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Uncovering associations between users' behaviour and their flow experience

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ABSTRACT
Flow experience is one of the most ambitious targets of any user interface designer. However, it has remained elusive to evaluate how well user interfaces give rise to flow experience outside conducting invasive self-reporting-based questionnaires, which remove the users from the flow experience and can't be massively applied. At the same time, otherwise, well-built systems do track the behaviour of users on the interface, and therefore, user behaviour data could act as a reliable proxy for assessing the experience of users. Currently, there is little empirical research or data about which indices of user behaviours might correspond with having a flow experience as well as the different psychological constituents of the flow experience. Therefore, facing the challenge of using users' behaviour data to model users' experience, we investigated the associations between users' behaviour data (e.g. mouse clicks, activity time in the system, and average response time) and their self-reported flow experience by using data mining (i.e. associations rules) analysing data from 204 subjects. Results demonstrate that the speed of users' actions negatively affects the flow experience antecedents while also positively affecting the loss of self-consciousness. Our study advances the literature, providing insights to identify users' flow experience through behaviour data.

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Flow experience; user interface; user experience; information systems; accessibility

1. Introduction

Today, one of the most essential goals in the fields of human-computer interaction, information technology, and service sciences is not only to provide 'accessibility' and 'ease of use', but also to further facilitate the formation of a fully immersive experience (e.g. flow experience) that leads into higher performance (Aizpurua, Harper, and Vigo 2016; Hassan et al. 2020; Hsu and Lu 2004; Kim and Ko 2019; Leung 2020; Li and Peng 2021). At the same time, flow experience has been deemed as an important antecedent for beneficial and productive behaviours in several fields such as education (Csikszentmihalyi 2014b; Salar et al. 2020; Tang, Zhang, and Jiang 2023), exercise/sports (Fang and Huang 2021; Jackson and Csikszentmihalyi 1999; Lin, Hung, and Yang 2023), playing music (Clementson 2019; Ding and Hung 2021; O'Neill 1999) and essentially any activity that requires in-the-moment concentration to the task at hand (Csikszentmihalyi 1997a).

To that end, general ease of use is considered one of the first and foremost antecedents for flow (Hyun, Thavisay, and Lee 2022; Mahfouz, Joonas, and Opara 2020). However, during recent years design directions, have emerged where the goal is not only to make the user interface easier to use but also to be more motivationally ergonomic (Aizpurua, Harper, and Vigo 2016; Grigera et al. 2017; Koivisto and Hamari 2019), then, among other things, use an information system longer or see more products in an online sales system. In essence, this demands that information systems can provide a flow experience to users during system usage (Abuhamdeh 2020; Leung 2020; Peifer et al. 2020).

However, one of the persistent challenges has been related to how can we detect whether users are experiencing the flow experience (Hamari and Koivisto 2014; Jackson and Marsh 1996; Lee, Jheng, and Hsiao 2014; Oliveira 2019; Semerci and Goularas 2020). Traditionally, flow experience is measured through self-reported questionnaires or psycho-physiological instruments during a given task (Oliveira et al. 2018; Oliveira, Pastushenko, et al. 2021). This kind of technique usually

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can inhibit users' responses, as well as prevent massive application (Lee, Jheng, and Hsiao 2014; Oliveira 2019; Oliveira et al. 2019). Accordingly, as with other psychological experiences (Ellis et al. 2019; Freihaut and Göritz 2021), there would be a need to devise new proxies for automatic, dynamic, and concurrent detection of users' flow state.

Thus, if, on the one hand, it is necessary to propose new ways to facilitate the users' flow experience identification (Oliveira 2019; Oliveira et al. 2019; Semerci and Goularas 2020), on the other hand, when using information systems, users generate data logs (e.g. number of logins/logouts, number of actions performed, time of use, page changes, and mouse clicks) that represent their behaviour in the system, and therefore, can be used to model their' experiences (Hooshyar, Pedaste, and Yang 2019; Rubin et al. 2019; Saura, Ribeiro-Soriano, and Palacios-Marqués 2021). Thus, using user behaviour data emerges as a promising possibility to model users' flow experience in information systems.

Therefore, to face the challenge of proposing new proxies to identify users' flow experience from their behaviour data, in this study ($N = 204$), we investigated the associations between users' behaviour data (i.e. mouse clicks, activity time in the system, average response time, proportion of correct steps/activities, consecutive hits, and total unique session views) and the self-reported 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) of the participants by using a robust data mining techniques (i.e. associations rules). Thus, we aimed to answer the following research question: **What are the associations between the users' behaviour data logs in an information system and their flow experience during the system usage?**

Our main results demonstrate that the speed of users' actions negatively affects the flow experience antecedents while also positively affecting the loss of self-consciousness, thus, indicating patterns between user data behaviour logs and their flow experience in a gamified learning system. Thus, this result also indicates that it is possible to step towards relating users' flow experience with their behaviour data in gamified learning systems.

Our results contribute to different fields, such as human-computer interaction and information system design by proving patterns that relate data logs to the user's flow experience, thus guiding the development of tools for automatically identifying the users' flow experience based on their data logs. We also contribute with a research agenda guiding the community in the conduction of new studies in this field toward automatic identification of users' flow experience in information systems.

2. Background

This section presents the study background (i.e. Flow Theory and flow experience measurement) and a comparison between the main related works.

2.1. Flow theory

The flow state, seminally proposed by Csikszentmihalyi and Csikszentmihalyi (1975), is characterised by a deep engagement during and with activity. The attainment of the flow state is often dependent on the characteristics of the activity as well as its relationship with the actor (Csikszentmihalyi 1997b; Csikszentmihalyi and Csikszentmihalyi 1975, 1992). Some of the main prerequisites for the flow state to emerge are the balance of the challenge of the task and the related skill of the actor, clear goals, clear feedback, and a sense of control of the task and the situation (Csikszentmihalyi and Csikszentmihalyi 1975). Some types of activity are more likely to bring an individual into a flow state, e.g. playing a game, playing a musical instrument, watching an intense movie, or even in many otherwise mundane work tasks that are structurally able to support flow-inducing activity (Csikszentmihalyi 2014a). The flow state and its emergence are a pervasive topic both in academia and in industry discussion when user interfaces are concerned (Kiili et al. 2012; L. Wu, Chiu, and Chen 2020; Shin and Kim 2008).

The Flow Theory research usually defines the flow experience in nine dimensions, organised into two categories, antecedents of flow and flow 'itself'. The antecedents are:

(1) The **challenge-skill balance** dimension represents 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 (Jackson, Eklund, and Martin 2011).
(2) The **clear goals** dimension indicates that goals are a 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 (Jackson and Eklund 2002; Jackson, Eklund, and Martin 2011).
(3) The dimension of **unambiguous feedback** represents when receiving feedback associated with a flow state, the individual does not need to stop and reflect on how things are progressing (Jackson, Eklund, and Martin 2011).

The dimensions directly related to the flow experience (the flow 'itself') are:

(1) The **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 (Jackson, Eklund, and Martin 2011).
(2) The **action-awareness merging** dimension is the unity of consciousness apparent in this flow dimension and illustrates the idea of growth in complexity that results from flow experiences (Jackson, Eklund, and Martin 2011).
(3) The dimension called **total concentration on the task at hand** defines one of the clearest indications of being in flow, that is, totally focussed in the present on a specific task being performed (Jackson, Eklund, and Martin 2011).
(4) The **loss of self-consciousness** is like a 'voice within our head' that questions whether we are living up to self- or other-imposed standards (Jackson, Eklund, and Martin 2011).
(5) The **transformation of time** dimension, 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) (Jackson, Eklund, and Martin 2011).
(6) Finally, the ***autotelic* experience:** is generally after completing a task, upon reflection, that the *autotelic* aspect of flow is realised and provides high motivation towards further involvement (Jackson, Eklund, and Martin 2011).

The goal of UI/UX designers has been to systematically eradicate extraneous hurdles to make the use of technology as seamless as possible as well as to let users be able to get into the flow state related to the activity at hand (Hart 2006; Hart and Staveland 1988; Hassenzahl and Tractinsky 2006). Recently, however, gamification and motivational information systems are attempting to build motivational, flow-inducing ergonomy into the UI (Hamari and Koivisto 2014; Koivisto and Hamari 2019), *i.e.* implementing the central flow experience dimensions, such as the merging of action and awareness, total concentration on the task, and transformation of time (Csikszentmihalyi 1997a, 1997b, 2014a).

