Smart Learning Environments

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The effects of personalized gamification on students' flow experience, motivation, and enjoyment

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This article is an extension of the conference paper conducted by Oliveira et al. (2020).

Abstract
Gamification refers to the attempt to transform different kinds of systems to be able to better invoke positive experiences such as the flow state. However, the ability of such intervention to invoke flow state is commonly believed to depend on several moderating factors including the user's traits. Currently, there is a dearth of research on the effect of user traits on the results of gamification. Gamer types (personality traits related to gaming styles and preferences) are considered some of the most relevant factors affecting the individual's susceptibility to gamification. Therefore, in this study we investigate how gamer types from the BrainHex taxonomy (achiever, conqueror, daredevil, mastermind, seeker, socializer and survivor) moderate the effects of personalized/non-personalized gamification on users' flow experience (challenge-skill balance, merging of action and awareness, clear goals, feedback, concentration, control, loss of self-consciousness and *autotelic* experience), enjoyment, perception of gamification and motivation. We conducted a mixed factorial within-subject experiment involving 121 elementary school students comparing a personalized version against a non-personalized version of a gamified education system. There were no main effects between personalization and students' flow experience, perception of gamification and motivation, and enjoyment. Our results also indicate patterns of characteristics that can lead students to the high flow experience (e.g., those who prefer to play multiplayer have a high flow experience in both personalized and non-personalized versions). Based on our results, we provided recommendations to advance the design of gamifed educational systems.

Keywords: Personalized gamification, Gamified education, Flow experience, User modeling, Experimental study

Introduction
The use of gamification in the last decade has increased significantly, especially in the field of education (Koivisto & Hamari, 2019; Bai et al., 2020; Klock et al., 2020). According to recent research, gamification is supposed to increase students' motivation and engagement in learning environments (Rapp et al., 2019; Zou 2020; Bai et al., 2020). However, the literature presents mixed results regarding improvement in learning and

motivation and some studies even suggest negative outcomes if a well-thought design is not followed (Toda et al., 2017; Koivisto & Hamari 2019; Bai et al., 2020). Thus, more in-depth studies are needed to understand the influence of gamification on student motivation in gamified educational environments (Oliveira & Bittencourt 2019c; Koivisto & Hamari, 2019; Klock et al., 2020; Bai et al., 2020).

One of the prevalent discussions within the literature is that the extant corpus has not being able to model or take into account individual differences of students concerning their susceptibility of the effects of gamification (Jagušt & Botički, 2019; Klock et al., 2020; Raj & Renumol, 2021). Some researches has began to consider that the students have different behavioral profiles (or gamer types[1]), being motivated by different gamification elements and this should be taken into account when developing personalized gamified educational systems (Orji, 2014; Monterrat et al., 2015; Oliveira & Bittencourt 2019b). For instance, when a student is a socializer, it is more likely that they prefer interact with their peers, thus they might also be reluctant to participate in a different gamified setting, for example, a competitive one (Böckle et al., 2017; Oliveira et al., 2020). Thus, according to the results of recent studies e.g., Oliveira et al. (2020), Santos et al. (2021), Rodrigues et al. (2021), depending on the approach used in these systems, the gamification design can negatively affect a student's experience (Toda et al., 2017).

Furthermore, recent studies have tried to investigate the influence of gamification on students' experience (Lavoué et al., 2018; Toda et al., 2019; Oliveira et al., 2020). These studies followed earlier work in the domain of persuasive games for health which showed that a non-personalized (or "one size fits all") design is significantly less effective than a design personalized to the gamer type of the user, measured by self-reported intention to engage in the behaviour, enjoyment and self-efficacy in playing the game (Orji et al., 014). These insights motivated further studies in analyzing the effectiveness of different combinations of game elements for different gamer profiles (Orji et al., 014; Böckle et al., 2017) and specifically, their influence on students' motivation in the domain of gamified learning environments (Lavoué et al., 2018).

At the same time, Flow Theory (Csikszentmihalyi 1997) is often used to provide a definition of motivation in the literature on gamification (Hamari & Koivisto 2014). The gameful experience (Högberg et al., 2019) resulting from gamification is commonly tied to the flow experience that is composed out of nine different dimensions (i.e., challenge-skill balance, merging of action and awareness, clear goals, feedback, concentration, control, loss of self-consciousness and *autotelic* experience) and directly related to students' motivation and engagement (Csikszentmihalyi 1997, 2014b; Oliveira et al., 2019). Thus, the flow experience can be highly related to the students' performance in a educational environment (Csikszentmihalyi 1997, 2000, 2014a). While there is some research investigating the effects of gamification on the flow state (Hamari et al., 2016; Xi & Hamari, 2019; Oliveira et al., 2020), there is a dearth of research investigating the how individual differences moderate the influence of gamification on the flow state in learners.

