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Augmented education within a physical space

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Abstract

This research aims to explore how to enhance student engagement in higher education institutions (HEIs) using a novel conversational system (chatbots). The study applies a design science research (DSR) methodology and is executed in three iterations: persona elicitation, survey and student engagement factor models (SEFMs), and chatbots interactions analysis. In the first iteration, two k-means clustering analyses are applied to student data, including engagement on campus and student interaction with a virtual learning environment (VLE). The first analysis produces four different types of students based on their engagement and performance data, while the second analysis produces two clusters based on the students' interactions with a VLE (in this case, Blackboard). The second iteration will produce SEFMs, which will include the factors that affect student engagement, confirmed using structural equation modelling (SEM). Finally, the third iteration will produce effective and usable chatbots that enhance student engagement. The pragmatic findings from this study will make three contributions to the current literature. Firstly, machine learning is used to build data-driven personas using k-means clustering. Secondly, a persona template is designed for university students, which supports the construction of data-driven personas. Thirdly, SEFMs will be built. Future iterations will build tailored interaction models for these personas and evaluate them using chatbots technology.

Keywords: *chatbots, conversational system, design science research, persona, persona template, student engagement*

1. Introduction

Student engagement refers to the extent to which students are interested or involved in their learning and how are they linked to other students, their classes and their institutions (Axelson and Flick 2010). Three dimensions of student engagement have been proposed: 1) behavioural engagement, represented by behavioural norms such as attendance and involvement; 2) emotional engagement, represented by emotions such as enjoyment, interest and a sense of belonging; and 3) cognitive engagement, represented by investing more time in learning beyond that required (Bloom 1965). This study focuses on behavioural and cognitive engagement.

Student engagement has received significant attention in the literature since the 1990s (Trowler 2010), particularly in terms of its value for learning and achievement

(Newmann 1992). Trowler and Trowler (2010, p.4) believe that "the value of engagement is no longer questioned". Student engagement is considered a predictor of student performance (Martin and Torres, 2000; Astin, 1984) and one of the main factors behind students' boredom, alienation, low performance and high dropout rates (Martin and Torres 2000). The literature shows that HEIs are facing a critical problem with low-level student engagement. Several teaching methods, tools and strategies have been developed to solve this problem. For example, with the significant increase in the number of internet users and mobile phone owners, there has been great interest in employing these devices in class and outside of class to improve student participation (Taylor and Parsons 2011; Lim 2017).

Furthermore, the literature shows that there are many benefits of using chatbots in education: chatbots are enjoyable, support continuous learning, enhance student motivation, enhance students' skills, offer an interesting form of encouragement (Shawar and Atwell 2007) and assist teachers in their jobs (Knill *et al.*, 2004; Shawar and Atwell, 2007). After analysing the literature, a literature gap has been identified: no previous study has investigated the use of novel conversational systems in HEIs to enhance student engagement.

2. Research Methodology

The DSR methodology is the principal research methodology for this study, adapted from Vaishnavi and Kuechler (2004) to meet the research aim. A valid information system (IS) research process is conducted through the building and evaluation of designed artefacts (Hevner et al. 2004). This research is conducted using incremental iterations, with each iteration utilised to expand on and refine the research problem. To achieve the study's aim and objectives, the study is conducted in three iterations: persona elicitation, survey and SEFMs, and chatbots interactions analysis, as shown in Figure 1. Each iteration is performed in four phases: 1) problem awareness, 2) suggestions, 3) development and 4) evaluation (Vaishnavi and Kuechler 2004). The iterations are described in the following sections.

