The Relationship between Users' Behavior and Their Flow Experience in Gamified Systems

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Modeling users' experience in gameful systems is one of the main contemporary challenges in the field of human-computer interaction. One of the most desired and complex experiences to be identified is the flow experience (*i.e.*, challenge-skill balance, action-awareness merging, clear goals, unambiguous feedback, concentration, sense of control, loss of self-consciousness, transformation of time, and autotelic experience). Facing this challenge, we conducted a quantitative study (N = 313) based on structural equation modeling, aiming to model and predict the users' flow experience through their behavior (represented by performance-related, interaction with gamification, as well as the time they take in different actions) in the system. The main results indicate that *i)* gamification (*i.e.*, doing well in points, badges, and leader-board) was positively related to users' experience of good challenge-skill balance, *ii)* whereas it was negatively related to users' concentration. Thirdly *iii)* user performance was positively related to users' concentration. However, overall, the results indicate that while associations between user behavior and flow experience could be established, there remains future work to be done to fully explain user flow experience while using a system. Our study contributes to the fields of human-computer interaction, gamification, and educational technologies, especially through insights related to modeling and predicting flow experiences in gameful systems through behavior data.

CCS Concepts: • **Human-centered computing → HCI design and evaluation methods**.

Additional Key Words and Phrases: User experience, flow experience, gameful systems, gamification, data-driven study

ACM Reference Format:
Wilk Oliveira, Juho Hamari, and Seiji Isotani. 2023. The Relationship between Users' Behavior and Their Flow Experience in Gamified Systems. *Proc. ACM Hum.-Comput. Interact.* 7, CHI PLAY, Article 386 (November 2023), 23 pages. https://doi.org/10.1145/3611032

1 INTRODUCTION

In recent years, several types of educational systems (*e.g.*, educational games [27, 57, 109], Massive Open Online Course (MOOCS) [11, 68, 129], and Intelligent Tutoring Systems (ITS) [20, 30, 78]) have emerged intending to improve the quality of online education [58]. The emergence in the use of educational technologies was further strengthened in 2020 due to the Covid-2019 pandemic [1, 72, 113]. These systems have been increasingly used by instructors and students from different

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2573-0142/2023/11-ART386
https://doi.org/10.1145/3611032

countries and have attracted the attention of researchers, that are investing in the design of this type of system [7, 73, 126]. The main idea is to improve the users' experience in this type [15, 19, 71].

A widely used technique to improve students' experience in educational systems is gamification (*i.e.*, "the process in which services, activities, and systems are transfigured to promote similar motivational benefits as found in games" [44, 64]) [6, 8, 85]. Gamification aims to improve the students' experience (*e.g.*, engagement [75], motivation [124], and flow [74]) in the educational systems [5, 64, 81], and depending on the application design, it can increase users' time in the systems and improve the students' learning experience [64].

At the same time, one of the most discussed experiences in studies on gamification in education is the flow experience [36, 107, 117], which is an experience of deep engagement which people can achieve during a certain activity [24] and is highly linked to the learning experience (*i.e.*, in general, who achieves a high flow experience can also achieve a high learning experience) [22, 96, 108]. Thus, the flow experience is seen as a key experience for general users to obtain a desired behavior when using a certain type of system [50, 61, 122].

However, one of the main challenges related to the studies on flow experience in gamified educational systems is the modeling and measurement of this experience [23, 28, 69, 82, 91, 106]. Often, the challenge is due to this analysis occurs through invasive approaches (*e.g.*, electroencephalograms (EEG) [10] and eye trackers [115]) or that cannot be applied massively (*e.g.*, interviews [112] and questionnaires [111]) [82], which makes it difficult to analyze the flow experience in gamified educational systems and consequently draw attention to the need for approaches that move towards the automatic identification of that experience [80, 91, 106].

To face this challenge, in this study (N = 313) we performed a data-driven analysis aiming to model and predict the students' flow experience (*i.e.*, challenge-skill balance, merging of action and awareness, clear goals, feedback, concentration, control, loss of self-consciousness and *autotelic* experience) in a gameful system (*i.e.*, a gamified educational system) based on the users' behavior data logs (*e.g.*, the average response time on correct answers, the proportion of correct steps/activities, and points) during the system usage. Then, we aimed to answer the following research questions: **How to model users' flow experience through their behavior data in gameful educational systems?** and **How to predict users' flow experience through their behavior data in gameful educational systems?** We used a robust data analysis technique (*i.e.*, partial least squares structural equation modeling (PLS-SEM)) to analyze the data.

The main results indicate that *i)* gamification (*i.e.*, points, based, and leader-board position) is positively related to users' challenge-skill balance, *ii)* gamification is negatively related to users' concentration, and *iii)* performance is positively related to users' concentration. However, despite the results regarding flow experience modeling through behavior data being significant, the internal prediction power is low, not allowing the generalization of the results. With this study, we contribute to different fields as such human-computer interaction, gamification, and educational technologies, providing insights on how to model users' flow experiences in gameful systems through behavior data. Based on the results, we also present a series of research directions that can be taken into account in future research.

2 BACKGROUND

In this section, we present the study background (*i.e.*, Gamification in education, Flow Theory and flow experience measurement) and a comparison between the main related works.

2.1 From gameful design to gamified education

Gameful refers to a state or quality of being like a game or having characteristics of a game [31, 67]. It can be used to describe something that is playful, enjoyable, and engaging, and that incorporates elements of game design into its structure [35, 48]. The goal of gameful design is to create an experience that is enjoyable, motivating, and meaningful, while still achieving the intended outcomes [48, 67].

From the general concept of "gameful", rise "gamification" ("the process in which services, activities, and systems are transfigured to promote similar motivational benefits as found in games" [44, 64]), used in recent years in several areas of knowledge (*e.g.*, marketing [121], health [128], and education [114]). However, the area with the most applications in education [6, 63, 64]. In education, gamification is studied in different aspects (*e.g.*, design, application, and evaluation) [100]. Especially, over the past few years, because of advances in gamified education, several gamified educational systems have been implemented and used in educational settings [101].