2.2. Flow experience measurement

Identifying the flow experience in users and measuring it has always been a research challenge since the original conceptualisation of the Flow Theory (Csikszentmihalyi 2014a; Csikszentmihalyi and Csikszentmihalyi 1975, 1992). Initially, the flow experience analysis was carried out through the use of equipment (e.g. radio-frequency communicators) that asked respondents to press a button whenever they reached a certain experience (i.e. flow experience) in a specific activity (Csikszentmihalyi 1997b). However, it was soon realised that this means of identification was costly and required the participant to provide a very subjective experience (Jackson, Eklund, and Martin 2011) as well as would detract them from the activity at hand (Jackson and Marsh 1996).

With this, new means of identifying the flow experience were proposed (Nakamura and Csikszentmihalyi 2014). One of the first means proposed was the interview made by specialised professionals (i.e. Psychologists who interviewed groups of participants (or an individual participant) and reported whether or not that person reached the flow experience (Borderie and Michinov 2016). With the perception that this approach required a high cost, as well as necessarily the presence of a professional, scales, were proposed for different contexts (e.g. physical activity Jackson and Eklund 2002; Jackson, Eklund, and Martin 2011, social networks Kaur et al. 2016, education Fu, Su, and Yu 2009, video games Cai, Cebollada, and Cortiñas 2022, and gamification Hamari and Koivisto 2014) to measure the users' flow experience by answering non-invasive questions.

With the various technological advances and the possibility of using tools attached to the body to identify human behaviours, patterns, and experiences, studies have begun to explore the possibility of exploring these devices to try to identify the flow experience of individuals. Usually, they are concerned with equipment such as eye trackers or electroencephalograms (De Kock 2014). However, these means either have high costs or are invasive, or cannot be applied massively (Oliveira et al. 2018).

Thus, in recent years, studies have highlighted the importance of proposing ways to identify the users' flow experience automatically (e.g. analysing behaviour data logs Lee, Jheng, and Hsiao 2014). In recent years, studies have sought to use behavioural data generated from user data logs in information systems to identify their flow experience (De Kock 2014; Oliveira 2019; Semerci and Goularas 2020). These studies have initially used theoretical approaches aiming to identify relationships between users' behaviour data and the flow experience dimensions (Oliveira et al. 2019). Next, the literature also presents qualitative studies (Oliveira et al. 2020), and finally, using quantitative analysis techniques (Lee, Jheng, and Hsiao 2014). The studies, despite being initial, present some promising aspects, indicating that there may be a way to predict users' flow experience. In the next section, we will present and compare the main related works.

2.3. Associating user behaviour and flow experience

The growing number of users of information systems in recent years has demanded analytical strategies to understand the user experience without the use of questionnaires or body-worn equipment (Chen et al. 2020; Dewan, Murshed, and Lin 2019; Giannakos et al. 2019). One of these strategies is the use of user behaviour data, obtained through their data logs, to map the user experience (Bond et al. 2019; Ghosh et al. 2019; Zhang et al. 2020).

These behavioural data have been used in different approaches, from recommending videos and music on web platforms (Z. Zhao et al. 2019) to associating them with different dimensions of the user experience, such as anxiety and Moshe et al. (2021). Recently, an emerging focus has been on investigating the relationship between behavioural data and user flow experience (Lee, Jheng, and Hsiao 2014).

Researchers have adopted theoretical (Oliveira et al. 2019), qualitative (Oliveira et al. 2020), and quantitative (Semerci and Goularas 2020) approaches to explore this association. Such studies aim to identify patterns in behavioural data that may indicate the presence or absence of the flow experience. The analysis of these patterns allows a better understanding of the factors that influence the occurrence of the flow, subsidising the development of strategies to promote it in the different information systems.

Despite the investigations carried out so far, there is still a vast territory to be explored in this area. The association between user behaviour data and their flow experience has significant potential to improve usability and user satisfaction. These investigations may provide valuable insights for improving design and interaction in information systems, with the aim of providing more engaging and satisfying experiences to users. In the next subsection, we explore the prior research on measuring the flow state from users' data.

2.4. Prior research on measuring the flow state from users' data

To identify the main related works and provide a deep field understanding, we analysed different systematic literature reviews (Oliveira et al. 2018; Oliveira, Pastushenko, et al. 2021; Perttula et al. 2017). We also analysed the general recent literature in search of other possible related works not covered in these reviews. The results show that in recent years, different techniques have been used to relate the users' flow experience with the data logs produced by them when using a certain type of system (Oliveira et al. 2018; Oliveira, Pastushenko, et al. 2021; Perttula et al. 2017), however, few effective results have been found (Oliveira et al. 2018). The incipient results identified in the literature reviews highlight the importance of proposing new approaches relating the users' flow experience with their behaviour data logs during the system's usage. The results also show that the vast majority of studies related to the identification of experience are conducted in the field of education, indicating the importance of analysing behaviour data logs that can be more generalised for other types of systems.

One of the first techniques used in an attempt to use users' behaviour data logs to model their flow experience was using EEG. De Kock (2014), for instance, 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. He used the abbreviated flow questionnaire (AFQ), an expensive approach, difficult access, and analysis, that can not be used massively.

In the same year, C. C. Wang and Hsu (2014) used a questionnaire associated with an EEG analysis aiming to investigate the effects of students' challenge-skill balance on their flow experience, as well as the effects of students' flow experience on their learning. Their results showed that the students' flow experience depends on the challenge-skill balance of learning materials (C. C. Wang and Hsu 2014). In this study, C. C. Wang and Hsu (2014) 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.

S. F. Wu, Lu, and Lien (2021) 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 behavioural pattern (detected by the EGG), thus opening space for other types of analysis.

Another technique used (but which apparently fell out of favour) was ontology (i.e. a way for presenting properties of an area, by defining different concepts and categories that represent the area). From our knowledge, Challco et al. (2016) is the only use of this technique aiming to relate users' behaviour data logs and flow experience. They 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. However, Challco et al. (2016) also operationalises the flow only as of the perception of the challenge-skill balance dimension, without considering the other Flow Theory dimensions.

More recently, other researchers have also invested in theoretical or qualitative approaches, to relate users' behaviour data logs to their flow experience. Oliveira et al. (2019) proposed a theory-driven theoretical 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 toward 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.

Oliveira et al. (2020) 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. 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.

The most used technique so far is statistical analysis (especially regression techniques). As far as we know, the first to use statistical analysis to relate users' data logs with their flow experience was Lee, Jheng, and Hsiao (2014). They conducted a study to identify whether the users are in a flow with 55 participants. Lee, Jheng, and Hsiao (2014) used step regression to analyse the student's data logs. Despite seeking to identify the flow experience, it used only one of the dimensions proposed in the theory (challenge-skill balance). Freihaut and Göritz (2021) investigated the possibility of measuring users' stress levels through their computer mouse usage by statistical analysis, identifying that no clear generalised relationship between mouse usage and stress (Freihaut and Göritz 2021). While the study does not analyse the flow experience, it makes room for new analyses related to other experiences (e.g. flow experience).

Semerci and Goularas (2020) 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 (Semerci and Goularas 2020). Analysing only 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 analysing all Flow Theory dimensions.

Oliveira, Hamari, and Isotani (2023); Oliveira, Isotani, et al. (2021); Oliveira et al. (2022); Oliveira, Tenório, et al. (2021) conducted a series of data-driven studies (by using structural equation modelling) modelling and predicting users' flow experience based on their behaviour data logs in different gamified educational system. These studies make clear the possibility of using user behaviour data to model and predict the flow experience in gamified systems, however, at the same time they make it clear that the results are still incipient and draw attention to the use of new data analysis techniques.

In summary, the related works demonstrate a growing interest in analysing the users' flow experience through non-invasive and no-cost techniques. However, it also demonstrates that studies are still incipient and focussed

Table 1. Related studies.

