A Methodology for Multimodal Learning Analytics and Flow Experience Identification within Gamified Assignments

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Abstract

Much research has sought to provide a flow experience for students in gamified educational systems to increase motivation and engagement. However, there is still a lack of quantitative research for evaluating the influence of the flow state on learning outcomes. One of the issues related to flow experience identification is that used techniques are often invasive or not suitable for massive applications. The current paper suggests a way to deal with this challenge. We describe a methodology based on multimodal learning analytics, aimed to provide automatic students' flow experience identification in the gamified assignments and measuring its influence on the learning outcomes. The application of the developed methodology showed that there are correlations between learning outcomes and flow state, but they depend on the initial level of the user. This finding suggests adding dynamic difficulty adjustment to the gamified assignment.

Author Keywords

gamification; flow theory; multimodal learning analytics; automatic identification; educational systems

CCS Concepts

•Human-centered computing → Human computer interaction (HCI); *User studies;* **•Applied computing → Interactive learning environments;**

Introduction

Gamification is the use of game elements characteristics (such as points, badges, progress bars, meaningful stories, profile development, etc.) in non-game contexts [8]. It is already widely used in the educational systems and has proved to have a positive impact on the educational process [10, 14, 32, 30]. However, the influence of gamification usage in higher education specifically still isn't covered well enough.

Recently the attention of the researches has shifted towards penalisation of the educational content and assignments [4, 24, 29]. To evaluate the user experience and set up the parameters for the penalisation, multimodal learning analytics might be used. *Multimodal learning analytics* (MMLA) is an intersection between multimodal teaching and learning, multimodal data, and computer-supported analysis [38]. It aims to model student learning in complex learning environments. Multimodality can be achieved by analyzing data from several sources (timing, speed, gaze, heart rate) [2, 3, 39]. Since this research focuses only on non-invasive data collection, the proposed methodology requires such data as clicks, time, amount of attempts, etc. The data is gathered on the background, while users are interacting with the tool .

At the same time, the *flow state* is a highly engaging experience that people can achieve in a given activity [6]. It is closely related to the learning experience [5]. In general, when a high flow experience in the educational activity is achieved, the educational impact of the activity is increasing [5, 34, 11]. Thus, many studies related to educational systems design seek to provide a flow experience for their students [1, 19, 11]. One of the biggest challenges is to provide its automatic identification [25]. It happens because, in general, the flow experience is identified based on questionnaires, electroencephalograms (EEG), or interviews [26], which are considered invasive or do not allow an application with many individuals at the same time.

Based on this premise, the main contribution of this research to the HCI community is the description and initial testing of a proposed methodology. It can be used for automated students' flow experience detection and measuring the learning outcomes simultaneously in gamified assignments. This methodology can also be utilized to find correlations between them. It extends existing similar researches, for example [12], by measuring the difference between perceived and actual metrics. The current paper focuses specifically on gamified assignments in higher education.

Background and Related Works

To identify the works related to user experience analysis, we conducted a systematic literature review (see Oliveira *et al.* [26]) and keep it regularly updated to keep track of the new studies. In this paper, we present only the main related works and extend the list with the literature about MMLA in gamified assignments.

Lee *et al.* [20] proposed a computational model for automatic student flow detection in games. They used step-regression to analyse the data, however, operationalized only the dimension of challenges and skills balance. Kock [7], proposed an approach with the same aim, however, using an EEG in 20 students during the use of an educational game. Besides being an intrusive approach, with difficult access and data analysis, also it cannot be used massively.

Oliveira *et al.* [27] conducted an exploratory data-driven study for collecting and identifying the users' game experience in an educational game using two different data-mining techniques aiming to associate the user's data logs

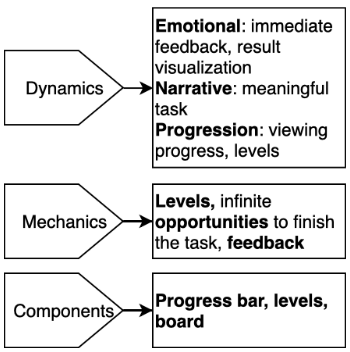

Figure 1: Model of the developed assignment, which decomposes if into *dynamics* (contexts in which the gamification is applied), *mechanics* (activities inside the assignment) and *components* (objects used in the mechanics) [37]

in the game with their game-like experience. Despite using the techniques we propose to use in the current study and having good outcomes, it does not deal with the flow experience.