The growing use of gamification in education is because gamification (when well-applied), can improve different students' experiences (*e.g.*, engagement, motivation, and flow) [74, 75, 124]. These experiences can lead to a better learning experience in educational environments [26, 93, 125]. However, the growing number of users of gamified educational systems has created the challenge of evaluating the users' experiences in the gamified educational systems [64], which is usually done through questionnaires [87].

Thus, one of the current challenges of gamification in education (*i.e.*, gamified educational systems) is to use student interaction data logs in the systems to model and predict students' experience during system usage [64, 80, 87]. One of the possibilities in this context is to analyze the users' own interaction with the gamification elements (*e.g.*, ranking, trophies, and points) and the relationship with the users' experience in the system.

2.2 Flow Theory and empirical flow experience

The Flow Theory was proposed by Csikszentmihalyi [24] and represents "an optimal experience that people have as a motivating factor in their daily activities" [37] or in a general summary, an experience of deep engagement that a person can achieve in a given activity [21, 24, 25]. Over time, several studies related to Flow Theory have been conducted in different areas such as sports [53], video games [14], and education [108]. The flow experience can be reached in different types of activities and is composed of nine different dimensions [22, 25, 52]: (1) challenge-skill balance (CSB); (2) unambiguous feedback (F); (3) clear goals (G); (4) action-awareness merging (MMA); (5) total concentration on the task at hand (C); (6) sense of control (CTRL); (7) loss of self-consciousness (LSC); (8) transformation of time (T); and (9) *autotelic* experience (A). These flow experience dimensions can be further organized into "antecedents of flow" and "flow itself".

There are three antecedents of the flow, and they are considered factors that need to be provided by a certain activity so that the other flow experience dimensions be reached. There are:

- **Challenge-skill balance**: represent when experiencing flow, a dynamic balance exists between challenges and skills. Challenges and skills, however, can be changed in any activity, making flow an accessible experience across all domains of functioning [52].
- **Unambiguous feedback**: represent when receiving feedback associated with a flow state, the individual does not need to stop and reflect on how things are progressing [52].
- **Clear goals** indicate that goals are necessary part of achieving something worthwhile in any endeavor and the focus that goals provide to actions also means that they are an integral component of the flow experience [52, 54].

The flow itself is composed of six dimensions, which need to be reached jointly by an individual, thus forming the flow experience.

- **Action-awareness merging**: the unity of consciousness apparent in this flow dimension and illustrates the idea of growth in complexity that results from flow experiences [52].

- **Total concentration on the task at hand** defines one of the clearest indications of being in flow, that is, totally focused in the present on a specific task being performed [52].
- **Sense of control** is like flow itself, the sense of control often lasts only a short period of time and this relates back to keeping at the cutting edge of the challenge-skill balance in a situation [52].
- **Loss of self-consciousness** is liberating to be free of the "voice within our head" that questions whether we are living up to self- or other-imposed standards [52].
- **Transformation of time**: experiencing time transformation is one of the liberating dimensions of flow (to feel free from the time dependence under which we live most of our lives) [52].
- ***Autotelic* experience:** is generally after completing a task, upon reflection, that the *autotelic* aspect of flow is realized and provides high motivation towards further involvement [52].

The flow experience is represented by the interconnection of these nine dimensions (antecedents and flow itself) [21, 52, 54]. That is, for a person to achieve the flow experience it is necessary that the activity provides all the antecedents of the flow and at the same time, the person feels the other six dimensions of the flow itself, at the same time [23, 25]. In education, the flow experience has also been extensively studied [47, 60, 92] and recent studies show that the flow experience is directly associated with the student's learning experience in different settings [36]. This means that if students can achieve a high level of flow experience in a given educational environment, they are more likely to have a high learning experience [93**?**]. Despite the various studies involving Flow Theory and Education, one of the main challenges still remaining related to Flow Theory in educational systems is the flow experience measurement [45, 54, 55, 69, 80].

2.3 Flow experience measurement

Flow experience measurement has been done in different ways over the years [83, 97]. Initially, the experience was measured using a system that requested that a certain person presses a button whenever they feel an experience of deep engagement (*i.e.*, the flow experience) [21]. This kind of measurement generates some biases, is expensive, and could not be conducted massively [80]. Therefore, to improve this situation, other methods have been proposed over the past four decades.

Initially, one of the first methods proposed was interviews and focus groups with people [25]. However, these methods are also costly and also do not allow for massive applications [80]. Thus, questionnaires/scales emerged as a way to measure the flow experience [55]. This technique has expanded and is still the most used method to measure the flow experience [83, 97]. Also, over the past few years, several questionnaires have been proposed and validated in different domains (*e.g.*, physical activity [54], sports [55], and gamification [45]).

Despite the advances, this method still presents problems such as the difficulty of application. Thus, in the last decade other methods have also been proposed, such as the use of EEG or eye trackers [3, 28, 118, 123]. Still, all of these methods fall into three problems, either they are costly or they are invasive or they cannot be applied massively [80].

Therefore, more promising methods are the proposal of approaches for the analysis of the flow experience based on the data of logs produced by users in educational systems [69, 88, 91, 106]. In general, these approaches relate to the users' flow experience to the data logs that are produced by those users. However, this approach is still incipient with few studies (see subsection 2.4), requiring further studies with high sample sizes and data analysis using different techniques.

2.4 Related work

To identify the main related works and provide a deep field understanding, we analyzed the results of three systematic literature reviews conducted by Perttula *et al.* [97], Oliveira *et al.* [82] and Oliveira *et al.* [87] who described the state of the art on Flow Theory and educational technologies (including the most used methods for identifying the students' flow experience in educational systems). Then we also performed an exploratory review aiming to find new studies. The results show that in recent years, few studies have sought to propose approaches to automatically identify the users' flow experience in educational systems [82], highlighting the importance of approaches that, for example, relate the students' flow experience with their data logs during the system's usage.