Studies	DDA	AFD	UDL	VTM	DAT	SS
De Kock (2014)	No	No	Yes	No	EEG	20
C. C. Wang and Hsu (2014)	Yes	No	No	No	EEG	148
S. F. Wu, Lu, and Lien (2021)	Yes	No	No	No	EEG	30
Challco et al. (2016)	No	No	Yes	No	Ontology	NA
Oliveira et al. (2019)	No	Yes	Yes	No	Experts opinion	3
Oliveira et al. (2020)	No	Yes	Yes	Yes	Think aloud	6
Lee, Jheng, and Hsiao (2014)	Yes	No	Yes	No	SA	55
Freihaut and Göritz (2021)	Yes	No	Yes	No	SA	53
Semerci and Goularas (2020)	Yes	No	Yes	No	Heatmaps and DNN	87
Oliveira et al. (2021)	Yes	No	Yes	No	SEM	23
Oliveira et al. (2021)	Yes	No	Yes	No	SEM	23
Oliveira et al. (2022)	Yes	No	Yes	No	SEM	24
Oliveira, Hamari, and Isotani (2023)	Yes	No	Yes	No	SEM	313
Our study	Yes	Yes	Yes	Yes	DM	204

Note: **Key:** DDA: used a data-driven approach; AFD: analysed all flow experience dimensions; UDL: Used users' data logs; VTM: used/validated a theoretical model; DAT: Used data analysis technique; SS: sample size; SA: statistical analysis; EEG: Electroencephalography; NA: Not available; DNN: deep neural networks; SEM: Structural equation modelling; DM: data mining.

on a specific area (i.e. education). Table 1 presents a comparison between the related works. Thus, as far as we know, our study is the first seeking to identify a pattern relation between the users' behaviour data logs produced by users' interaction in an information system and their flow experience in the system, through an empirical data-driven study using a data mining technique (i.e. association rules), as well, using a validated theoretical model (considering all the nine flow experience dimensions Csikszentmihalyi 1997a; Csikszentmihalyi and Csikszentmihalyi 1975; Jackson and Eklund 2002) to obtain the user data logs. At the same time, we are the first to obtain positive insights into automatic flow experience identification in educational systems, considering the nine flow experience dimensions.

3. Study design

According to Dhar (2013), a data-driven study can be defined as a kind of empirical study based on the analysis of real data. This analysis is usually conducted through statistical models and artificial intelligence (AI) techniques (e.g. data mining). Based on the need for a computational approach for the automatic identification of the flow experience in user-centred systems (Lee, Jheng, and Hsiao 2014; Oliveira et al. 2019; Pastushenko et al. 2020), the main goal of this study is to identify associations between the users' behaviour data logs in an information system and their flow experience during the system usage. Based on our goal, the following research question was defined: **What are the associations between the users' behaviour data logs in an information system and their flow experience during the system usage?**

3.1. Materials

To obtain the users' behaviour data logs we used a gamified system (for this study, we consider gamification as 'the process in which services, activities, and systems are transfigured to promote similar motivational benefits as found in games' Hamari 2019; Koivisto and Hamari 2019)), which provides the most popular game design elements (i.e. points, badges, leader boards, and progress bars) defined according to recent secondary studies (Bai, Hew, and Huang 2020; Dicheva et al. 2015; Koivisto and Hamari 2019). Initially, the system had a page for users to include demographic data and sign the participation agreement in the system. Then, after signing the agreement terms, users could select an avatar and answer 20 questions about logical reasoning (i.e. quizzes requesting the association between images). The avatar is not intended to affect the flow experience, it is just a system element. The activity was chosen because it is a common type of activity and is widely explored in education systems in general. At the same time, this kind of question can directly (or indirectly) affect the user's experience, and can positively or negatively interfere with the flow experience of users. The objective is not to analyse which activities more or less affect the flow experience, only to provide the simulation of a gamified educational system where students may or may not reach the flow experience and subsequently map the relationship between behavioural data (log data) and users' flow experience.

Finally, the system presented the flow state scale to be answered by the user based on their experience when using the system. Figure 1 presents a case study for the system usage/experiment. The system was chosen for convenience and because it is open-source, as well, it was evaluated at different times to improve its design and provide a better user experience. Figure 2, on the left side, present an example of avatar choice, and on the right side, an example of the logical reasoning question.

To capture the users' data logs in the system, we implemented a module to get eight different user data

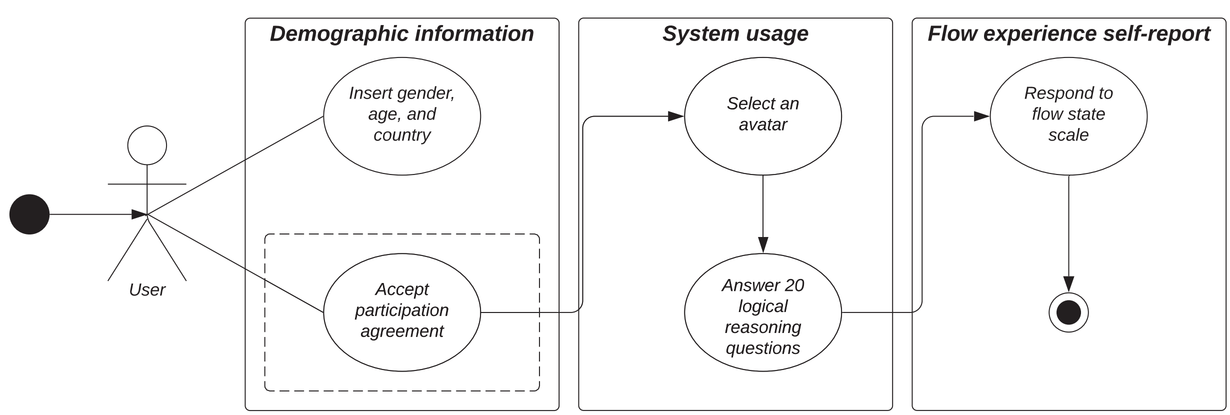
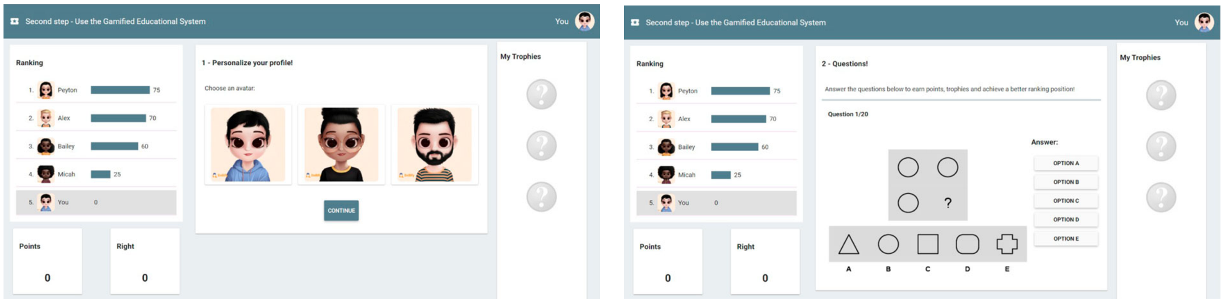


Figure 1. Experiment flow.



(a) Home page (b) Activity

Figure 2. Examples for the system. (a) Home page and (b) Activity.

logs during the system usage. The data logs were chosen based on the theoretical model proposed in the study conducted by Oliveira et al. (2019), which presents eight data logs that can be used to identify the users' flow experience in educational systems. We choose this theoretical model because, as far as we know, it is the only model based on the nine original (Csikszentmihalyi and Csikszentmihalyi 1975) flow experience dimensions (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). Table 2 present a summary of the collected users' data logs.

To obtain the users' flow experience in the system, we used the flow state scale (FSS) developed and validated by Jackson and Eklund (2002). The scale was also based on the nine original (Csikszentmihalyi and Csikszentmihalyi 1975) flow experience dimensions and was also validated by Hamari and Koivisto (2014) for the gamification domain (i.e. to be used in gamified settings). For this study, we used the short FSS (composed of nine questions) following the original 'Manual for the Flow Scales' (Jackson, Eklund, and Martin 2011). This scale was chosen because according to the secondary study conducted by Oliveira et al. (2018), the scale uses the nine original flow experience dimensions proposed by Csikszentmihalyi (1997b). Also, as far as we know, is the only one validated to measure flow experience in the gamification domain. The instrument was presented in a five-point Likert scale (Likert 1932), recommended by Jackson and Eklund (2002) and Hamari and Koivisto (2014). The used scale is presented in Appendix 1.