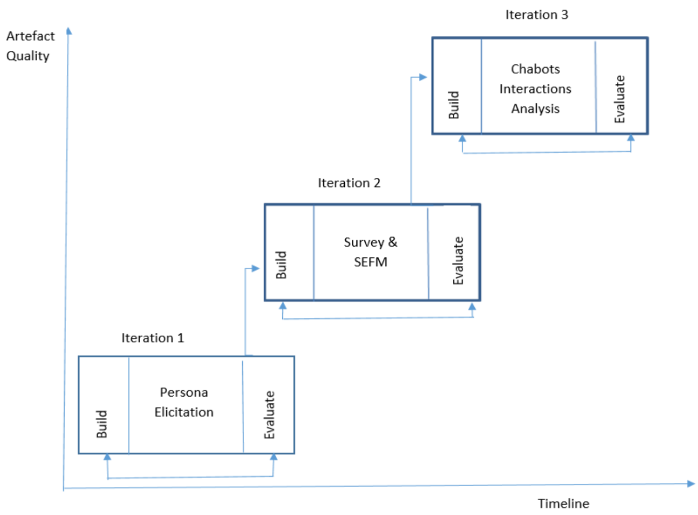

Figure 1. Research iterations

2.1 Persona Elicitation

The objective of the first iteration, persona elicitation, is to identify different types of university students by building data-driven personas. The problem awareness phase includes conducting a literature review on student engagement and the state of the art of mobile educational technologies (e.g. chatbots). In the suggestions phase, a proposed persona template for university students is developed. Further suggestions are to identify different groups of students in the Computer Science Department at Brunel University London by utilising a machine learning framework, applying k-means clustering analysis and building student personas. The sample included second-year Computer Science students at Brunel University London in 2014 and 2016. The two sets of student data are 1) engagement on campus data, containing students' engagement and performance data, and 2) VLE data, including active participation and interaction with materials on Blackboard. The development phase includes building a university student template based on the literature review and an understanding of the users' backgrounds and skills.

The literature shows that persona templates have been covered in many studies (Roussou et al. 2013). Their elements differ based on their reasons for creation. A persona template usually includes demographic data (Roussou et al. 2013) such as name (Hill et al. 2017), age (Nieters, Ivaturi, and Ahmed 2007; Roussou et al. 2013; Hill et al. 2017), gender (Nieters, Ivaturi, and Ahmed 2007), job (Hill et al. 2017), language (Roussou et al. 2013), place of residence (Hill et al. 2017) and picture

(Nieters, Ivaturi and Ahmed, 2007; Roussou *et al.*, 2013; Hill *et al.*, 2017; Guo and Razikin, 2015). Furthermore, it can include users' interests (Roussou *et al.*, 2013; Hill *et al.*, 2017), activities (Guo and Razikin 2015), preferences (Hill et al. 2017) and attitudes in daily life (Guo and Razikin 2015). Moreover, it can cover skills and experience, such as educational level (Roussou et al. 2013) and IT certification. The initial student persona template proposed in this study consists of the following categories: demographic data (Nieters, Ivaturi and Ahmed, 2007; Roussou *et al.*, 2013; Hill *et al.*, 2017), motivations and interests (Roussou et al. 2013; Hill et al. 2017), and skills and experience (Roussou et al. 2013). A further template will be added after the data analysis.

A k-means clustering method is implemented in R programming language. The k-values are identified using well-known methods: elbow, silhouette and gap statistic methods (Kodinariya and Makwana 2013; Tibshirani, Walther, and Hastie 2001). Descriptions of the main attributes of the first dataset, engagement on campus data, are shown in Table 1. The first data analysis resulted in four student clusters. Figure 2 presents the distribution of the student data in each cluster. Statistical summaries of the first phase of data analysis are shown in Tables 2a, 2b, 2c and 2d.

Attribute	**Description**
Attendance	Represents the total lab attendance by each student out of 12 labs
Grade	Represents the final grade in that module, ranging from 1 to 17, where 1 represents F and 17 represents A*

Table 1. Engagement on campus data

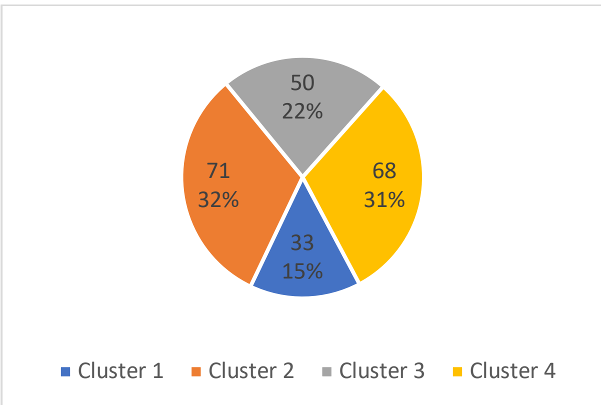

Figure 2. The four clusters from the first phase of data analysis

Cluster 1 includes students with low grades and low attendance rates. Table 2a shows that the median of student attendance was 4 out of 12 labs (30%); the median of the grade attained was 3 out of 17 (17%). The attendance of students in Cluster 1 ranged between 0% and 66%. Similarly, their grades were all less than 50% (F to D). Cluster 1 is referred to as "very low engagement and very low performance" (Table 2a).

	Mean	SD	Median	Trimmed	Mad	Min	Max	Range
Attendance	4.00	2.11	4	4.04	2.97	0	8	8
Grade	3.36	1.71	3	3.26	1.48	1	6	5

Table 2a. Statistical summary from the first phase of data analysis: Cluster 1

Cluster 2 includes students with high attendance rates and high grades. Table 2b shows that the median of student attendance was 10 out of 12 labs (83%); the median of the grade attained was also high at 15 out of 17 (88%). Their attendance rates ranged between 56% and 100%, and their grades ranged from 12 to 16 (B to A+). Cluster 2 is referred to as "high engagement and high performance" (Table 2b).