2.4.1 Measuring flow experience. Wang and Hsu [118] used a questionnaire associated with an EEG analysis aiming to investigate the effects of students' challenge-skill balance on their flow experience, as well the effects of students' flow experience on their learning. Their results showed that the students' flow experience depends on a challenge-skill balance of learning materials [118]. In this study, Wang and Hsu [118] also investigated the possibility of using an inexpensive non-medical EEG device to research the association between flow experience and challenge-skill balance in the system.

Akcan [3] used a flow scale to measure the players' flow experience in advergames (considering the nine flow experience dimensions). At the same time, the author also analyzed the participants' eye movements using eye-tracking data. The study does not present an analysis of the correlation between the players' flow experience level, the places of the games where the players looked the most or their eye movements. However, the study opens up the possibility of correlating the flow experience of players with eye movements.

Wu *et al.* [123] used an EEG to measure the EEG-detected real-time flow states of different students this study revealed a whole-part association between students' momentary and overall reflective flow experiences. The study results indicate that it is possible to correlate the students' flow experience with their behavioral pattern (detected by the EGG), thus opening space for other types of analyses [123].

2.4.2 Measuring flow experience through behavior data logs. Lee *et al.* [69] conducted a study to identify whether the users are in a flow experience, where was experimented with a sample of 55 participants. They used step regression (*i.e.*, a data mining technique) to analyze the student's data logs and compare the students' data logs (*i.e.*, students' behavior) with their flow experience. In their study, Lee *et al.* [69] implemented one of the nine flow experience dimension (*i.e.*, challenge-skill balance).

Kock [28], proposed an approach to automate the flow state identification using an EEG with 20 participants during the use of an educational game aiming to associate seven different brain dimensions with the participants' flow experience. To access the participants' flow experience, the author used the Abbreviated Flow Questionnaire (AFQ). Their results show an association between the participants' flow experience and some specific brain dimensions [28].

Challco *et al.* [13] conducted a study proposing a framework to integrate the learner's growth process with the flow state to lead and maintain the students in flow during the educational system usage. Challco *et al.* [13] also operationalizes the flow only as of the perception of the challenge-skill balance dimension, without considering the other flow experience dimensions.

Oliveira *et al.* [91] proposed a theory-driven conceptual model, associating students' interaction data logs with each of the flow experience dimensions. They evaluated the proposal with three different experts. Despite representing an advancement towards automatic flow experience identification in educational systems, the model has not been evaluated with real data and the authors recommend its validation with real data produced in educational systems [91].

Oliveira *et al.* [88] conducted a qualitative study (with six participants) through the think-aloud protocol to associate user data logs with the user flow experience within an educational system. The study identified a relation between four types of data logs and seven of the nine flow experience dimensions [88]. Despite these promising results, the results were obtained through a qualitative study and need to be confirmed through quantitative studies based on data from more users.

Semerci and Goularas [106] conducted a study to capture the interaction of students in an e-learning environment automatically and use these data for evaluating their flow state in a course. With a sample composed of 87 students from two different departments of different faculties [106]. Analyzing data through heatmaps and deep neural networks, they found a significant correlation between the survey results (flow experience) and students' performance and activity. These results highlight the need to carry out similar studies, including new types of data logs and individually analyzing all Flow Theory dimensions.

In a sequence of more recent studies, Oliveira *et al.* [86, 89, 90] conducted studies based on behavior data logs aiming to model the flow experience in games and gamified systems. The results showed that some behavioral data can be associated with some flow experience dimensions. However, both studies were conducted with limited samples, and according to the authors themselves, despite representing an advance in the literature, the results need to be further investigated, especially with larger samples in different systems [86, 89, 90].

Muramatsu *et al.* [77] utilizing behavioral data produced by users, evaluated the applicability of employing one single type of behavior data (*i.e.*, mouse click frequency) as an exclusive metric to model and to predict students' flow experience. In two data-driven studies (N1= 25 | N2= 101), they identified that the mouse click frequency on its own is not able to predict the flow experience [77].

2.4.3 Summary. The studies aiming to model or predict students' (although one of the reviews was conducted free of the domain and exploratory review, only studies in the general field of education were identified) flow experience through data logs focus on analyzing a single flow experience dimension or they present more exploratory analytical approaches, which do not allow obtaining more confirmatory insights related to modeling and predicting the flow experience through behavior data. As far we know, our study is the first study aiming to model and predict students' flow experience through users' behavior data logs in gamified educational systems, using a validated theoretical model (considering all the nine flow experience dimensions [22, 24, 54]).

3 RESEARCH DESIGN

Our study is characterized as a data-driven study [32], analyzing data of participants using a gamified educational system.

3.1 Research questions and hypothesis

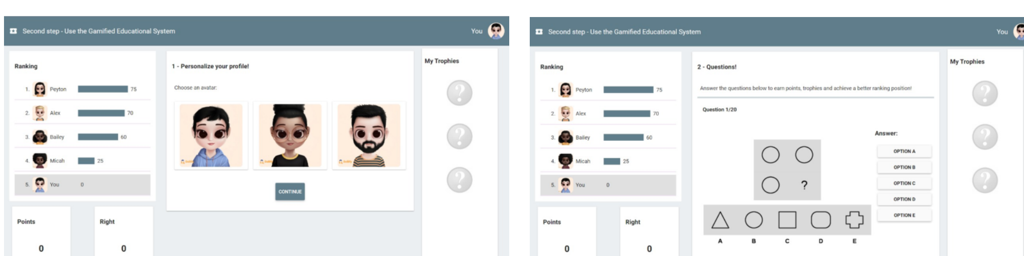
Our study aims to model and predict users' flow experience in gamified educational systems through their behavior data logs produced during the system usage. Thus, we aim to answer the following research questions (RQs): **How to model users' flow experience through their behavior data in gameful educational systems?** and **How to predict users' flow experience through their behavior data in gameful educational systems?**

Over the years, studies have shown that the flow experience is an experience highly related to the student's learning experience in educational settings [23, 36, 96, 108]. At the same time, different recent studies proposed that there is a relationship between different types of user experience and the data logs produced by these users in the systems [49, 51, 130]. Additionally, studies have proposed that there is a direct relationship between the users' flow experience in educational systems and the data logs that are produced by these students in the system [28, 69, 80, 88, 106]. Thus, in this study, we hypothesized that **is possible to model and predict the students' flow experience through their behavior data in a gamified educational system**.

