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Towards Automatic Flow Experience Identification in Educational Systems: A Qualitative Study

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Abstract. *One of the main challenges in the field of learning technologies is the automatic students' flow experience identification in educational systems. This challenge occurs because the flow experience identification is usually conducted by using invasive techniques (e.g., eye trackers or electroencephalograms) or approaches that are not able to handle a large number of students at the same time (e.g., questionnaires/scales or interviews). Despite recent studies proposed to analyze students' flow experience based on user data logs, most of these studies are theoretical without data-based analysis. To move towards the automatic flow experience identification in educational systems, we conducted a qualitative study to analyze possible relations between the students' interaction data logs, behavior, and flow experience in an educational system. The results show that some data logs are related to the students' flow experience. Our results provide insights into the relations amongst the data logs, the flow experience, and students' behavior, which could be beneficial to the development of an approach for automatic identification of the flow experience in educational systems.*

1. Introduction

In the last few years, many studies have been conducted to measure the influence of different kinds of educational systems in students' experiences as such motivation and engagement [Bai et al. 2020]. Nonetheless, one of the experiences that is being recently investigated is the flow experience[1] [Shi and Cristea 2016, Marinho et al. 2019, Oliveira et al. 2020]. The flow experience is a feeling highly related to the learning experience [Csikszentmihalyi 2014], and, consequently, when a person reaches the flow experience in an educational context, it is likely that they also have a meaningful learning experience [Csikszentmihalyi 2014, Buil et al. 2019].

However, there is a challenge to investigate when this experience occurs because the current approaches either use invasive methods or cannot be massively applied [Oliveira et al. 2018]. These approaches are still adopted, because, up to date, there are no concrete alternatives to automatically detect students' flow experience when using an educational system [Lee et al. 2014, Oliveira et al. 2018]. Thus, providing an approach to automatically identifying the students' flow experience while using an educational system remains a challenge [Oliveira and Isotani 2019], and, once resolved, it would allow for a

[1]"Mental state in which a person performing an activity is fully immersed and involved" [Csikszentmihalyi 1997a].

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faster assessment, to understand if the systems could provide a good learning experience to students [Oliveira et al. 2018, Oliveira and Isotani 2019, Oliveira et al. 2019].

To perform a step forward towards tackling this challenge, [Oliveira et al. 2019] proposed a novel approach relating students' data logs in educational systems to their flow experience. However, this approach is theoretical and still needs to be tested and validated in real environments [Oliveira et al. 2019]. Therefore, as suggested by the authors, as well in other recent studies, *e.g.* [Oliveira and Isotani 2019, Pastushenko et al. 2020], it is crucial to advance the literature through different studies that can test this approach in real environments (*i.e.*, educational systems), and assess whether it is possible to relate the data logs produced by students' interactions in educational systems with their flow experience. To address this challenge, in this paper, we present the results of a qualitative study that sought to analyze the relationships between students' data logs (*e.g.*, the number of correct steps, time to do a task after feedback, the average time to finish a task and others), and their flow experience and behavior in an educational system.

We conducted a study with six Master of Business Administration (MBA) students using the think-aloud protocol [Fonteyn et al. 1993, Alhadreti and Mayhew 2016]. Then, we associated the students' flow experience with their data logs and experience/behavior observed in the think-aloud protocol. Henceforth, our study aims to answer: **how can we relate flow experience and students' data logs in educational systems through a qualitative approach?** Our results show different relationships between some students' data logs and their flow experience in the system. In total, we observed five relationships between the students' data logs and their flow experience, thus, presenting results similar to what was proposed by [Oliveira et al. 2019] and other studies in the field of Flow Theory [Csikszentmihalyi 1997a, Csikszentmihalyi 2014, Lee et al. 2014, Csikszentmihalyi 2020]. Our results contribute to the field of educational technologies providing new insights into the development of approaches to automatically identify the students' flow experience in educational systems.