Therefore, in this article we investigate how gamer types (achiever, conqueror, daredevil, mastermind, seeker, socializer and survivor) moderate the effects of personalized/

[1] The term "gamer type" is commonly used to refer the different personality types exhibited by people in game-play (Orji et al., 2013; Masthoff & Vassileva 2015).

non-personalized gamification on learners' flow experience (i.e., challenge-skill balance, merging of action and awareness, clear goals, feedback, concentration, control, loss of self-consciousness and *autotelic* experience), and also on their enjoyment, perception of gamification and motivation. Then, we aim to answer the following research question: **Does the personalization of gamification based on gamer type affect students' flow experience, enjoyment, perception of gamification and motivation in gamified educational systems?** To answer this research question, we conducted a mixed factorial between-subjects experiment among 121 elementary school students comparing a personalized version against a non-personalized version of a gamified education system, using statistical tests and data mining techniques.

The results of this study indicate that there was no significant relationship between personalization and the students' flow experience, perception of gamification, motivation, and enjoyment. The results also present 12 association rules which indicate patterns of characteristics that can lead students to the high flow experience (e.g., for example, those who prefer to play multiplayer games have a high flow experience in both the personalized and non-personalized versions). Our results contribute with insights for the design of personalized gamified educational systems and open space for further studies in this field. Thus, based on our results, we also propose a research agenda, with recommendations for future studies.

Background

This section presents a theoretical framework of the main topics addressed in this study, including tailored and personalized gamification, gamer types, and Flow Theory in the field of education. We also present a comparison between the main related works.

Tailored and personalized gamification in education

"Throughout history, many have advocated the use of play, games, and game-inspired design to improve the human condition" (Nacke and Deterding 2017). With this, gamification has become a popular approach to enriching information technologies in different types of applications, including educational ones (Hamari et al., 2014; Rapp et al., 2019; Hallifax et al., 2019; Koivisto & Hamari, 2019; Bai et al., 2020). An important aspect of gamification is the understanding of which gamification elements are adequate in each context (Orji et al., 014; Koivisto & Hamari, 2019; Santos et al., 2021).

In the last years, studies on gamification have found contradictory results (Toda et al., 2017), and started investigating whether personalization can improve the effectiveness of gamification giving rise to the concepts of "tailored gamification" and "personalized gamification" (Oliveira & Bittencourt, 2019c; Tondello et al., 2019; Klock et al., 2020). According to Oliveira and Bittencourt (2019c), personalized gamification is related to the dynamic adaptation to the individual user during usage time, while tailored gamification means that it is adapted at design time, usually based on one or a hand-full of selected features (stereotype).

Although it is known that personalized education is more efficient than non-personalized education (Jagušt & Botički, 2019; Raj & Renumol, 2021), studies that explore this kind of analysis in gamified educational systems are still scarce (Böckle et al., 2017; Koivisto & Hamari, 2019; Raj & Renumol, 2021). It is also known that people have different perceptions towards gamification elements that are affected by their demographic and behavioral profiles, which prompts the need to explore those variables through in-depth studies (Toda et al., 2019; Oliveira & Bittencourt, 2019b; Oliveira et al., 2020).

Gamer types/user types in education

Summarizing (Orji et al., 014), gamer types are behavioral profiles that describe the user preferences in gameplay. Hamari and Tuunanen (2014) conducted a meta-synthesis about gamer types, analyzing the main studies conducted in this field, and concluded that the field of study in gamer types is perhaps surprisingly uniform (most of the studies prose the same topic). In essence, the study can be synthesized into five key dimensions pertaining to motivations of play/orientation of the player: Achievement, Exploration, Sociability, Domination, and Immersion. Additionally, insights into how intense the mode of play was commonly articulated as continuum or dichotomy between hardcoreness and casualness were largely presented in most studies.

The first gamer type model was proposed by Bartle (1996). The author designed this model through a qualitative study and it was used by many studies up to today. However, recent studies illustrated the limitations of using this model (Yee 2006; Bateman & Boon, 2005; Bateman et al., 2011; Fullerton 2014; Hamari & Tuunanen, 2014), guiding studies to create new models that are more appropriate to the field of gamification. The first model with some focus on gamification studies was proposed by Nacke et al. (2014), based on neuropscychological study of game-players. This model, called *BrainHex*, comprises seven gamer types (i.e., Seeker, Survivor, Daredevil, Mastermind, Conqueror, Socializer, and Achiever) and classifies the players in class and sub-class related to each other, supporting a more accurate classification.

More recently, the *Hexad* model was proposed by Marczewski (2015) and validated by Tondello et al. (2019). The *Hexad* model defines six types of users classified according to types of motivation (i.e., intrinsic and extrinsic motivation). The Hexad model was the first model designed exclusively for the gamification domain. In our study, we opted for the *BrainHex* model since it assumes that the gamer types are not mutually exclusive, allowing us to conduct a more in-depth analysis of users' preferences towards game elements. At the same time, the instrument does not require users to introspectively choose their gamer type from several categories.