3.2. Procedure

The procedure for this study was organised in four different steps as described below and organised in the Figure 3:

1 – Pilot studies: In this step, first, we invited a limited number of participants ($N = 6$) to use and evaluate the system. We also analysed if the module to get the users' data logs was running correctly. Our participants

Table 2. Collected data logs.

Data log	Acronym	Type	Description
Active time in the system	ActTS	SUA	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	SUA	Total time that a user uses to finish a specific action in the system
Average response time in correct answers	ArtCA	SUA	Average time that a user uses to finish a specific action correctly in the system
Average response time in (IN)correct answers	ArtIA	SUA	Average time that a user uses to finish a specific action incorrectly in the system
Average response time after a positive feedback	ArtPF	SUA	Average time a user spends to answer a task after receiving a positive feedback from the system
Average response time after a negative feedback	ArtNF	SUA	Average time a user spends to answer a task after receiving a negative feedback from the system
Proportion of correct steps/activities	ProCS	SRUA	Average of user' correct answers in a group of tasks in the system
Proportion of correct steps/activities after a feedback	ProCSF	SRUA	Average times an user has correctly answered a step/activity after a feedback message stating the step/activity result
Total of consecutive hits	TCH	SRUA	Total of consecutive hits of a user in the system
Average of consecutive hits	ACH	SRUA	Average of consecutive hits of a user in the system
Total unique session views	TV	FUA	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	FUA	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)

Note: **Key**: SUA: Speed of user action; SRUA: Success rate of user action; FUA: Frequency of user action.

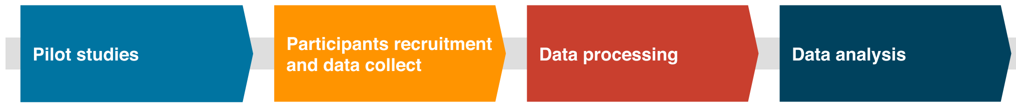


Figure 3. Data-driven study (step-by-step).

were six graduate students enrolled in a Master of Business Administration (MBA) in the field of financial sciences. To evaluate the system's usability, we used the think-aloud protocol, which provides rich verbal data about reasoning during a problem-solving task (Fonteyn, Kuipers, and Grobe 1993). After the analysis, we fixed the identified problems in the system. Second, we also conducted a second pilot study with 10 participants to ask what the fair value is to be charged for the research.

2- Participants recruitment and data collection: In this step, after fixing the problems identified in the pilot study (i.e. fixed a system bug that caused some images to not load correctly), as well as, identifying a fair value for study participants, we started to recruit the participants (see Subsection 3.4). Participants who agreed to participate in the study were directed to the system where they answered the surveys and used the system (to obtain data logs). This step was organised into three different sub-steps:

2.1 – Demographic survey: Before starting the system usage, the participants were invited to answer a demographic survey asking for the following users' information: *(a)* gender, *(b)* age, *(c)* country, and *(d)* academic degree. **2.2 – System usage:** Participants used the system and answered a sequence of 20 questions (multi-choice questions with 5 options) about logical reasoning. During this step, we also collected their interaction data logs based on the model proposed by Oliveira et al. (2019) (previously described). To simulate the real use of a system, no minimum or maximum time of use was stipulated. The average use of the system was 30 min, considering outliers. **2.3 – Flow experience measurement method:** After the system usage, the participants answered the short FSS (Hamari and Koivisto 2014; Jackson, Eklund, and Martin 2011) containing the non-invasive questions about their experience in the system (the scale has nine questions, one on each of the nine original (Csikszentmihalyi 1997b) Flow Theory dimensions). We also inserted an 'attention-check statement' (i.e. If you are filling out the form carefully, answer 4.) presented in random order to respond aiming to identify potential respondents who did not have the proper attention to respond to the scale, as recommended by the literature (Hallifax et al. 2019; Oliveira et al. 2020; Orji, Tondello, and Nacke 2018). After answering the questions, participants could immediately see their flow experience level in the system (measured based on scale) and finish their participation in the experiment. In total, 220 subjects participated in the study.

3 – Data processing: In this step, the data were collected from the system, organised in spreadsheets, and properly handled. Then, the data were organised to be processed in R, using the software RStudio.

4 – Data analysis: In this step, the obtained data were analysed to generate different models relating the users' data logs generated through their interactions in the system with each flow experience dimension. In this study, we used a gamified system, which may have interfered with the behaviour of our subjects, however, the analyses carried out in this study are not related to the effects of gamification on the participants' behaviour.

3.3. Measurement

We used rule-based machine learning (association rule mining (ARM)) (Piatetsky-Shapiro 1991), an unsupervised method based on the concept of strong rules (Agrawal, Imieliński, and Swami 1993), widely used to discover data patterns (Adomavicius and Tuzhilin 2001). To use ARM, the continuous variables (users' behaviour data log) are transformed into categorical ones. The transformation occurred based on the five-number summary (Shi et al. 2020) analysis, as conducted in recent similar studies (Oliveira et al. 2019). ARM was used instead of other techniques (e.g. machine learning) because it allowed exploring the existence of patterns in categorical data even without big data (Adomavicius and Tuzhilin 2001; Agrawal, Imieliński, and Swami 1993). As exemplified in the Figure 4, the ARM was used considering each flow experience dimension.

3.4. Participants

Participants were recruited through the Amazon Mechanical Turk (MTurk)[1], a crowdsourcing marketplace service highly used and recommended for experiments with humans (because it decreases the probability of multiple responses from the same individual and dishonest responses while increasing the heterogeneity of

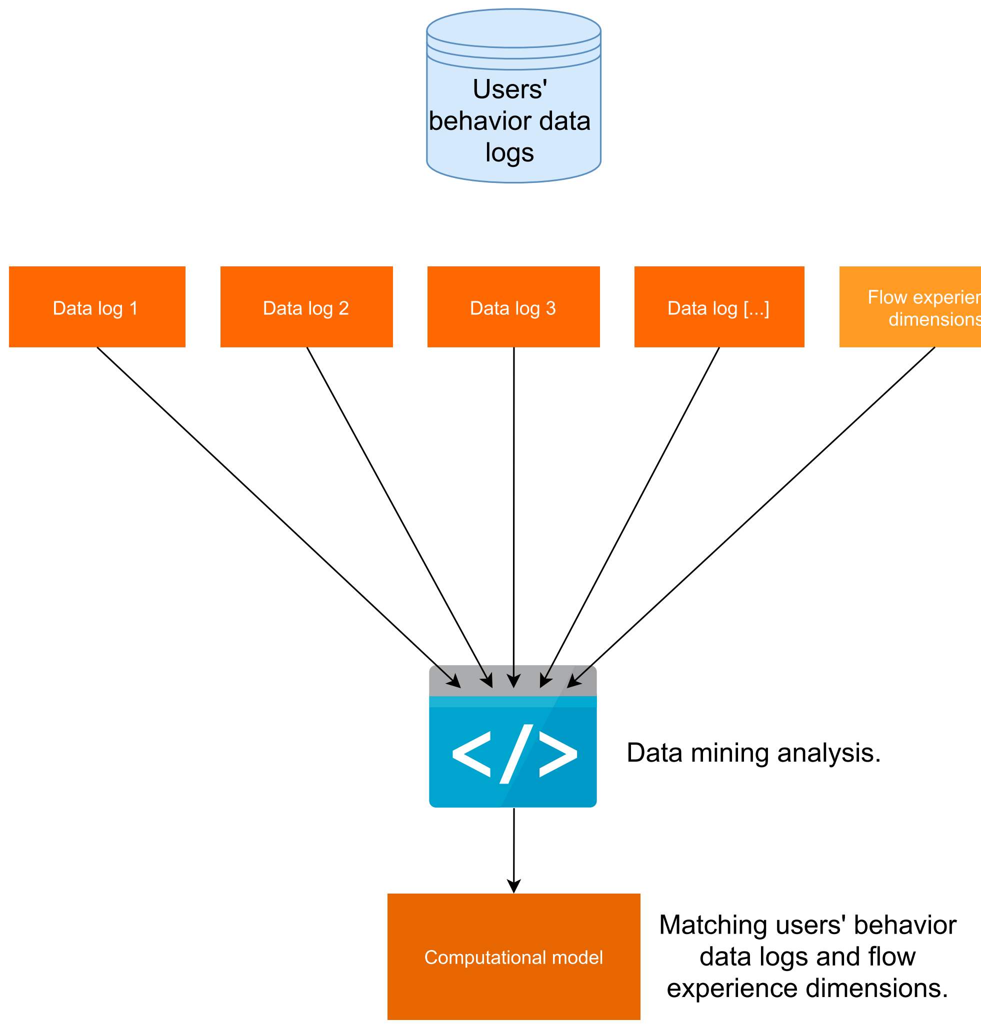


Figure 4. Data-driven study.

respondents) (Paolacci, Chandler, and Ipeirotis 2010). Each participant received 25 cents for their participation. No initial exclusion criteria (e.g. age, gender, or country) were used. We eliminated participants that missed the 'attention-check statement' and organised our data set. In total, 16 participants have eliminated by wrong the attention-check statement, resulting in a data set composed of 204 participants (105 male and 99 female), with an average age of 25 years old.