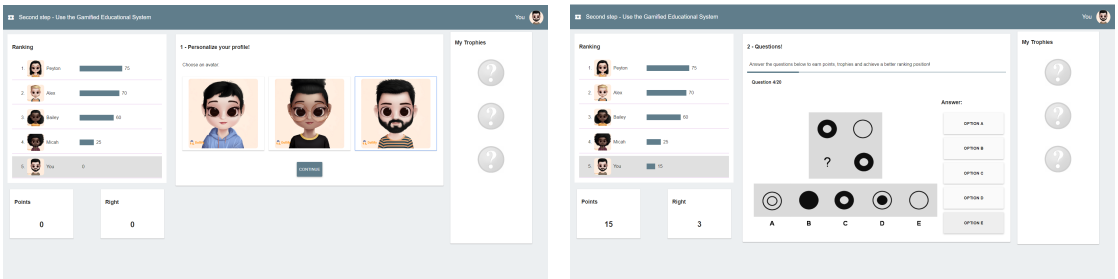
2. Study Design

Our study aimed to analyze possible relations between the data logs produced by students' interaction in a educational system and their flow experience during the system usage. Thus, our research question is: **how can we relate flow experience and students' data logs in educational systems through a qualitative approach?**

2.1. Materials, method and participants

The system used in this study to collect the students data logs is an e-learning system. The system features a series of game elements (points, badges, leader boards, progress and avatars). It allows for including different multiple choice questions associated with these game elements. In our study, in its pedagogical model, the system provided 20 questions about logical reasoning. The system was chosen because it is freely accessible for editing for academic purposes. Figure 1 presents an example for the system.

To identify the students' flow experience, we used the flow state scale (FSS) developed by [Jackson and Eklund 2002], which provides 36 non-intrusive questions related to the nine original flow experience dimensions [Csikszentmihalyi 1997a]. We used a 5-points Liker scale [Likert 1932] to obtain the users' responses, following the recommendations of [Jackson and Eklund 2002]. We chose to use this scale because it is based



(a) Home page (b) Activities page

Figure 1. System example

on the nine Flow Theory dimensions and it was identified to be the most used scale in studies related to the measurement of the flow experience in educational environments [Oliveira et al. 2018]. At the same time, as far as we know, it is the only one validated for the gamification domain [Hamari and Koivisto 2014], since we use a gamified educational system.

To collect students' data logs, we used the theoretical model proposed by [Oliveira et al. 2019], which associates eight different types of data logs to the nine flow experience dimensions, including *(i)* Active time in the system; *(ii)* Used time to finish a step/activity; *(iii)* Proportion of correct steps/activities; *(iv)* Proportion of help requests; *(v)* Proportion of answers that were incorrect and received *error message*; *(vi)* Average response time after a feedback; *(vii)* Total unique session views; and *(viii)* Number of mouse click out of buttons". In this study, we used six from the nine data logs proposed (see Table 1). The six types of data logs were chosen because of the domain of the system, which, for example, does not have the option to view an activity multiple times, so it is not possible to capture the "total unique session views".

To collect, interpret and analyze the students' behavior, we used the think-aloud protocol, which provides rich verbal data about reasoning during a problem-solving task [Fonteyn et al. 1993]. The think-aloud protocol allow observing different types of human reactions, perceptions and opinions when using a certain product (*e.g.*, educational systems), which are normally not possible to be measured using scales or interviews [Fonteyn et al. 1993, Charters 2003]. Besides, it allows generating interesting insights with reduced samples, being able to capture details that in addition to those that are captured through scales and other similar instruments [Trenor et al. 2011]. The think-aloud protocol is also a good strategy to validate information collected through scales when the sample is small [Trenor et al. 2011]. Thus, an expert in human-computer studies (over five years of experience) followed the terms of the protocol as proposed by [Fonteyn et al. 1993] and [Charters 2003], explaining how the protocol works for the participants and slicing so that each participant spoke out loud every action they would do in the system and what they were thinking about when performing each action.

The expert also analyzed the recorded videos (recording of users' faces and voice while using the system[2]). The expert analyzed the participants individually (making a transcription of verbal data a logbook) as recommended by [Braun and Clarke 2006]. As

[2]Students declared at the beginning of the recording that they accepted the videos to be recorded.

described by [Riessman 1993]. The expert also coded the data following the recommendations of [Braun and Clarke 2006]. The encoded data was stored in spreadsheets. The study design was organized in the following three successive steps:

In the **first step**, participants were explained how the step-by-step should be conducted. In the **second step**, participants were invited to used the system independently (to mitigate potential threats that participants might influence each other). The participants answered the demographic questionnaire containing the following questions: *i)* gender[3]; *ii)* age; and *iii)* education degree; Next, participants used the system performing the educational activities. In the **third step**, participants answered the FSS developed by [Jackson and Eklund 2002] and validated by [Hamari and Koivisto 2014] for the gamification domain (immediately after using the system).