3.2 Materials/instruments and method

To carry out the study, we used the system "Learning in Flow" [4], a gamified educational prototype composed of a series of educational activities related to Logical Reasoning. The activities available in the system are 20 logical reasoning activities. The activities are of different levels, from the easy to the difficult (in sequential order). The questions were initially defined and analyzed by Albuquerque *et al.*, [4, 77, 104]. No minimum time was defined for using the system to make the activity as free as possible, maximizing the chances of participants having a less forced and more spontaneous experience when using the system. The activity was considered finished only after all 20 tasks were answered.

The system used was chosen because it was created specifically for carrying out this type of study. At the same time, the system has the most used gamification elements in gamified educational systems (*i.e.*, points, badges, ranking, levels, progress bars, and avatars [29, 46, 64]). The system was also already used and analyzed in other recent studies [4]. Figure 1 presents the system home page (where participants can select an avatar to represent itself in the system) and activity page (where participants can do the activities).



(a) Home page (b) Activity

Fig. 1. Examples of the system used in the study: two figures showing the system used in the study. The figure on the left side presents a ranking (with leaderboards), avatar options that can be chosen by users, and a space where trophies will appear. The figure on the right side shows a ranking (with leaderboards), a logical reasoning quiz (one of the questions answered by the study participants), and the space where the trophies will appear.

To collect the students' data logs during system usage, a module was implemented to collect the users' data logs in the system. The model collected nine different data logs according to the theoretical model proposed by Oliveira *et al.* [91] for the automatic students' flow experience in educational systems:

- **Active time in the system (ActTS):** Total time that a user spends in each session in the system (from the login until the logout).
- **Used time to finish a step/activity (Art):** Different from the first information, this information represents the total time that a user uses to finish a specific activity/task or a step in the system (in our study we divide this data into two types: *a)* average response time in correct answers (ArtCA) and *b)* in incorrect answers (ArtIA)).

- **Proportion of correct steps/activities (ProCS):** Average of user's correct answers in a group of activities/tasks on the system.
- **Proportion of help requests (ProHR):** Average of a user's help requests for completing an activity/task in the system[1].
- **Proportion of correct steps/activities after feedback (ProCSF):** Average times a user has correctly answered a step/activity after a feedback message stating the step/activity result.
- **Average response time after a feedback:** Average time a user spends to answer a question/task after receiving feedback from the system (in our study, we divide this data into two types: *a)* average response time after positive feedback (ArtPF) and *b)* after negative feedback (ArtNF)).
- **Total unique session views (TV):** Number of times that a user tries to do the same activity/task (*e.g.*, number of times the user sees the same tutorial).
- **Number of mouse clicks out of buttons (NMC):** Average time a user clicks on the screen (neutral) that does not bring any action back to the user (*e.g.*, clicks on a text area). In addition to the data proposed in the study of [91], we also take the total of consecutive hits (TCH) and the average of consecutive hits (ACH). We decided to include this new data to have more data related to the performance of the participants in the system.

To identify the students' flow experience, we used the short flow state scale (short FSS) proposed by Jackson and Eklund [54], which consists of nine questions representing the nine original flow experience dimensions proposed by Csikszentmihalyi [24]. The questionnaire was chosen because it is the most used questionnaire in studies related to Flow Theory and technologies in education [82]. The questionnaire was also previously validated by Hamari and Koivisto [45] for the gamification domain. The instrument was applied through a five-point Likert scale [70] as recommended in the flow "Flow State Manual" developed by Jackson *et al.* [52]. Additionally, to mitigate threats to validity related to the participants' attention during the study, following the recommendation of Kung *et al.* [65] and the example of other studies in our field [84, 90, 103], we added an "attention check statement" (*i.e.*, if you are filling out the form carefully, answer 4). Students who missed the attention check question were removed from the final data analysis. In the appendix **??**, we present the short FSS used in our study.

Regarding the method, we organized the study into *four* steps. Initially, in the *first step*, as Connelly [18] recommended, a pilot study was conducted with 10 participants. The pilot study analyzed whether the system was working correctly and whether the amount paid to participants was sufficient.

After conducting the pilot study, in the *second step*, we started the recruitment phase of the study participants. We used two different platforms to recruit participants, Amazon Mechanical Turk (MTurk)[2], a crowdsourcing marketplace service highly used and recommended for experiments with humans [95]. To collect the user data using MTurk, we followed the 10 good practices (recommendations) proposed by Aguinis *et al.* [2], especially, we defined clear reward rules for participants, allowing participants to judge whether the reward amount was appropriate for the study they had participated in. Each participant received 25 cents for their participation.

Prolific platform[3], is another crowd-sourcing marketplace service highly used and recommended for experiments with humans [94]. In this step, each participant received 0.63 £ for their participation. On this platform, the cost is calculated automatically according to the time of the experiment. The choice to use these two platforms was due to the objective of recruiting participants from

[1]This data was not used in our study, as the system used does not present an option for the user to ask for help.
[2]https://www.mturk.com/
[3]https://prolific.co/

different countries, with different cultures, thus having a heterogeneous group of participants in demographic aspects. To have participants with different profiles, no criteria for participation were previously stipulated. The data was collected in January 2020. Then the data was organized and processed in the correct format for data analysis. Figure 2 present the study organization.