To explore data from participants with different cultural backgrounds, we organised our study without country restrictions, thus receiving data from different countries. Participants came from 11 different countries (Canada, Germany, Mexico, Romaine, Spain, and Trinidad (1 each), Italy 2, UK 3, Brazil 5, India 53, and USA 135). Our study sample size is aligned with suggestions made in the literature, according to Bentler and Chou (1987), there must be a minimum ratio of 5 respondents per construct in the model (in our case, nine constructs, that is the nine flow experience dimensions). According to Loehlin (1998) at least 100 participants are required for a complete sample size in this kind of study. The student who finished the study the fastest completed it in six seconds, while the one who took the longest completed the study in over two hours (7308 seconds). When conducting a study simulating a real environment, it is important to analyse the data considering any possibility of use. Thus, cases like these where participants used the system for a very short time, or for a long time (far below or above average), in fact, can occur in a real environment. At the same time, these behaviours may be related to some flow experience dimension. Therefore, in this study, we chose not to remove outliers.

4. Results

We initially calculated the users' flow experience to analyse the data based on the short FSS (Hamari and

Koivisto 2014; Jackson and Eklund 2002). After that, we organised the users' behaviour data logs. After organising our data, we applied the data mining techniques. First, we conducted the ARM process, which was used to identify *if-then* significant patterns, as well as to check whether those corroborate the theoretical studies previously conducted. To implement the ARM, we used the Apriori algorithm, which uses a breadth-first search strategy to count the support of *itemsets* and uses a candidate generation function that exploits the downward closure property of support (Agrawal and Srikant 1994), and is one of the most popular ARM algorithms (X. Wu et al. 2008). We conducted these analysis using the programming language *R*[2] and free software *RStudio*[3] (with the packages 'Arules' and 'arulesViz').

In the ARM, to ensure a high quality of the results, we considered only rules with a confidence level (i.e. an indication of how often the rule has been found to be true) ≥ 0.600, lift (i.e. the ratio of the observed support to that expected if X and Y were independent) ≥ 1.200 and support (i.e. indication of how frequently the itemset appears in the dataset) ≥ 0.100, following the literature recommendations for studies involving ARM (Dhar 2013; Hornik, Grün, and Hahsler 2005). As recommended by different studies (Adomavicius and Tuzhilin 2001; Lemnaru, Firte, and Potolea 2011), we also used the 'Pruning' technique to prune redundant rules. where three experts analysed the rules to discard inconsistent rules, as well as validate the found rules. Thus, we identified a total of 22 significant rules. Finally, to ensure the semantic quality of the obtained rules, we validated the rules obtained with three experts, who analysed and discussed the semantics of the rules found. In the supplementary materials, we present the complete data set used in our study, as well as all the codes used in the data analysis. Table 3 presents the descriptive analysis results regarding the users' behaviour data. Time-related data was measured in seconds. Table 4 presents the results of the descriptive analysis results for each flow experience dimension (according to the short FSS answers). Table 5 presents the main rules found in the data mining analysis.

Rules one to 10 are related to flow experience antecedents and rules from 11 to 22 are related to the flow experience itself. The first three rules indicate that when the participants' active time in the system and/or their average response time in the correct answers and average response time after positive feedback was low, the challenge-skill balance dimension was very low. Rule 4 shows that when the participants' average response time after negative feedback was very high, their action-awareness merging experience was very low. Rules five to seven show patterns related to the clear-goals dimension and indicate that when the users spend little time using the system and responding to activities (regardless of having received positive or negative feedback on activities), they are unable to achieve the clear-goals experience (see Table 5).

In rules 8 and 9, it is possible to perceive a pattern that relates different data logs with the unambiguous feedback dimension. The patterns indicate when the total consecutive hits were very low, as well as when the average response time in the correct answers and the proportion of correct steps/activities was also very low, and the unambiguous feedback was very low. At the same time, rule 10 indicates that when the average response time after positive feedback and the total consecutive hits were very low, the unambiguous feedback was also very low. Rules 11, 12, and 13, in summary, demonstrate that when the participants' active time in the system and average response time (even after positive or negative feedback) was very high, their concentration was low.

Rules 14, 15, and 16 present patterns that lead to the identification of the sense of control dimension. For the first time, a rule was found setting a standard for identifying when the experience was high. Rule 14 indicates that when the participants' average response time after positive feedback was very low and their proportion of correct steps/activities was also very low, then, the sense of control dimension was high (see Table 5).

Table 3. Behavior-data analysis.

	Mean	Med	Var	SD
ActTS	2990	3000	2512	1585
ArtCA	2990	3000	2512	1585
ProCS	2691	2000	2283	1511
TCH	2873	2000	2466	1570
ACH	2917	2000	2550	1597
ArtPF	2990	3000	2512	1585
ArtNF	2990	3000	2512	1585
NMC	2892	2000	2648	1627

Note: **Key**: ActTS: Active time in the system; ArtCA: Average response time on correct answers; ProCS: Proportion of correct steps/activities; TCH: Total of consecutive hits; ACH: Average of consecutive hits; ArtPF: Average response time after a positive feedback; ArtNF: Average response time after a negative feedback; NMC: Number of mouse click out of buttons; Med: median; Var: variance; DS: standard deviation.

Table 4. Flow experience analysis.

	Mean	Med	Var	SD
Challenge-skill balance	4069	4000	0803	0896
Action-awareness merging	3029	3000	1812	1346
Clear goals	4132	4000	0795	0892
Unambiguous feedback	4098	4000	0759	0871
Total concentration on the task at hand	4466	5000	0546	0739
Sense of control	4221	4000	0882	0939
Loss of self-consciousness	3995	4000	1286	1134
Transformation of time	3368	4000	1820	1349
Autotelic experience	3770	4000	1114	1056

Note: **Key:** Med: median; Var: variance; DS: standard deviation.

Table 5. Association rules.

Id	If	Then	Supp.	Conf.	Lift
1	ArtCA *is* low	CSB *is* very low	0196	0800	1236
2	ArtCA *is* low *and* ActTS *is* low	CSB *is* very low	0123	0781	1207
3	ArtCA *is* low *and* ArtPF *is* low	CSB *is* very low	0137	0800	1236
4	*ArtNF is very high*	*MMA is very low*	0147	0600	1654
5	ActTS *is* very low *and* Art *is* very low *and* ACH *is* very low *and* ArtNF *is* very low	G *is* very low	0113	0793	1315
6	ArtNF *is* very low *and* TCH *is* very low	G *is* very low	0123	0758	1256
7	ArtPF *is* very low *and* TCH is very low	G *is* very low	0123	0758	1256
8	TCH *is* very low	F is very low	0230	0783	1202
9	ArtCA *is* very low *and* ProCS *is* very low	F *is* very low	0118	0800	1227
10	ArtPF *is* very low *and* TCH *is* very low	F *is* very low	0127	0788	1208
11	ActTS *is* very high *and* Art *is* very high *and* ArtPF *is* very high	C *is* low	0172	0761	1272
12	ArtNF *is* very high *and* Art *is* very high	C *is* low	0132	0750	1254
13	ArtNF *is* very high *and* Art *is* very high *and* ArtPF *is* very high	C *is* low	0118	0750	1254
14	ArtPF is very low and ProCS is very low	CTRL is high	0108	0667	1374
15	Art is high and ArtCA is high	CTRL is very low	0127	0650	1263
16	ActTS is high and Art is high and ArtCA is high	CTRL is very low	0127	0650	1263
17	ArtNF *is* low	LSC *is* high	0152	0620	1421
18	ArtNF *is* low *and* ActTS *is* low *and* Art *is* low	LSC *is* high	0108	0629	1441
19	Art *is* low *and* ArtPF *is* low	LSC *is* high	0113	0605	1387
20	ActTS *is* very low *and* Art *is* very low *and* ACH *is* very low *and* ArtNF *is* very low	T *is* low	0108	0759	1532
21	Art *is* very low *and* ACH *is* very low *and* ActTS *is* very low	T *is* low	0108	0733	1481
22	ACH *is* very low *and* TCH *is* very low *and* ProCS *is* very low	T *is* low	0113	0676	1366