Our participants were six MBA students from a Brazilian University. Most of the students are female and are more than 30 years old. The students were randomly selected from a group of 12 students. We decided to select only six students because it is an acceptable number for a qualitative study based on the think-aloud protocol [Fonteyn et al. 1993, Charters 2003], considering that the protocol was applied by one expert. More importantly, we aimed to analyze more deeply the experience of a single user or a small group of users [Charters 2003] and compare the differences in participants' flow experiences. After data collection, the researcher calculated the average students' flow experience, data logs and the data from the think-aloud protocol. To conduct a deeper analysis, following the recommendations of [Charters 2003], we opted to analyze the data of each subject individually, and then compare the results among themselves, also generating an overall result.

3. Results and Discussions

Initially, we analyzed the students' data logs produced from their interactions within the system, as shown in Table 1. Thereafter, we analyzed the overall flow experience of each participant, as well as their experience in each flow dimension individually (see Table 2).

The **first participant** had the lowest flow experience (Flow = 2,833, see Table 2) among the six participants. He was the participant with the most mistakes in the learning tasks (11 mistakes our of 20) and the participant with the highest number of mouse clicks. This result goes together with the theory proposed by [Csikszentmihalyi 1997a] and is very similar to part of the model proposed by [Oliveira et al. 2019], which proposes that if a student fails in most of the activities attempted, it is possible to identify that the overall level of task challenge is greater than the student' abilities [Oliveira et al. 2019]; likewise, if a student has a low proportion of correct steps in the system, it is possible to conclude that the goal of the steps is not clear to the student [Oliveira et al. 2019]. At the same time, the model proposed by [Oliveira et al. 2019] poses that when having too many clicks, a user may have a low concentration, directly resulting in a low flow experience. This case also confirms part of Oliveira's model, especially indicating that having many mistakes in performing the tasks and making unnecessary clicks may directly imply three flow

[3]There are different genders that could be put as an option, yet we used only two gender options (male and female). We decided to include the options "male", "female", "other", "I prefer do not inform", similar with other recent studies in HCI [Orji et al. 2014, Oliveira et al. 2020] (no participant scored any options other than "male" or "female").

Table 1. Students' data logs analysis (time is shown in minutes:seconds)

Subject	Stype	AtE	AtS	UtFS	PcS	PrEM	ArF	McB
1	Male	21:36	07:25	06:22	9	11	00:20	4
2	Default	27:02	06:11	05:12	13	7	00:16	0
3	Male	13:46	05:27	05:04	15	5	00:16	0
4	Male	11:20	02:10	01:54	12	8	00:06	0
5	Female	16:48	05:43	05:11	12	8	00:16	1
6	Default	15:52	09:05	08:29	15	5	00:27	3

Key: STyepe: System type; AtE: Active time in the experiment; AtS: Active time in the system; UtFS: Used time to finish a step/activity; PcS: proportion of correct steps/activities; PrEM: Proportion of answers that were incorrect and received "error message"; ArF: Average response time after a feedback; McB: Number of mouse click out of buttons.

Table 2. Participants flow experience

Subject	CSB	MMA	G	F	C	CTRL	LSC	T	A	Flow
1	2,500	3,250	2,500	2,250	4,000	1,500	3,250	3,000	3,250	2,833
2	3,250	3,000	3,000	3,250	2,750	2,500	3,500	2,750	3,250	3,028
3	4,500	4,500	4,250	4,250	3,500	4,000	3,750	4,500	4,500	4,194
4	3,500	2,750	4,000	4,250	2,750	4,250	3,250	3,000	4,750	3,611
5	4,250	3,250	4,750	3,500	3,000	4,250	4,750	4,000	4,250	4,000
6	4,250	2,500	2,250	3,750	4,000	4,250	3,250	2,000	2,000	3,139

Key: CSB: challenge-skill balance ; MMA: action-awareness merging; G: clear goals; F: unambiguous feedback; C: total concentration on the task at hand; CTRL: sense of control; LSC: loss of self-consciousness; T: transformation of time; and A: *autotelic* experience.

experience dimensions (*i.e.*, challenge-skill balance, clear goals, and total concentration on the task at hand). Besides, in codes from the think-aloud protocol, it was possible to perceive his dissatisfaction with the system and with the proposed activities design, contributing to his low flow experience.