Usage of gamification in education is broadly covered in several literature reviews, such as [9, 22, 23]. Framework for assignments' personalisation based on the results of MMLA is suggested in [29]. The gamification of educational tools was already covered in previous CHI editions. For example, Roy *et al.* [36] studies what users seek when they select a gamified educational system and Shaban *et al.* [33] presents a gamified framework for supporting children with disabilities. There was also a course aimed to describe main gamification tools and evaluation techniques [35].

The major novelty of current research is that we developed the methodology for evaluating learning outcomes and the influence of the flow state in gamified assignments with an open end. This evaluation also takes into account the difference between perceived and actual learning outcomes. Thus, as far as we know, our study is the first to propose an approach for automatic students' flow experience identification using data logs in gamified assignments associated with the learning outcomes and the influence of the flow state.

Method

This study was organized in three different general steps: *i)* gamified assignment design and implementation; *ii)* data collection; and *iii)* data analysis.

In the *first step*, we developed the gamified assignment aimed to improve students' knowledge of jQuery[1]. Figure 1 describes the developed assignment in accordance with

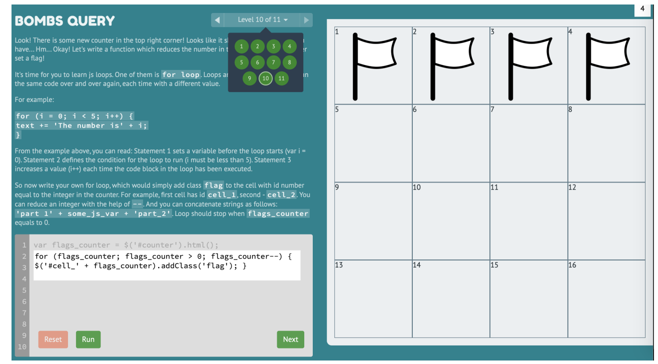

Figure 2: Interface of one of the bombsQuery levels

the model proposed by Werbach and Hunter [37]. The initial testing of the assignment with the students is described in [31]. The assignment consists of 11 levels, each one covering a different topic. Each level has some theory and examples, and a "textarea" where students need to enter their solution. On the right side of the screen the minefield is displayed, and the playful goal of the assignments is to clear the filed form all bombs (Fig. 2). If the answer was wrong - students had an infinite amount of tries to improve it. If the answer was correct - the next level starts automatically. For their convenience, it is also possible to navigate to already solved levels, to check the entered answer, or read the given theory once again. In the *second step*, the students firstly answered the questionnaire composed specifically for this research, aimed to measure their level of jQuery knowledge. Afterward, they played the game for at least 5 minutes and then answered the flow state scale and learning outcomes survey. In the *third step*, we analysed the data using two different data mining techniques.

Figure 3 visualises all steps of the developed methodology.

[1] https://lirael.github.io/bombsQuery/task.html

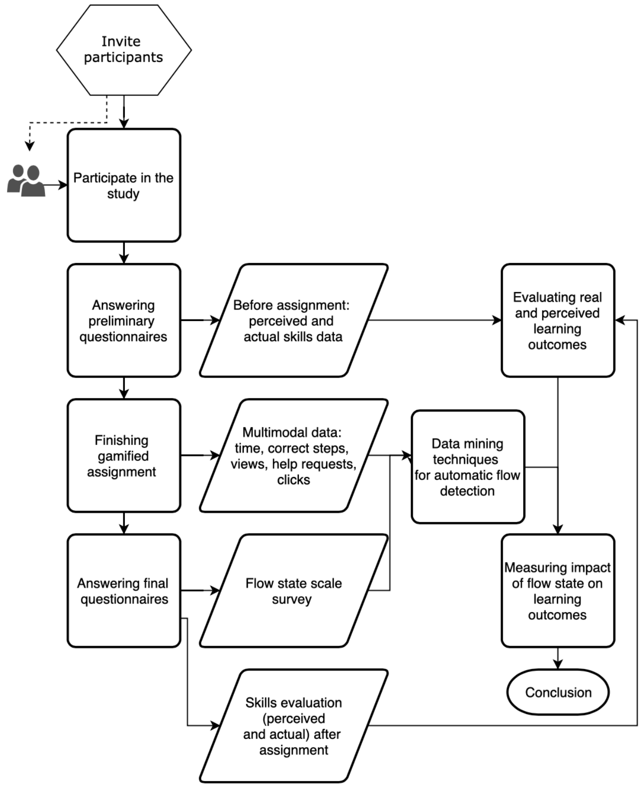

Figure 3: A methodology for the multimodal learning analytics including automated flow detection