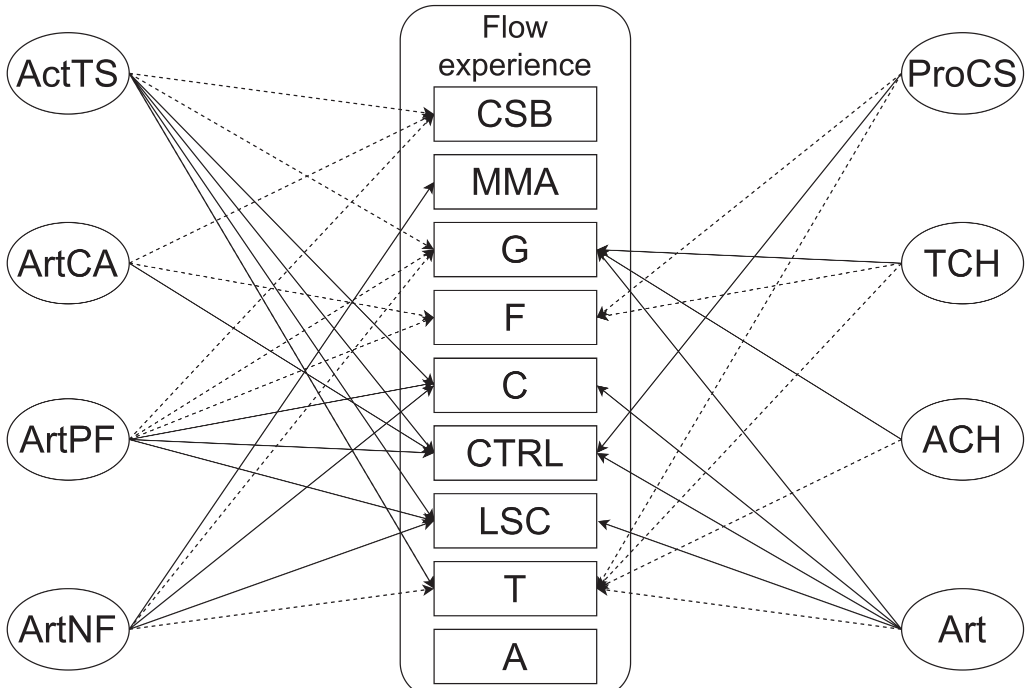
Note: **Key:** ArtCA: average response time on correct answers; ActTS: Active time in the system; ArtPF: average response time after positive feedback; ArtNF: average response time after negative feedback; Art: Used time to finish a step/activity; TCH: total of consecutive hits; ProCS: Proportion of correct steps/activities; 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; and LSC: loss of self-consciousness; T: transformation of time; Supp: support; Conf.: confidence.

Rules 17, 18, and 19 define patterns related to the participants' data logs with the loss of the self-consciousness dimension. The rules indicate that for those who had average response time (after positive or negative feedback) and active time in the system low, then, their loss of self-consciousness was high. Finally, rules 20, 21, and 22 demonstrate patterns for the transformation of the time dimension. In essence, the rules indicate that when the participants' active time in the system, the average response time (especially after negative feedback), the proportion of correct steps/activities, and the total and average of consecutive hits were very low, the transformation of time experience was low (see Table 5). Figure 5 presents the rules/patterns identified in our study, showing which users' behaviour data logs can be used to explain each flow experience dimension.

In summary, we can organise our results by understanding that through the data logs, it is possible to model eight flow experience dimensions:

- Average response time on correct answers, active time in the system, and average response time after positive feedback are negatively related to challenge-skill balance.
- Average response time after negative feedback is crosswise related to action-awareness merging.
- Active time in the system, used time to finish a step/activity, and average response time are negatively related to clear goals.
- Total of consecutive hits, the average response time on correct answers, the proportion of correct steps/activities, and average response time after positive feedback negatively affect unambiguous feedback.
- Active time in the system, used time to finish a step/activity, and average response time are crosswise related to concentration.
- Average response time after positive feedback, proportion of correct steps/activities, used time to finish a step/activity, average response time on correct answers, and used time to finish a step/activity are crosswise related to control.
- Average response time, active time in the system, and used time to finish a step/activity are crosswise related to loss of self-consciousness.
- Active time in the system, used time to finish a step/activity, average response time after negative feedback, consecutive hits, and proportion of correct steps/activities are negatively related to the transformation of time.

Finally, the results demonstrate that it is possible to identify a relationship/pattern between users' data logs in information systems and their flow experience in the system. Specially, we identified that the speed of users' actions negatively affects the flow experience antecedents and positively affects the loss of self-consciousness. At the same time, especially, active time in the system negatively affects challenge-skill balance.



Key: ActTS: Active time in the system; ArtCA: average response time in correct answers; ArtPF: average response time after positive feedback; ArtNF: average response time after negative feedback; ProCS: Proportion of correct steps/activities; TCH: total of consecutive hits; ACH: the average of consecutive hits; Art: Used time to finish a step/activity; 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; and LSC: loss of self-consciousness; T: transformation of time; A: *autotelic* experience; ---➤ : negatively affect; ⟶ : crosswise effects.

Figure 5. Significant patterns.

4.1. Discussions

One of the challenges related to the analysis of user experience in information systems is the automatic identification of users' flow experience during the usage of a system (Challco et al. 2016; De Kock 2014; Lee, Jheng, and Hsiao 2014; Oliveira 2019; Oliveira et al. 2019). In this article, we conducted a data-driven study with 204 participants where we analysed the relationships between user interactions in an educational system (i.e. data logs) and their flow experience during the system usage. Through data mining techniques, we found 22 significant relationships (i.e. association rules), thus, explaining eight flow experience dimensions. Next, we will discuss the results of our study, comparing not only our results with those of other studies that used the same scale but also with studies that used other scales or only measured one flow experience dimension. Thus, we stand out from the technical discussion and also delve into the theoretical field.

Considering the theory that organised the flow experience in 'antecedents of flow' and 'the flow itself' (Csikszentmihalyi 1997b; Csikszentmihalyi and Csikszentmihalyi 1975; Jackson and Csikszentmihalyi 1999), we note that the data explains all the antecedents of flow (challenge-skill balance, clear goals, and unambiguous feedback). The results demonstrate that the speed of user action negatively affects the flow experience antecedents (see Table 5). This result corroborates the theoretical model proposed by Oliveira et al. (2019) which relates different data logs related to the speed of user actions with the flow experience antecedents. At the same time, this result may occur due to the fact that, as it is a study carried out over a period of about 30 min, the antecedents of the flow experience may have started to be activated more quickly in the participants, also considering that the system may have provided the antecedents of the flow experience.

Also, this result especially contributes to the design of information systems, since antecedents of flow are the key for an individual to achieve a complete flow experience in a system (Csikszentmihalyi 2014a, 2014b; Csikszentmihalyi and Csikszentmihalyi 1992). This result can contribute, for example, to the identification of the flow antecedents through behaviour data logs and allow designs to make design changes in the information systems (i.e. change the system design if the user does not reach the flow attendants). This result is also similar to the results of previous studies (Lee, Jheng, and Hsiao 2014; Semerci and Goularas 2020), which, in general, focussed on analysing the antecedents of the flow experience.