The **second participant** had a low flow experience (Flow = 3,028 see Table 2) and was the one that took the longest time to complete the task (27:02), as presented in Table 1. In most of the other data logs (*e.g.*, average response time after feedback and proportion of correct steps/activities), this participant's data logs were similar to the average of the other participants'. This complies with the model proposed by [Oliveira et al. 2019], that when students are active in the system for a long time, it is possible that they are not in an "action-awareness mergin" state but are focused on things external from the system, so the time is not transformed in their mind [Oliveira et al. 2019]. This explains why the "action-awareness merging" dimension (3,000), in particular, "transformation of time" dimension (2,750) were not high (see Table 2). This participant had a high proportion of answers that were incorrectly answered and received "error message" compared to the others. This also corroborates the model proposed by [Oliveira et al. 2019], which proposes that if a student answers a question incorrectly after receiving a "bug message", we can deduce that they do not have a sense of control concerning the question or task that they are doing at the moment, which influences negatively in the "sense of control" dimension. This also is lined up with different theoretical studies [Csikszentmihalyi 1997a, Csikszentmihalyi 2014, Jackson and Eklund 2002] and with some parts of the Oliveira's model, indicating, especially, that the activity time in the system directly influences on the "action-awareness merging" and "transformation of time" dimensions. Similarly, the proportion of answers that were incorrect and received "error message" are directly related to the "sense of control" dimension. In the think-aloud study, we perceived that this participant was unable to focus on activities sequentially, affecting in the "sense of control" dimension, aggregating the initial result.

The **third participant** was the one that got more hits concerning the other participants in the educational activities (15 out of 20). This participant did not click with the mouse at unnecessary moments. She also had the highest flow experience among the participants (highest flow score, *i.e.* 4,194). The model proposed by [Oliveira et al. 2019] indicates that students who perform more educational activities (not necessarily every time) tend to have a better feeling of challenge-skill balance and more clearly understand actions/activities ("clear goals" dimension), also following some theoretical insights [Csikszentmihalyi 1997b, Heutte et al. 2016, Erhel and Jamet 2019]. Similarly, the model indicates that if a student didn't click outside of a specific button (clicks without purpose), their concentration was not impaired. This explains the high flow experience and especially, the "challenge-skill balance", "clear goals", and "concentration" dimensions. In the case of this participant, our finds also are similar with the Oliveira's model, proposing a relation between the proportion of correct steps/activities and the dimensions of "challenge-skill balance", "clear goals", as well as the number of "mouse clicks" out of buttons to have a direct relationship with dimension of "concentration". More specifically, if a student has a high average correct answers in the activities (yet, not getting them all correct), they tend to have a good experience in terms of challenge-skill balance and clear goals.

The **fourth participant** had the average flow experience (flow = 3,611) amongst the participants. This participant had a very fast response time after feedback (only six seconds). The model proposed by [Oliveira et al. 2019] proposes that if a student takes very little time to complete a given task, the difficulty level of the task may be less than the student's skill level. In this case, different from the others, it was not possible to perceive a direct relation between Oliveira's model and the student experience (his challenge-skill balance experience was 3,500). This participant also performed more than half of the educational activities (even with the fast response time after feedback). According to the model, this may impact negatively on the user flow experience [Oliveira et al. 2019], because if a student can do many activities correctly in a short period, the difficulty of the activities is not balanced with his abilities. In the think-aloud study, the participant showed confidence when conducted the activities, corroborating the results previously mentioned.

The **fifth participant**' data logs were similar to **fourth participant**. However, her flow experience was higher (4,000). According to the model proposed by [Oliveira et al. 2019], this may have occurred because the participant did not perform the activities very quickly and took too long (average). The think-aloud protocol showed that this participant also demonstrated confidence during the study. Based on previews theoretical studies [Jackson et al. 2011, Csikszentmihalyi 2014], we believe that if a student performs an average number of tasks using an average period (among the total population that used the system), the level of difficulty of the activity is balanced with the student's skill level.

The **sixth participant** had the longest response time after feedback among the participants, with an average flow experience (3,139). The think-aloud study showed that the participant remained focused and reflective about the answers to the quiz. According to the model proposed by [Oliveira et al. 2019], if a student takes a long time to complete a certain activity or to perform a certain task after receiving a feedback message, the difficulty level of the task may be higher than the student' skill level. However, for this student, the "challenge-skill balance" dimension was 4,250, contradicting this part of the proposed model.