Participants

Participants were 31 bachelor students of Brno University of Technology, who volunteered to take part in the study. Five data sets have been excluded because students spent less than 5 minutes on the assignment. For verification purposes, a "test question", asking to select a specific answer (number 3), was included in the questionnaire. Three data sets have been excluded because of the wrong answer to this question, which means that the questionnaire wasn't answered carefully. We therefore included 23 participants (mean age = 21.54 years old, SD = 1.33; 6 women, 13 men, 4 preferred not to disclose gender). Students received the link to the questionnaires and the assignment, and they could work on it in their pace and preferred time. Data needed for the flow detection was gathered on the background, while they interacted with the UI.

Flow experience detection

In order to provide the flow experience identification in the gamified assignment, we implemented a model to collect eighth different user data logs: *(i)* Active time in the system; *(ii)* Used time to finish a step/activity; *(iii)* Proportion of correct steps/activities; *(iv)* Proportion of answers that were incorrect and received "error message"; *(v)* Average response time after a feedback; *(vi)* Total unique session views; *(vii)* Number of mouse click out of buttons. These data logs were collected based on the framework proposed by Oliveira *et al*. [28] for automatic flow experience identification in educational systems. In addition to the usage logs, we also collected the flow experience data based on the flow state scale proposed and validated by Jackson *et al*. [16]. According to the age of the experiment participants and the design of the experiment, following the recommendations of Jackson *et al*. [15] we decided to use the short flow state scale.

To analyse the data, we calculated the flow experience based on the flow state scale. After, we analysed the generated user data logs. For this, we aim to use two different data mining techniques (decision tree (DT) and Association Rule Mining (ARM)). DT is a non-parametric supervised learning technique that provides a classification and regression, deducing interpretable classifiers (*e.g.*, why a student'

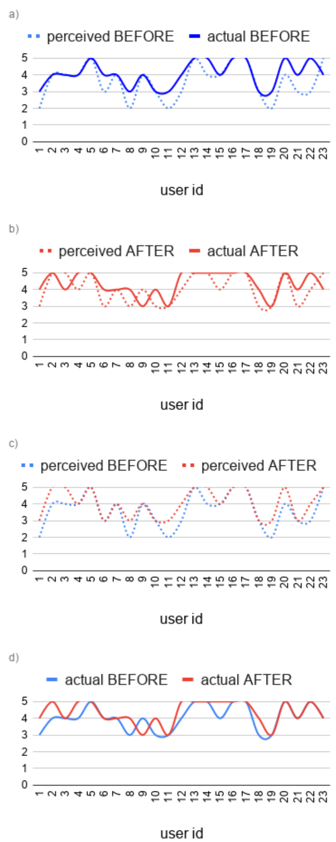

Figure 4: The analysis of the learning outcomes: a) comparing perceived and actual jQuery levels before completing the assignment; b) comparing perceived and actual levels after the assignment; c) comparing perceived levels at both stages; d) comparing actual levels at both stages.

flow experience was low) [13]. We aim to use the J48 algorithm, an open-source Java implementation for the C4.5 algorithm [17]. This is one of the most widely used decision tree algorithms and can perform well in terms of accuracy regardless of the data set [18]. The ARM, is used to identify *if-then* additional patterns, if not found by DT, and to check whether those corroborate. To implement the ARM, we aim to use the Apriori algorithm, one of the most popular to find frequent *itemsets* from a transaction data set and derive association rules [40].

Learning outcomes

Measuring of learning outcomes consisted of 2 parts: evaluation of the self-perceived level of the students, and their real jQuery knowledge. For this purpose, they have been asked to answer the same questionnaire before and after finishing the assignment. It contained a question about their perceived level on a scale from 1 to 5, and 8 theoretical questions to measure the actual level, including one verification question. Some questions were open-ended, others - with one or multiple choice. The verification question explicitly asked them to select item number 3. After data was collected and validated, we evaluated the difference between initial jQuery knowledge levels (perceived and actual) with the ones after finishing the assignment for each student. After, we compared mean values for the same parameters, to see if there was any shift in general for the whole group.

As a final step, learning outcomes results for each student have been compared to their flow state detection results, in order to find any possible correlations.

Results, Discussions and Limitations

The primary practical value of this research is the description of the methodology for the evaluation of learning outcomes and the influence of the detected flow state. This section discusses the results of the MMLA from several perspectives.