About the results related to the challenge-skills balance dimension, analysing the literature on Flow Theory (Csikszentmihalyi 1997a, 2014a; Csikszentmihalyi and Csikszentmihalyi 1975) and the model proposed by Oliveira et al. (2019), we realised that to achieve a challenge-skill balance experience, the individual's skill level must not be greater than the task's difficulty level. At the same time, our results (the rules one to three) indicate that participants who were able to answer questions quickly and correctly (higher level of skill than the difficulty of the activity), failed to achieve the challenge-skill balance experience thus, confirming the Flow Theory (Csikszentmihalyi 1997a, 2014a; Csikszentmihalyi and Csikszentmihalyi 1975) and the model proposed by Oliveira et al. (2019), who hypothesised this relationship in their theoretical study. Our results are also similar to the results obtained by Lee, Jheng, and Hsiao (2014) in terms of data logs related to the challenge-skills balance dimension.

Regarding the action-awareness merging, when analysing the original studies of Flow Theory (Csikszentmihalyi 1997a, 2014a; Csikszentmihalyi and Csikszentmihalyi 1975), it is possible to realise that for someone to achieve the experience of action-awareness merging, it is necessary that during the activity, they always maintain a clear awareness of what he is doing. So, as demonstrated by rule 4 (see Table 5), if a user even receiving negative feedback takes a long time to reflect on how to solve the following challenges, they are not keeping clear awareness of what they are doing, so their action-awareness merges will be not high. The model proposed by Oliveira et al. (2019) do not account for this possibility, hence, through this rule, it is also possible to expand the model.

At the same time, we also did not identify the relationship identified by Oliveira et al. (2020) (i.e. a relationship between the 'active time in the system' and the action-awareness merging). In this case, the results of our data-driven study do not confirm the data from the theoretical study proposed by Oliveira et al. (2019). This result may have occurred due to the low generability of the qualitative study conducted by Oliveira et al. (2020). At the same time, these results call attention to the realisation of new studies based on data (e.g. using different statistical models or machine learning).

Regarding the dimension of the clear goal, Csikszentmihalyi and Csikszentmihalyi (1975) proposed that if a person cannot clearly understand the objectives of an activity (or is not concerned with understanding the objectives of an activity) (Csikszentmihalyi and Csikszentmihalyi 1975), then it is not possible to achieve most of the flow experience dimensions. The proposition of Csikszentmihalyi and Csikszentmihalyi (1975) can be corroborated by our results (especially, considering the rules five, six, and seven). These rules, in addition to confirming the relationships proposed in the theoretical model proposed by Oliveira et al. (2019), also allow the model to be improved through the identification of a new relationship (i.e. speed of user action).

If on the one hand, these results confirm the results of the theoretical model proposed by Oliveira et al. (2019), on the other hand, our results are different from the results obtained by Oliveira et al. (2020). In the study of Oliveira et al. (2020) identified only one relationship between the clear goals dimension and the proportion of correct steps/activities. Therefore, the results of our data-based study do not confirm those of the qualitative study of Oliveira et al. (2020). This result may have occurred because they were conducted in different settings and analysed using different techniques. Thus, once again, our results call attention to the importance of new studies based on data that can conduct analyses in different contexts.

When we compared our results about the unambiguous feedback dimension (also an antecedent of flow), with different studies on Flow Theory (Csikszentmihalyi 1997a, 2014a; Csikszentmihalyi and Csikszentmihalyi 1975), we confirm that this dimension has a direct relationship with the dimension of clear goals previously discussed, because if an individual did not clearly understand the objective of the activity, it is difficult to interpret the feedback given unambiguously. At the same time, if a person cannot interpret the feedback unambiguously, they will not spend enough time responding to the activities with attention and concentration and you will not be able to achieve a good performance in the activities, as indicated by the rules eight, nine and 10 (see Table 5). These patterns corroborated to the theoretical model proposed by Oliveira et al. (2019) that hypothesised only a relationship between data logs and the unambiguous feedback dimension.

In terms of concentration, we identified that when the participants stay a long time in the system and it takes a long time to do the tasks, their concentration was low (see Table 5). This probably occurred because concentration is usually associated with being able to maintain a certain level of focus on an activity (Csikszentmihalyi 1997b), so if a person takes a long time to finish a sequence of activities (even when receiving positive and/or negative feedback), their concentration will be not high on those activities. This result also confirms one of the relationships proposed by Oliveira et al. (2019) in their theoretical model.

Also about the concentration dimension, the model proposed by Oliveira et al. (2019) expected that if a user had a large number of mouse clicks out of buttons, their contraction would be low or very low. The results of the qualitative study conducted by Oliveira et al. (2020), also confirm the proposition of the theoretical model proposed by Oliveira et al. (2019). However, our study did not identify assassination rules related to the number of mouse clicks. Our result corroborates the findings of Muramatsu et al. (2023), who did not identify any relationship between the number of mouse clicks and the dimensions of the participants' flow experience in their study.

In particular, this result (combined with the results of the Muramatsu et al. (2023)' study) can point out two directions. The first is that although early theoretical and qualitative studies hypothesised a relationship between the number of mouse clicks and users' flow experience, this hypothesis is not supported by data-driven studies. This result demonstrates that the number of mouse clicks cannot be used to model flow experience. The second direction is that using only one type of data log can be unfavourable to identifying the users' flow experience. This result opens space to invest in using groups of data (e.g. as latent variables) representing specific behaviours of users to try to model and predict users' flow experience.

Regarding the control dimension, the previous literature on Flow Theory (Csikszentmihalyi 2014a; Csikszentmihalyi and Csikszentmihalyi 1975; Jackson, Eklund, and Martin 2011) indicates that if a person received positive feedback, they started to feel a greater sense of control (for having realised that did the activity correctly). However, at the same time, this made the individual possibly not take due care with the next activities, and end up missing those activities. Confirming these theoretical studies rules 15 and 16 (see Table 5), in turn, indicate that when the participants' average response time, average response time in the correct answers, and active time in the system were high, then, their sense of control was very low. These rules are explained since if an individual spends a long time doing a certain activity even when they did the activities correctly, they were not feeling in control of the situation and therefore need to think a little more about the actions they would take, as well as foreseen in some of the relationships proposed in the study by Oliveira et al. (2019).

Regarding the self-consciousness dimension, the rules indicated that the participants were able to reach a higher level of immersion in the system, thus achieving the self-consciousness dimension during the system usage and, then, performing the activities quickly. However, they failed to reach the other dimensions of the flow experience. This rule also confirms the relationship between the participants' data logs and the loss of self-consciousness experience proposed by Oliveira et al. (2019) and is in line with the original theoretical studies of Flow Theory.

Last but not least, in terms of the time transformation dimension, concerning active time in the system, the average response time (especially after negative feedback), can be explained because if a certain user spent little time using the system, they were possibly concerned about factors other than activities and not being able to focus on activity, a key factor to achieve the transformation of time experience (Csikszentmihalyi 1997b; Csikszentmihalyi and Csikszentmihalyi 1975; Kiili et al. 2012). The rest of the relationship is explained because if a particular user is unable to concentrate and achieve the transformation of time, will probably not have enough attention to do the activities. The identified relationships also confirm the relations proposed by Oliveira et al. (2019).

Leaving the discussion related to the associations between the flow experience dimensions and the behaviour data to bring a discussion on other aspects related to the results of this study, we identified that the mean of flow experience was around three to four for all dimensions. Although there are no classical theoretical models that define a difference between an 'almost-flow', 'medium-flow', or 'extreme-flow', we believe that these results may be related to the type of activity used in our study. We hypothesised this, as other recent studies that analysed the experience of flow in educational environments found similar results (Hong et al. 2019; J. Zhao and Li 2020; P. Y. Wang, Chiu, and Lee 2021).

Our results provided new insights towards solving one important challenge of information systems, which is the automatic identification of the users' flow experience in the systems (Lee, Jheng, and Hsiao 2014; Oliveira et al. 2018, 2019). In particular, we found a series of patterns that relate data logs to eight of the nine flow experience dimensions. According to the secondary studies conducted by Perttula et al. (2017) and Oliveira et al. (2018); Oliveira, Pastushenko, et al. (2021) until then, no other study had been able to analyse and find data that would allow the modelling of more than one of the nine flow experience dimensions. Thus, from our study, it will be possible, to start to propose algorithms to be plugged into educational systems, receiving the users' data logs as input and providing the information as output if the users have managed to achieve any of the dimensions of the flow experience, based on the patterns identified in this study.