	Mean	SD	Median	Trimmed	Mad	Min	Max	Range
Attendance	9.97	1.62	10	10.09	1.48	7	12	5
Grade	14.80	1.21	15	15.00	0.00	12	16	4

Table 2b. Statistical summary of the first phase of data analysis: Cluster 2

Cluster 3 includes students with low attendance rates and very good grades. Table 2c shows that the median of student attendance was only 4 out of 12 labs (30%), and the median of the grade attained was 12 out of 17 (70%). The rates of attendance were all less than 50%, while the grades ranged between 52% and 88% (C to A). Cluster 3 is referred to as "low engagement and high performance" (Table 2c).

	Mean	SD	Median	Trimmed	Mad	Min	Max	Range
Attendance	3.92	1.43	4	3.95	1.48	1	6	5
Grade	12.48	2.13	12	12.60	4.45	9	15	6

Table 2c. Statistical summary of the first phase of data analysis: Cluster 3

Finally, Cluster 4 includes students with good attendance rates and low grades. Table 2d shows that the median of student attendance was 7 out of 12 labs (58%), and the median grade of the grade was 9 out of 17 (52%). The attendance ranged between 5 and 12 (40% to 100%), while the grades ranged between 35% and 70%. Cluster 4 is referred to as "better engagement and low performance" (Table 2d). Descriptions of the four clusters that resulted from the analysis of the first dataset, along with their rules, are provided in Table 3.

	Mean	SD	Median	Trimmed	Mad	Min	Max	Range
Attendance	7.56	1.51	7	7.52	1.48	5	12	7
Grade	10.19	1.57	9	10.18	0.00	6	12	6

Table 2d. Statistical summary of the first phase of data analysis: Cluster 4

<table>
<tr><th>Cluster Number</th><th>Cluster Title</th><th>Description</th><th>Rule</th></tr>
<tr><td>1</td><td>Very low engagement and very low performance</td><td rowspan="2">Positive correlation between student engagement and performance</td><td>Attendance around 30%; grade around 17%</td></tr>
<tr><td>2</td><td>High engagement and high performance</td><td>Attendance around 83%; grade around 88%</td></tr>
<tr><td>3</td><td>Low engagement and high performance</td><td rowspan="2">Negative correlation between student engagement and performance</td><td>Attendance around 30%; grade around 70%</td></tr>
<tr><td>4</td><td>Better engagement and low performance</td><td>Attendance around 58%; grade around 52%</td></tr>
</table>

Table 3. The four clusters' descriptions and rules

The clustering analysis for the second dataset, the VLE dataset, which is described in Table 4, produced two clusters. Most students were in Cluster 1 (87%), and a minority were in Cluster 2 (13%) (Figure 3). Cluster 1 is referred to as "less active" students, and Cluster 2 is referred to as "more active" students. Interestingly, most students were less active – they did not spend a lot of time interacting with materials in the VLE. All variables in Cluster 1 had mean values less than Cluster 2, except for grade. Students in Cluster 2 spends more hours on course activity (course access), content (content access), collaboration (course user participation) and communication (user form participation), but they had the same median value as students in Cluster 1.

However, the mean grade values for Cluster 1 and Cluster 2 were the same. An interesting finding is that active participation in the VLE, which was found to be an indicator of student engagement (Dale and Lane 2007), did not influence student performance. The two clusters had the same grade results, as represented by the median grade in Table 5. Descriptions of the two clusters that resulted from the second analysis, along with their rules, are shown in Table 6.

Attribute	Description
Course activity	The total amount of course activity in hours the user completed
Content	The total amount of time in hours that the user spent accessing content for the course (files, links and videos)
Collaboration	The total amount of time in hours that the user spent on collaborative activities
Communication	The total amount of time in hours that the user spent engaging in discussion boards/forums
Grade	The final student grade in the specific module

Table 4. Attribute descriptions for the VLE data

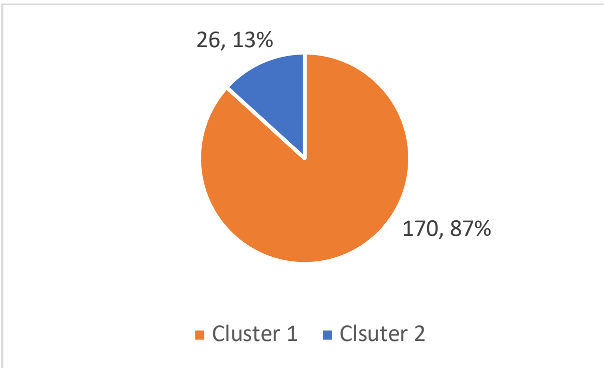

Figure 3. The two clusters from the second phase of data analysis

		Course Activity	Content	Collaboration	Communication	Grade
Cluster 1	Median	4.96	10.00	13.00	1.00	12.00
	Min	0.39	1.00	1.00	0.00	1.00
	Max	25.62	31.00	55.00	9.00	16.00
	Average	6.11	10.88	16.04	1.43	10.97
Cluster 2	Median	13.32	32.00	42.50	6.00	11.50
	Min	6.25	8.00	13.00	0.00	3.00
	Max	34.55	53.00	682.00	24.00	16.00
	Average	17.05	31.27	71.73	6.69	10.96