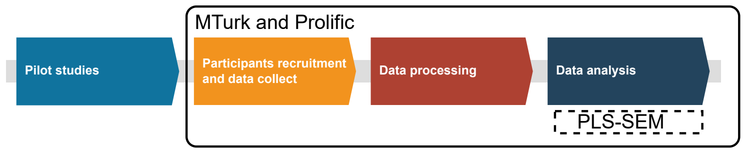


Fig. 2. Study organization: figure with four balloons ("Pilot studies", "Participant recruitment and data collection", "Data processing", and "Data analysis") in a sequence, describing the study organization.

3.3 Participants and data analysis

We initially received 330 responses. 17 were removed because answered wrong the attention check question. Our final participants were 313 (174 self-declared as male, 137 self-declared as female, and two preferred not to inform), from 32 different countries with an average age of 23 years old (Table 1 present our sample size details). To calculate our sample size, we used the method of "a-prior analysis" based on the anticipated effect size, and the desired probability and statistical power levels [17, 120]. We calculated the necessary sample size using the Online Calculator provided by Soper [110]. In our study, given the nature of the study, we calculated the sample size considering the anticipated effect size: 0.3 (medium), Desired statistical power level: 0.8 (by convention), and probability level: 0.05 (by convention) [17, 120]. The sample size of our study is also considered adequate for the measurements considering different types of metrics: according to Bentler and Chou [9], there must be a minimum ratio of five respondents per construct in a model (in our study, we have nine constructs (*i.e.*, the nine flow experience dimensions)). At the same time, Kyriazos *et. al.*, [66] defines that at least 100 participants are required for the minimum sample size in this kind of study.

Table 1. Sample details

Countries	**N**
USA	135
India	53
Portugal	29
Poland	20
Mexico	16
Italy	9
Spain	8
Brazil and UK	5
Chile and Greece	4
Italy, USA and China	2
Estonia, France, Germany, Hungary, India, Ireland, Latvia, Morocco, New Zealand, Panama, Slovenia, Turkey, Canada, Germany, Mexico, Romaine, Spain, and Trinidad	1

Key: N: number of participants per country listed in the "countries" column.

To analyze the data, we used partial least squares structural equation modeling (PLS-SEM) [42], which is a useful technique for evaluating complex theoretical relationships between multiple variables, especially when conducting social science [42, 43, 116]. Two fundamental SEM methods have been proposed and used over time, which are covariance-based structural equation modeling (CB-SEM) and partial least squares structural equation modeling (PLS-SEM) [40]. We decided to use PLS-SEM because it is especially useful when the user's structural model objective is to predict and explain the target outcomes as obtained by the in-sample and out-of-sample metrics [56], thus, allowing model relationships between variables (β), analyzing the statistical significance of these relationships (p), and identifying the internal predictive power of the estimated model (R^2). The technique has been widely used in recent studies in the field of gamification [98, 103, 119] as it allows performing this type of analysis with a high level of reliability, even in smaller samples (*e.g.*, N < 1000) [66].

In our study, observable variables related to user behavior (*i.e.*, users' data logs) were modeled as latent variables (*i.e.*, variables modeled from other observable variables that can be directly observed or measured [34]) based on the type of data collected. Thus, the data were transformed into three (*i.e.*, gamification, performance, and time) latent variables, representing the users' behavior:

- **Usage time**: *i)* active time in the system, *ii)* used time to finish a step/activity, *iii)* average response time after negative feedback, and *iv)* average response time after positive feedback.
- **Users' performance**: *i)* average of consecutive hits and *ii)* total of consecutive hits.
- **Gamification**: *i)* total of points, *ii)* total of badges and *iii)* ranking position.

4 RESULTS

Initially, before performing the main analysis of the study, we analyzed the simple correlation between the variables related to user behavior and the flow experience dimensions (including flow in general). As these are non-linear relations, we chose to use Kendall's correlation [16]. The Kendall rank coefficient is usually used to test statistical hypotheses to establish whether two variables are statistically dependent [59]. Table 2 present Kendall's correlation between all variables measured in the study. The results show that, although some relationships are significant, the correlations are weak.

Table 2. Kendall's correlation

	CSB	**MMA**	**G**	**F**	**C**	**CTRL**	**LSC**	**T**	**A**	**FE**
ProCS	.208**	-.159**	.081	.215**	.056	.022	.033	-.135**	-.013	.030
TCH	.197**	-.159**	.066	.203**	.068	.015	.041	-.127**	-.005	.028
ACH	.142**	-.107*	.085	.217**	.058	.012	-.032	-.092*	.030	.019
NMC	-.011	-.043	-.045	-.067	.004	-.004	-.033	-.023	-.040	-.040
Points	.213**	-.146**	.083	.209**	.051	.020	.032	-.129**	-.003	.036
Badges	.025	-.229**	.050	.127*	.056	-.028	.036	-.121*	-.050	-.057
LB	-.231**	.154**	-.107*	-.218**	-.050	-.022	-.048	.121**	.000	-.045

Key: ProCS: Proportion of correct steps/activities; TCH: total of consecutive hits; ACH: average of consecutive hits; NMC: number of mouse clicks; LB: Leaderboards; 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; FE: flow experience.

