach such as learning analytics.

Learners' involvement in crafting their own representations in the whole scheme of design requires a set of tools and techniques tested to facilitate collaboration between learners, designers and tutors. In this case Personas designed in collaboration provides a collective view on what represents a learner and how they see themselves as users in this context.

3.2 Persona profile template

An initial template was crafted by the lead designer based on what tutors and researchers stablished as main interests. This template includes fields starting with what values are being endorse as nurses in training, learners' goals, and open topics that may not be expressed in other ways as students. Other practical fields include the media they prefer and what other activities they do after class.

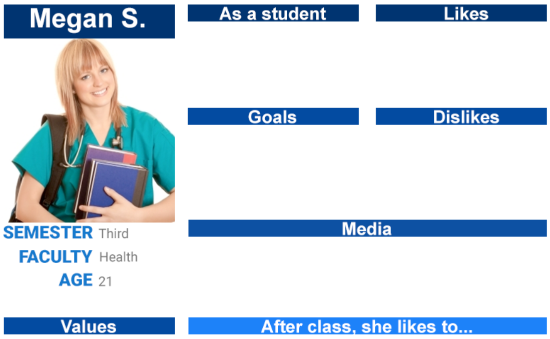

Figure 1: Template provided as an initial representation object.

A series of co-design sessions were conducted with students. The sessions were distributed with 15 (N=15) students across 5 group sessions (GS=5). The research team conducted a focus group approach with a guided scheme of activities. Learners were asked to use the template as an initial description to fill while conversations were recorded for further analysis.

3.3 Preliminary analysis

After conducting the sessions, we gathered and compared the different profiles built by participants. Field and notes were added to our initial template based on learners' feedback and observations. The new fields added were on specific goals for the simulations, the different uses of social media and the reason behind wanting to become a nurse.

In table 1 we describe observations gathered from the conversations during the activity and new fields requested based on learners' feedback.

Group	Observations	New fields

1	• Personal and global values are hard to express in one single field. • Media sources used by learners differs based on technology expertise.	• Personal goals and academic goals. • Social media and LMS preferences.
2	• After class activities can be used to express leisure and additional hobbies.	• A field for open comments on personal traits.
3	• Values generates discussion since this term is not used by tutors or any resource provided by the faculty.	• Concerns.
4	• Academic goals are different from personal goals.	• Academic goals.
5	• A different template for seniors and new students.	• Current challenges.

Table 1- Observations and new fields requested by leaners per session.

To continue with our study, some recommendations are being followed based on these preliminary results. The first one is to complement our Persona profiles with comments provided by learners and show this to the design team. Some components on the template are mere suggestion than designer may not followed but now they become aware in case additional information back up the suggestion. After a further analysis on how the session was conducted and current observations from participants, we describe two main recommendations that may help researchers to improve representations of learners in collaboration.

Encourage discussion and decision: When writing something down in the template encourage learners to decide at least three terms and ask them to explain why that information is relevant.

Template customization: Diversified groups may require a different template based on the group composition. Changes on the template between session can make the analysis process more challenging but allows to gather more data that can reviewed further down the design process.

4 CONCLUSION

Building collaborative representations by using a Persona template helps researchers and designers to open the design process to learners. The resulting objects can be used in the future to generate usage scenarios where learning analytics innovations can be deployed. Also, these objects become a resource for designers and other stakeholders to comprehend user intentions without going into technicalities. For the following sessions, some other techniques from PD and Co-design areas will be tested to gather additional information and support collaboration through the whole design process of LA tools.

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