Table 5. Statistical summary of the second phase of data analysis

Cluster Number	Cluster Title	Description	Rules
1	Less active or less engaged	The means of all the variables were two or three times lower than those for Cluster 2, except the grade variable	The means were 6.11, 10.88, 16.04, 1.43 and 10.97 for course activity, content, collaboration, communication and grade, respectively
2	More active or more engaged	The means of all the variables were two or three times higher than those for Cluster 1, except the grade variable	The means were 17.05, 31.27, 71.73, 6.69 and 10.96 for course activity, content, communication and grade, respectively

Table 6. The two clusters' descriptions and rules

Based on the literature review discussed previously, the proposed university student persona consists of demographic data, educational data, motivations and interests, and skills and experience. However, there are also other essential elements that should be included in the persona template for university students: educational data, interaction with the VLE, engagement and performance data, as shown in Table 7. These were extracted from the two data analyses explained above. The proposed persona template for university students is shown in Figure 4.

Components of the Student Persona Template	
Demographic Data	Educational Data
Interaction with the VLE	Engagement and performance
Motivations and interests	Skills and experience

Table 7. Components of the student persona template

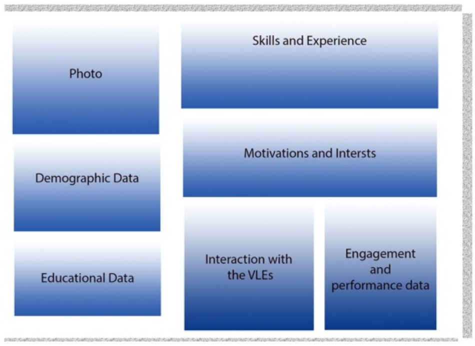

Figure 4. A persona template for university students

In the evaluation phase, student perspectives will be explored using a survey and chatbots instantiation.

2.2 Survey and SEFMs

The objective of the second iteration, a survey and SEFMs, will be to build SEFMs. The problem awareness step will draw on the results of the first iteration. In the suggestions phase, a literature review will be conducted to identify the factors that affect student engagement. In the development phase, an SEFM will be created and will only include factors that can be tested using chatbots. The evaluation phase will consist of the validation of the SEFM using a semi-structured survey sent via email to all Computer Science students at Brunel University London. The data will be analysed using SEM statistical techniques to produce the final version of the SEFM, which will be fed into the next iteration.

2.3 Chatbots Interactions Analysis

The objective of the third iteration, chatbots interactions analysis, will be to evaluate the effectiveness of using chatbots to enhance student engagement. The problem awareness phase will draw from the results of the SEFM. In the suggestions phase, chatbots will be designed and developed, based on the student persona, survey and SEFM results (the first and second iterations). In the development phase, chatbots will be designed and developed to match the requirements proposed in the suggestions phase; the code will be written in JavaScript and will run on Amazon Echo devices (Alexa) and mobile devices. In the evaluation phase, the chatbots will be evaluated in terms of usability and effectiveness in enhancing student engagement using the System Usability Scale (SUS), and evaluated pre-test and post-test.

3. Expected Contributions

The contributions of this study will stem from the three iterations. The data analysis of the first iteration produced a university student template and four distinct university student personas using k-means clustering analysis, which is applicable, cheap and straightforward compared to the other methods used by Cisco and Microsoft (Nieters, Ivaturi and Ahmed, 2007; McGinn and Kotamraju, 2008). Interestingly, the results of the data analysis show that engagement does not always affect student performance. In addition, active participation does not influence student engagement. There might be other factors that affect student engagement. The data analysis of the semi-structured survey will be used to produce an SEFM, which will be tested by the chatbots. Finally, the chatbots interactions analysis iteration will be the main contribution of this study; developing effective and usable chatbots that will enhance student engagement.

4. Conclusion

In conclusion, the purpose of this study is to address the problem of low-level student engagement in HEIs in a creative way using DSR methods, performed in three iterations. The persona elicitation (first iteration) has been done, producing robust results, and two more iterations will be performed in the next nine months: 1) a survey and SEFM and 2) chatbots interactions analysis.

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