Next, we start modeling and internally predicting the relationships between user behavior data logs and their flow experience during the system usage. Thus, we first calculated the composite reliability (CR) and average variance extracted (AVE) of the latent variables used in the model. CR measure is used to measure the internal consistency of a group of items used to measure a latent variable in SEM, thus, indicating the extent to which the items measure the same underlying construct consistently (ranging from 0 to 1, with higher values indicating greater internal consistency of the indicators, where a value of 0.700 or above is generally considered acceptable) [39, 41, 99]. AVE measures the convergent validity in SEM indicating the amount of variance that a latent construct shares with its indicators relative to the amount of variance due to measurement error, calculated as the average of the squared correlations between a latent construct and its indicators, divided by the sum of the variances of the indicators. AVE value of 0.5 or higher is typically considered acceptable, indicating that the indicators adequately measure the latent construct [39, 41, 62]. In our study, both CR and AVE analysis only serves to observe the relationship between the observable variables that compose each latent variable, instead of being used to analyze the quality of the model, as in others that use the same technique. Table 3 present the composite reliability results.

Table 3. Composite reliability

	α	RHO A	CR	AVE
Time	0.859	0.980	0.917	0.751
Gamification	-1.463	0.895	0.467	0.773
Performance	0.748	0.857	0.883	0.791

Key: α: Cronbach's; RHO A: Jöreskog's rho; CR: Composite Reliability; AVE: Average Variance Extracted.

Next, we calculated the discriminant validity (DV) [12], a technique to measure whether the concepts that are not supposed to be related are actually unrelated, thus referring to the ability of a construct to be distinguished from other constructs in the same model. Ideally, the correlation coefficients should be low or non-significant between constructs that are theoretically unrelated [39, 41, 62]. In our study, this calculation also has a more observational character, considering that we are not seeking to propose a model, but rather to analyze the relationships between variables. Table 4 present the discriminant validity.

Table 4. Discriminant validity (complete bootstrapping, sample=5000)

	A	C	CSB	CTRL	F	G	Gamification	LSC	MMA	Performance	T	Time
A	1.000											
C	0.161	1.000										
CSB	0.327	0.059	1.000									
CTRL	0.226	0.137	0.375	1.000								
F	0.153	0.117	0.415	0.264	1.000							
G	0.266	0.200	0.442	0.231	0.409	1.000						
Gamification	-0.026	-0.019	0.212	0.074	0.217	0.088	0.879					
LSC	0.124	0.140	0.199	0.167	0.069	0.040	-0.066	1.000				
MMA	0.248	0.018	0.217	0.125	0.092	0.136	-0.245	0.170	1.000			
Performance	-0.007	0.031	0.169	0.040	0.219	0.056	0.918	-0.082	-0.225	0.889		
T	0.341	0.121	0.114	0.020	0.038	0.076	-0.167	0.089	0.403	-0.159	1.000	
Time	-0.013	-0.115	0.030	0.014	0.041	0.049	0.195	-0.118	-0.129	0.181	-0.038	0.867

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.

Finally, we conducted analyses to model and observe the internal predictive power (*i.e.*, the ability of a model to predict the observed variables within the model) between the users' behavior data logs and their flow experience when using the system. Especially, the internal predictive power was measured based on R^2 values, which measure the proportion of variance in the observed variables that the latent variables in the mode can explain. R^2 values range from 0 to 1, with higher values indicating better predictive power[39, 41, 105]. Table 5 presents the path coefficients, and Table 6 presents the internal predictive power of the model.

Table 5. Path coefficients

				CI (BC)	
	β	**SD**	**P-values**	**2.5%**	**97.5%**
Gamification → A	-0.124	0.153	0.417	-0.414	0.178
Gamification → C	-0.279*	0.140	**0.047**	-0.687	-0.053
Gamification → CSB	0.366*	0.143	**0.011**	0.095	0.621
Gamification → CTRL	0.238	0.138	0.085	-0.025	0.546
Gamification → F	0.102	0.139	0.465	-0.160	0.386
Gamification → G	0.227	0.155	0.145	-0.060	0.540
Gamification → LSC	0.078	0.142	0.583	-0.202	0.337
Gamification → MMA	-0.229	0.150	0.127	-0.531	0.056
Gamification → T	-0.129	0.133	0.333	-0.367	0.156
Performance → A	0.108	0.151	0.473	-0.203	0.405
Performance → C	0.308*	0.130	**0.018**	0.084	0.572
Performance → CSB	-0.165	0.141	0.241	-0.433	0.083
Performance → CTRL	-0.179	0.149	0.231	-0.515	0.094
Performance → F	0.126	0.150	0.401	-0.173	0.419
Performance → G	-0.158	0.154	0.307	-0.486	0.110
Performance → LSC	-0.134	0.142	0.344	-0.422	0.148
Performance → MMA	0.000	0.138	0.998	-0.266	0.275
Performance → T	-0.040	0.134	0.763	-0.322	0.204
Time → A	-0.009	0.050	0.861	-0.077	0.109
Time → C	-0.117	0.074	0.117	-0.227	0.037
Time → CSB	-0.011	0.048	0.817	-0.103	0.033
Time → CTRL	0.000	0.056	0.996	-0.120	0.052
Time → F	-0.002	0.038	0.958	-0.090	0.060
Time → G	0.033	0.039	0.397	-0.087	0.094
Time → LSC	-0.109	0.059	0.067	-0.197	0.034
Time → MMA	-0.084	0.054	0.122	-0.162	0.060
Time → T	-0.005	0.048	0.914	-0.101	0.112

Key: Bold values are significant associations; β: Regression Coefficient; CI: Confidence Interval; BC: bias-corrected; SD; Standard deviation; 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.

Then, we performed the same analyses, now considering no longer the flow experience dimensions individually, but, the flow experience in general. We chose to carry out the analyzes in different models inspired by the literature that treats the flow experience with an association in all dimensions, at the same time that studies usually analyze each of the dimensions separately.

Table 6. Internal predictive power

	R^2	**Adjusted** R^2
A	0.003	-0.007
C	0.028	0.019
CSB	0.049	0.040
CTRL	0.010	0.001
F	0.050	0.040
G	0.013	0.003
LSC	0.019	0.009
MMA	0.067	0.058
T	0.028	0.019

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.