The result of the knowledge levels data analysis is displayed on Figure 4. It shows that for the majority of users, both actual and perceived skill levels increased. It also illustrates the importance of measuring both perceived and actual learning outcomes because the values are different. Bigger part (43.5 %) of students evaluated their skills lower than the level retrieved from the test result. Figure 5 displays the mean values for all measured metrics. While the number of users was not big enough, the preliminary results already show the shift in the mean calculated knowledge levels before finishing the assignment (4.04 out of 5, SD = 0.77) and after it (4.35, SD = 0.71). Also, it shows that the mean value for the evaluated flow state is quite high (4.19, SD = 0.41). Full list of calculated metrics is in the Table 1. Analysis of the data shows that the lowest flow experience was achieved for the users with too low skill levels (users 1, 18, 19) or the highly skilled users (users 14, 22). This corresponds with the notion that for achieving the flow state, the challenge of the task should correlate with the level of the user [5]. In order to maintain a higher flow state level for the users, dynamic difficulty adjustment might be used. The same conclusion was made after analysing students' experience questionnaires in [31].

The study generated some limitations that are inherent in the type of study. Nevertheless, we try to mitigate and describe these limitations to enable future replication of the study. Initially, students may be tired or dissatisfied, impairing their performance and attention when answering the questionnaires. To mitigate this limitation, participation in the study is voluntary for the students, and we also allow them to finish the assignment remotely (online) and un-

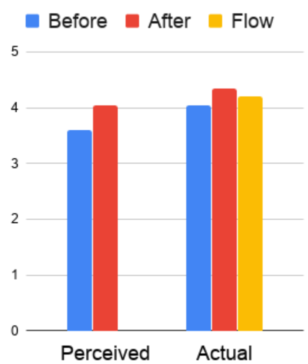

Figure 5: Mean values for the perceived and actual knowledge levels of the students before and after completing the assignment, and the evaluated flow state, on the scales from 1 to 5.

	Before		After			
User	*Perc.*	*Act.*	*Perc.*	*Act.*	Flow	Flow (text)
1	2	3	3	4	3.667	high
2	4	4	5	5	4.444	very high
3	4	4	5	4	4.222	very high
4	4	4	4	5	4.333	very high
5	5	5	5	5	4.555	very high
6	3	4	3	4	3.778	high
7	4	4	4	4	4.556	very high
8	2	3	3	4	4.000	very high
9	4	4	4	3	4.000	very high
10	3	3	3	4	4.111	very high
11	2	3	3	3	4.222	very high
12	3	4	4	5	4.333	very high
13	5	5	5	5	4.444	very high
14	4	5	5	5	3.889	high
15	4	4	4	5	3.889	high
16	5	5	5	5	4.778	very high
17	5	5	5	5	4.889	very high
18	3	3	3	4	3.889	high
19	2	3	3	3	3.444	high
20	4	5	5	5	4.444	very high
21	3	4	3	2	3.667	high
22	3	5	4	5	3.889	high
23	5	4	5	4	5.000	very high

Table 1: The measured perceived and actual skill levels before and after finishing the assignment, and evaluated flow experience of the students.

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observed, while setting a minimum system usage time to consider data for analysis. We also inserted attention test questions into the questionnaire and removed participants who did not answer the test questions accurately.

Another limitation is the sample size. It was enough to have the initial test of the described model, however, was not enough to use data mining algorithms and perform certain statistical tests (where at least 100 participants are required as described by Loehlin [21]). In order to mitigate this limitation, applications of the study with a larger number of participants will be conducted.

Conclusion and Future Work

In this paper, we have described a methodology for measuring the impact of the state of the flow on learning outcomes in gamified assignments. The methodology includes non-invasive methods only, such as questionnaires and multimodal learning analytics, gathering data on the background. While preliminary, the findings are positive: they show a positive shift in the knowledge levels of the students and high levels of the achieved flow state. This study also confirms previous findings [31].

While gamification research is not new, we try to contribute to the field of HCI and learning analytics by combining both learning outcomes and flow evaluation, and by extending the existing research with the description of the methodology for automated students' flow experience detection in gamified assignments.

Now, after we have proven that the methodology is working, the main goal is to run a bigger study (at least 100 verified participants). This will lead to valid results from the automated flow detection process, described in section . Also one more step should be included - follow up questionnaire about the jQuery knowlege, two weeks after the initial study. This will help to evaluate the impact of the flow state on the long term learning outcomes.

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