In all, we collected nine different users' behaviour data logs. From these nine data logs, only the number of mouse clicks out of buttons was not found in the patterns for any of the dimensions (confirming the recent finds of Muramatsu et al. 2023). Our results also allowed us to confirm most of the relationships proposed by Oliveira et al. (2019) in their theoretical model. Besides, we were also able to deepen the proposed model by discovering new relationships that until then had been proposed even in theoretical studies. Thus, in summary, **our results show 22 significant rules/patterns, explaining eight from the nine flow experience dimensions**, however, **our results also reveal no clear generalised relationship between users' data logs and flow**.

4.2. Threats to validity and limitations

Because it is a study with humans, our study generated different threats to the validity inherent in the study itself. Initially, we analysed the users' flow experience which is a subjective experience that may not be easy to identify. To mitigate these threats, we used only validated instruments in our study. Our results may not be generalised to other contexts. To mitigate this limitation, we use sample significance calculations and collect data from a significant amount of respondents. As for the algorithms that were used, different studies state that ARM provides the same results independent of the used algorithm (X. Wu et al. 2008). Thus, we used the Apriori algorithm (due to its popularity).

In our study, we had participants from different countries, who can be motivated differently and have different levels of flow experience during system usage. Likewise, in our study, we paid a fee to each participant, which may have interfered with the participants' flow experience. However, in both cases, these factors do not influence the ultimate goal, which is to discover patterns between the participants' data logs and their flow experience. Finally, some patterns found in our analysis may not represent the general realism of the data. To mitigate this threat, in addition to using techniques inherent to the data mining algorithms themselves (i.e. pruning), we also conducted a 'human pruning' to ensure the semantic quality of rules.

As the limitations of our study, in most of the flow experience dimensions, no relevant rules were found to demonstrate data patterns where the users' experience was high or very high (i.e. positive effects). This result draws attention to the need to replicate our study in different systems and to use different techniques to identify new patterns when the participants' flow experience is high. While there are different ways to operationalise the measurement of the users' behaviour in educational systems, in our study, we operationalise users' behaviour as the flow experience.

To ensure that we operate the flow correctly, we associate the data logs with the experience measured using an FSS previously validated and widely used in the literature (Hamari and Koivisto 2014; Jackson and Eklund 2002). In our study, we chose to use the short FSS. Despite being a previously validated and widely disseminated scale, this scale can bring limitations concerning the individual understanding of each flow experience dimension. The average time students spent using the system (i.e. 4.5 min) may not be enough to take students through a full-flow experience. Some behaviour data logs used in our study may not be generalisable to all types of information systems. Finally, few researchers have focussed on the topic, which can limit the comparative discussion between studies by different authors. At the same time, it an open space for new studies (from different research groups).

4.3. Research agenda

In this study, we step towards answering a question hitherto open in the literature (Lee, Jheng, and Hsiao 2014; Oliveira et al. 2018, 2019) and provide novel results advancing the state-of-the-art in the field of human-computer interaction. Based on these insights, we propose a research agenda to deepen our results:

Predictive analysis: in our study, after testing different techniques, the data mining techniques presented the best results, thus, we opted to use the data mining technique because it is a widespread technique capable of finding patterns in large amounts of data (Dhar 2013; Toda et al. 2019; X. Wu et al. 2008). However, there is still the possibility to collect data from more participants and using different kinds of predictive analytics techniques such as Machine Learning, Regression, and/or Partial Least Squares (Hair Jr et al. 2016), which can be helpful for example predicting the users' flow experience in an educational system, based on the patterns identified in our study (Hair Jr et al. 2016; Henseler, Ringle, and Sinkovics 2009).

Context-based analysis: In our study, we focussed on relating general data logs (e.g. active time in the

Table 6. Research agenda.

What to do	Motivation	How to do
Predictive analysis	Prediction can favour automatic, real-time identification in educational systems	Machine learning techniques for prediction (e.g. Naive Bayes and Support Vector Machines)
Context-based analysis	The flow experience can be changed according to the context	Conducting studies (e.g. replication of this study) in different contexts and systems (for example, educational games and intelligent tutoring systems).
Longitudinal analysis	The flow experience can change over time	Conducting studies (e.g. replication of this study) for a long period of time (e.g. six months) with continuous interventions (e.g. weekly).
Real-time flow experience identification	Real-time identification can provide a better way to intervene in the system or activities to improve the experience of the participants.	Propose algorithms (e.g. based on the rules found in this study) to take users' data logs and show in real-time whether or not users are in a flow experience

system, used time to finish a step/activity, and proportion of correct steps/activities) with users' flow experience during the system usage. However, often, each kind of system has some characteristics inherent to its context, for instance, gamified educational systems have characteristics such as points, ranking, and badges. It is important to conduct new studies aiming to identify patterns relating to the users' flow experience with more specific characteristics of each system, for example, with the users' interaction with the gamification elements, in the case of gamified educational systems.

Longitudinal analysis: this research area is still very new, and most studies have started to be published in the last five years (Oliveira et al. 2018; Oliveira, Pastushenko, et al. 2021; Perttula et al. 2017). At the beginning of an area, short-term studies must be carried out to start obtaining the initial results. However, with the deepening of the area, longitudinal studies must be conducted to avoid factors such as novelty effects (Koivisto and Hamari 2019). Thus, we suggest that in the next years, researchers may begin to propose to conduct longitudinal studies relating to the users' data logs with their' flow experience, with different interventions.

Real-time flow experience identification: so far, studies have focussed on finding patterns between users' data logs and their flow experience. In the future, after different studies are conducted in different contexts, it is important that new studies are conducted to identify the users' flow experience in real time when using educational systems. This will also benefit the teachers and instructors in making faster decisions. Table 6 presents a summary with our recommendations for future studies.

5. Concluding remarks

One of the main goals of information systems is to produce a rewarding experience for users. Accordingly, one of the main challenges is to measure when users achieve some experience (e.g. flow experience) in a system, as in general, this evaluation is often using invasive means (e.g. electroencephalogram), or that cannot be applied massively (e.g. interviews). We tackled this challenge by conducting a study to discover patterns relating the users' data logs to their flow experience. Our results show that data logs were able to explain eight of the nine flow experience dimensions, thus, indicating that it is possible to identify the flow experience automatically. We aim in future studies to conduct longitudinal experiments in different kinds of systems using new data mining, statistical analysis, and deep learning techniques to improve the results obtained in this study.

Notes

Previous studies of this project have been published: Oliveira et al. (2018); Oliveira, Pastushenko, et al. (2021) conducted secondary studies on the intersection between Flow Theory, Educational Technologies, and Gameful Environments; Oliveira (2019) presented his initial Ph.D. project overview; Oliveira et al. (2019) proposed a theoretical model relating students' data logs and their flow experience in educational systems; Oliveira et al. (2020) conducted a qualitative study (by using the thinking aloud protocol) exploring the relation between students' data logs and their flow experience in educational systems; Oliveira, Isotani, et al. (2021); Oliveira, Tenório, et al. (2021) conducted data-driven studies (by using structural equation modelling) modelling and predicting (respectively) students' flow experience based on their behaviour data logs in a single gamified educational system; Oliveira, Hamari, and Isotani (2023); Oliveira et al. (2022) investigated (by using structural equation modelling) the relationship between students' flow experience and their behaviour in different gamified educational systems. The study presented in this article advances previous studies of this project investigating (by using data mining) the associations between users' behaviour data and their self-reported flow experience. This article closes a cycle of studies related to the main author's doctoral project, investigating the possibility of using user behaviour data in gamified educational systems to understand their flow experience. A new cycle of related studies is started by Oliveira and Hamari (2024), analysing the global trends in Flow Theory Research within Gameful Environments.

Notes

1. https://www.mturk.com/
2. https://www.r-project.org/
3. https://rstudio.com/

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Data availability statement

All the materials, data, and codes can be found in the Open Science Framework at https://osf.io/ae3gu/.

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