Table 7 present the CR, Table 8 present the DV, Table 9 present the path coefficients, and Table 10 present the internal predictive power.

Table 7. Composite reliability (flow)

	α	**RHO A**	**CR**	**AVE**
Flow	0.674	0.308	0.060	0.158
Gamification	-1.463	0.895	0.467	0.773
Performance	0.748	0.898	0.881	0.788
Time	0.859	0.940	0.917	0.748

Key: α: Cronbach's; RHO A: Jöreskog's rho; CR: Composite Reliability; AVE: Average Variance Extracted.

Table 8. Discriminant validity for the overall flow experience (complete bootstrapping, sample=5000)

	Flow	**Gamification**	**Performance**	**Time**
Flow	0.397			
Gamification	-0.387	0.879		
Performance	-0.346	0.923	0.888	
Time	-0.147	0.208	0.196	0.865

Table 9. Path coefficients (flow)

	β	**SD**	**P-values**	**CI (BC)** 2.5%	**97.5%**
Gamification → Flow	-0.441	0.411	0.284	-0.852	0.633
Performance → Flow	0.074	0.212	0.726	-0.248	0.599
Time → Flow	-0.070	0.089	0.430	-0.219	0.105

Key: β: Regression Coefficient; CI: Confidence Interval; BC: bias-corrected; SD; Standard deviation.

Table 10. Predictive power (flow)

	R^2	**Adjusted** R^2
Flow	0.155	0.147

4.1 Discussion

Identifying the flow experience is a challenge that has been dealt with for decades. Several alternatives have been proposed over time to analyze the flow experience. Most methods require participants to answer scales or use body-worn equipment. Facing this challenge, we explored the possibility of using user behavior data logs from a gamified system to model and predict users' flow experience. The results indicate that behavior data can be used to model some dimensions of the flow experience. However, the results also indicate that the predictive power is low, and it is not possible to predict users' flow experience based on their behavior log data.

Initially, gamification (*i.e.*, number of points and badges and raking position) was positively associated with one of the flow experience antecedents. *i.e.*, challenge-skill balance (β = 0.366 | p= 0.011). This result suggests that users with high performance in gamification tend to have a greater sense of challenge-skill balance during the tasks. This dimension is considered by many studies to be the main antecedent of the flow experience [33, 38, 76]. Thus, this result suggests that gamification may have to represent a factor that directly affects an antecedent of the participants' flow experience.

On the other hand, gamification was negatively associated with participants' concentration (β = 0.279 | p= 0.047). One of the possible reasons for this result may be the fact that the participants with better performance in relation to gamification were unable to maintain proper attention in the system, dividing their attention between activities and gamification and, consequently, losing concentration. The study reported in this article was conducted in a short period. Thus, this result corroborates the results of other recent studies that draw attention to the fact that gamification can have a more immediate effect on the users' perception [102].

This result is also supported by the result that indicates that participants with better performance had a higher concentration (β = 0.308 | p = 0.018). This result happens due to the fact that participants with better performance (regardless of the gamification), managed to keep their attention only on the activities and, consequently, maintain a higher level of concentration.

In our study, time did not significantly affect any of the dimensions of the flow experience. If, on the one hand, this result contradicts the results of other studies [91], at the same time it may have a direct relationship with the nature of the study. That is because it is a quasi-experimental study, where all participants need to perform the same activities (including the same amount of activities), and time cannot directly affect any of the dimensions of the flow experience.

Regarding the internal prediction level (R^2), the results indicate that even where the modeling results were significant, the internal prediction levels remained low. These results can occur due to two different factors. The first is because the observable variables, which were the latent variables, have values that are not strongly correlated, which reduces the levels of prediction. Another possibility is directly related to the sample size, indicating that although the results of the relationships (*i.e.*, modeling) were high, a larger sample is needed to attest to significant levels of prediction.

Regarding modeling the users' flow experience itself, no significant results were identified. In general, our results indicate that there is no relationship between user behavior data in the system and their flow experience. This result confirms most of the results found in the literature. In general, the literature avoids identifying the flow experience itself, seeking to analyze only the antecedents of the flow experience [69], or analyzing only the flow experience dimensions individually [91, 106]. This decision by most studies is generally based on the inherent difficulty of analyzing the flow experience itself, given its level of depth.

In a general comparison, our results are in the same direction as the recent literature, indicating that there is no direct relationship between user behavior data in gamified systems and their flow experience when using the system. However, our results indicate that behavioral data hold promise for modeling and predicting some of the dimensions of the flow experience.

Our results offer some theoretical and practical contributions. The first concerns the role of gamification elements (*i.e.*, points, badges, and leaderboards) in the user flow experience. We identified that these elements influence the total concentration on the task at hand, which suggests that gamification can be an effective strategy to increase user engagement in various activities. Furthermore, we identified that gamification also affects the balance between perceived challenge and user skills. This finding highlights the importance of carefully considering the design of gamification elements to promote a flow experience.

Another contribution of our research is related to the impact of users' performance on the balance between challenge and skills. We identified that users' performance affects perceptions of this balance, suggesting a bidirectional relationship between the flow experience and personal achievement. This finding may have important implications for promoting intrinsic motivation and developing users' skills. The results indicate that interventions aimed at improving performance can potentially influence users' flow experience, reinforcing the importance of promoting an environment conducive to personal growth/performance.

Finally, our research contributes to the theoretical understanding of the flow experience by exploring the use of user behavior records in a gamified system. By employing behavioral data as indicators of the flow experience, we provide valuable insights for researchers and practitioners interested in understanding and facilitating flow in different contexts. This innovative approach expands the possibilities of analyzing the flow experience, allowing future research to explore further the relationships between user behavior, systems design, and subjective experience, deepening our understanding of this critical theoretical construct.