This participant was the participant who took the longest time using the system (09 minutes and 05 seconds). According to the Oliveira's model, if a student spends little time in each section of the system, or if s/he starts and finishes the sections in the system many different times (various login and logout in a short time), it is possible that the student is focused on things external from the system and therefore the time was not transformed in their mind (the same occurs in term of students' *autotelic* experience). These were the dimensions with the lowest score for this participant. This may indicate that for a student to have a transformation of time and an *autotelic* experience, in addition to not spending much time in the system, as proposed in [Oliveira et al. 2019], the student should not spend too much time doing the activities.

Therefore, summarizing our finds, we can infer a possible relation between four types of data logs (active time in the system; the proportion of correct steps/activities; the proportion of error message; and the number of mouse clicks out of the buttons) and seven of the nine flow experience dimensions (challenge-skill balance; action-awareness merging; clear goals; total concentration on the task at hand; Sense of control; transformation of time; and *autotelic* experience). In particular, our study provides insights into the following relationships: **Active time in the system** influenced the dimensions "action-awareness merging", "transformation of time" and "*Autotelic* experience". **Proportion of correct steps/activities** influenced the dimension of "clear goals". **Proportion of error message** influenced the dimension of "sense of control". **Number of mouse click out of buttons** influenced the dimension of "total concentration on the task at hand", thus partially supporting the approach proposed by [Oliveira et al. 2019], by providing insights on five out of the 19 relationships proposed (notice that some of them were not verified).

Overall, our results show insights that some types of data logs presented a relationship with student's flow experience (*e.g.*, average response time after feedback, the proportion of answers that were incorrect and received "error message", and proportion of correct steps/activities). The relationships observed in this study corroborate the theoretical model proposed by [Oliveira et al. 2019]. Despite that, our results also highlight the importance of conducting new studies, especially data-driven approaches (*i.e.*, which is the use of computational algorithms to corroborate/identify the relationships between the students' data logs and their flow experience), to provide more robust and reliable results [Hair Jr et al. 2016].

3.1. Limitations

Our study has some limitations, generally inherent to qualitative studies, that should be taken into consideration when conducting future similar studies. About the **study design**, we decided to randomly select six from 12 MBA students (female as the majority) and our results cannot be generalized to other contexts or samples. Despite that, we chose to follow a qualitative approach, based on reliable methods for conducting studies with few subjects (*i.e.*, think-aloud method). The flow experience is a subjective experience, which can vary from person to person and is difficult to measure. To mitigate this limitation, we used only validated and widely used methods in the literature to conduct data collection and analysis.

About the **internal limitations**, the protocol used in the study asks participants to keep "thinking aloud" (*i.e.*, describing what they are thinking) when using the system. This protocol can make it more difficult for participants to achieve some of the flow experience dimensions (*e.g.*, loss of self-consciousness, concentration on the task at hand, and transformation of time) that depend on a deep concentration on the action at hand. Although it does not lessen the effects, we measure and analyze each the flow experience dimensions separately and independently. Despite the option to use the "retrospective" think-aloud protocol, this option may depend on visual stimuli for the participants to remember their actions in the system, which was not possible in our study. At the same time, some nuances may not be correctly-observed using this specific protocol.

Regarding **external limitations**, there was an imbalance in the number of males and females who participated in the study (one male and five female participants). To mitigate this limitation, we conducted our analyzes observing possible gender characteristics that influence the flow experience. We also suggest that further studies could be conducted taking into account a balance between the participants' gender. Finally, external factors related to the individual emotions of each study participant may have influenced their behavior when using the educational system. Despite the methods used in our study to mitigate this limitation, we suggest that further studies can be conducted using different qualitative methods (*e.g.*, interviews, focus groups and external observation).

4. Conclusions and Future Works

One of the main contemporary challenges in the field of educational technologies is the automatic students' flow experience identification in educational systems. In this paper, we presented the results of a qualitative study that verified the association between students' data logs and their flow experience in an educational system, through a think-aloud approach, thus, moving towards an approach capable of measuring students' flow experience automatically, through the use of data logs. The main results suggest some relationships between the students' data logs and their flow experience in the system, providing an advance of the literature towards automatic identification of students' flow experience in educational systems. For future studies, we aim and recommend to conduct data-driven studies to confirm the relationship between the students' data logs and their flow experience through an approach based on larger amounts of real data. After further studies have been done relating log data to the students' flow experience in educational systems, we recommend the development of algorithms that can be plugged into educational systems and inform the students' flow experience in the systems.

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