4.2 Threats to validity and limitations

Our study was conducted with human beings, which leads to the generation of possible threats due to limitations inherent to the character of the study. Next, we will describe how each of these limitations or threats has been dealt with/mitigated. Initially, the flow experience is considered by some researchers to be a subjective experience and may depend on each individual [23, 24, 52]. This can make identifying the flow experience complex. To mitigate this threat to validity, in our study, we used only previously validated instruments to analyze the users' flow experience (*i.e.*, short FSS proposed by [54] and analyzed psychometrically by [45] for the gamification domain).

Similarly, the relationship between log data and user flow experience is not yet established in the literature. So to mitigate threats related to which type of data to collect, we collected data according to the theoretical model proposed by Oliveira *et al.* [91]. A difficulty also inherent in this type of analysis is collecting data from people from different cultures. To ensure the greatest power of generality of the results in terms of participants' culture, we chose to perform the study on international platforms (*i.e.*, MTurk and Prolific) for data collection, so that we receive data from participants from different countries and consequently different background profiles (increasing the results generability power).

Studies of this type require a large sample to increase the generalization power of the results. Thus, our sample may not be sufficient to ensure the generality of the results. To mitigate this limitation, we chose to use a modern technique, capable of producing reliable results even with smaller samples (PLS-SEM). Using this technique, our sample is sufficient to perform multilevel modeling and SEM [127], as well as bootstrap estimation [79]. Likewise, the study was performed on a single system, so the results may not be generalizable to other systems.

The study was conducted online, without real-time observation of the participant's actions. Thus, external factors may have affected the participants' experience. To mitigate this limitation, we conducted a study with pre-defined tasks for all participants, as well as, we chose not to remove possible outliers, thus avoiding losing data that present a plausible behavior of a user when using the system. Although the MTurk and Prolific platforms are widely used in studies in the area, their limitations are recognized. Thus, many studies in the area tend to have limitations inherent to the use of these tools. Faced with the impediment of using only data from voluntary participants, we decided to merge data from voluntary participants with paid participants from the two different platforms, thus making the data more generalizable, also following good practices in the use of these platforms.

4.3 Recommendations for future studies

As the use of gamified systems continues to increase, understanding how users engage with these systems and the factors that contribute to their experience is becoming increasingly important. Behavior data logs provide a wealth of information that can be used to model and predict users' flow experience in these systems. In our study, we advanced the literature, however, there are also numerous challenges associated with the collection and analysis of behavior data, as well as opportunities for future research in this area. Next, we will explore some of these challenges and opportunities based on the results of our study.

- **The eternal problem of sample size**: in our study, as in the vast majority of studies in the area, the sample size is sufficient to conduct adequate analyses. However, it is not sufficient to provide generalized results. This is due to a series of factors, ranging from the time dedicated to research projects to financial reasons (lack of resources to carry out some projects). For the results of this type of analysis to occur, as has been recurrently recommended in studies in the area, it is important to conduct studies with much larger samples (N > 1000 participants). Therefore, *we recommend that the community make an effort (e.g., joining and mixing resources from different research groups) to carry out studies with larger samples that allow greater power of generalization.*
- **Beyond current behavioral data**: In all studies conducted to date, behavioral data boils down to data coming from user interactions on desktop/laptop computers. However, it is increasingly noticeable migration of users to other types of devices, ranging from smartphones to metaverse devices. On these devices, the behavior data can be completely different, needing

to be analyzed individually. Given this, *we recommend that future studies invest in using behavioral data from other devices.*

- **Multiple associations**: In our study, we associated users' behavior data logs with their flow experience collected through a scale. However, flow experience can be collected in other ways (*e.g.*, eye-tracking, and EEG). EEG and eye-tracking data provide objective measures of users' cognitive and physiological responses to gamified systems, which can complement and enrich the insights obtained from self-reported data. Thus, to ensure even more accurate analysis, we recommend that future studies associate users' behavior data logs with multiple sources of data, including data collected through electroencephalography (EEG) and eye tracking.
- **Measuring the flow over time**: One of the main challenges in modeling and predicting users' flow experience in gamified systems is that the experience can vary over time. In our study (and in the other studies in this field) the studies and proposed approaches only measure the flow experience at a particular point in time. Thus, we recommend exploring approaches that can automatically and continuously monitor users' flow experience over time.

5 CONCLUDING REMARKS

In this study, we explored the possibility of using user behavior data logs in a gamified system to model and predict the participants' flow experience. The data was analyzed to identify relationships between the users' behavior data logs and their flow experience. The main results of the study indicate that gamification is positively related to users' challenge-skill balance, which is a key factor in promoting the flow experience. In addition, the results showed that performance has a positive effect on users' concentration, which is another important aspect of the flow experience. In future studies, we aim to replicate this study with a larger sample size to validate the findings and explore the relationship between user behavior data and the flow experience more comprehensively. Additionally, in future studies, we aim to include different types of data analysis methods, such as machine learning and predictive modeling, which could enable more accurate predictions of the flow experience.

NOTES

Previous studies of this project have been published: Oliveira *et al.* [82] conducted a systematic literature review about Flow Theory and Educational Technologies; Oliveira [80] presented the project overview; Oliveira *et al.* [91] proposed a theoretical model relating students' data logs and their flow experience in educational systems; Oliveira *et al.* [88] conducted a qualitative study analyzing students' data logs and their flow experience in educational systems; and Oliveira *et al.* [86, 90] conducted data-driven studies modeling and predicting (respectively) students' flow experience based on their data logs in a gamified educational system; Oliveira *et al.* [89] investigated the relationship between students' flow experience and their behavior data in a gamified educational system.

ACKNOWLEDGMENTS

This work has been supported by the Academy of Finland Flagship Programme [Grant No. 337653 - Forest-Human-Machine Interplay (UNITE)]. This work has been supported by the São Paulo Research Foundation (FAPESP), Projects: 2018/07688-1 and 2020/02801-4.

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Received 2023-02-21; accepted 2023-07-07