Flow theory and its application in education

The idea of "flow state" was introduced by Csikszentmihalyi (1997) as a technical term to describe a good feeling or "optimal experience" that people have as a motivating factor in their daily activities, such as at work, sports, and artistic performance (Faiola et al., 2013). The key to understanding the flow state is the "*autotelic* experience" which is the result of an activity or situation that produces its own intrinsic motivation, rewards, or incentives, specifically without any outside goals or rewards. Several studies have been conducted to describe this kind of experience (Csikszentmihalyi, 1997).

According to a recent literature review conducted by Oliveira et al. (2018), the most commonly used is the initial Flow Theory (Csikszentmihalyi, 2000), where Csikszentmihalyi (2000) describes nine necessary dimensions for an activity to prompt a flow state: Challenge-skill balance (CSB), Action-awareness merging (MMA), Clear goals (G), Unambiguous feedback (F), Total concentration on the task at hand (C), Sense of control (CTRL), Loss of self-consciousness (LSC), Transformation of time (T), and *autotelic* experience (A), as summarized below:

1. **Challenge-skill balance:** When in flow, a dynamic balance exists between challenges and skills. Challenges and skills, however, can be modified in any activity, making flow an accessible experience across all domains of functioning (Jackson et al., 2011).
2. **Action-awareness merging:** The unity of consciousness apparent in this flow dimension illustrates the idea of growth in complexity that results from flow experiences (Jackson et al., 2011).
3. **Clear goals:** 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 et al., 2011; Jackson & Eklund, 2002).
4. **Unambiguous feedback:** When receiving feedback associated with a flow state, the individual does not need to stop and reflect on how things are progressing (Jackson et al., 2011).
5. **Total concentration on the task at hand:** This dimension defines one of the clearest indications of being in flow, that is, totally focused in the present on a specific task being performed (Jackson et al., 2011).
6. **Sense of control:** Like flow itself, the sense of control often lasts only a short time and this relates back to keeping at the cutting edge of the challenge-skill balance within a situation (Jackson et al., 2011).
7. **Loss of self-consciousness:** It is liberating to be free of the "voice within our head" that questions whether we are living up to self- or other-imposed standards (Jackson et al., 2011).
8. **Transformation of time:** When the time transformation is experienced, it is one of the liberating dimensions of flow (to feel free from the time dependence under which we live most of our lives) (Jackson et al., 2011).
9. ***Autotelic experience:*** It is generally after completing an activity, upon reflection, that the *autotelic* aspect of flow is realized and provides high motivation towards further involvement (Jackson et al., 2011).

Over time, different conceptual models have been proposed to describe the flow state. These models grounded parameters to measure the flow state level, through flow state scales and other instruments. In the first model, Csikszentmihalyi (1997) describes flow as an emotional state that people can feel during specific activities, especially, activities that provide a balance between the person's skill level and the activity's challenge level with immediate feedback. According to Oliveira et al. (2018), this is still the most popular representation in the field of educational technologies.

Related studies

This section presents the main related studies. To identify and compare the related works, we analyzed the results of four systematic literature reviews conducted by Oliveira et al. (2018), Hallifax et al. (2019), Klock et al. (2020), and Rodrigues et al.

(2020). We analyzed studies published in the last 10 years that explicitly addressed the use of personalized/tailored gamified educational systems, without limit the search to works with empirical evidence since most of these studies are theoretical.

In general, the studies found were conducted in the last 60 years and have related specific objectives, such as the proposition of approaches [e.g., architectures (Monterrat et al., 2014a) or frameworks (Monterrat et al., 2014b)] to personalize the gamification design of educational systems. In the sequence of studies conducted by Monterrat et al. (2014a, 2014b, 2015), Lavoué et al. (2018), the results tend to show that students can be motivated in different ways according to the gamification design of the system. In the study conducted by Lavoué et al. (2018), the personalized gamification positively affected the students' experience (i.e., students' using the adapted version of the gamified system spend significantly more time in the system).

Similar, Sajjadi et al. (2014) proposed approaches to help adapt gamified educational systems, through computational approaches capable of being plugged or implemented in general gamified educational systems, and then adapt the system. Other two related studies analyzed students' experience in personalized gamified systems. In the first one, Gil et al. (2015) developed game mechanics based on the functionalities of an educational system and investigated the effectiveness of learning based on the proposed mechanics. In the second one (Marinho et al., 2019) investigated whether students' flow experience varies according to the gamification design settings and the gamer types and gender of participants.

Gil et al. (2015) identified that some gamification mechanics were more relevant in terms of their use and student assessments, also showing that personalized gamification is more effective in improving students' experience during a gamified system usage. On the other hand, Marinho et al. (2019) did not identify significant differences in the students' flow experience in the using the personalized setting in comparison with the students that used non-personalized setting.

Most recently, Stuart et al. (2020) simulated different adaptation techniques in a gamified educational system. They identified that students using the personalized versions were positively affected in terms of motivation and engaging. They also identified that personalization can improve intrinsic motivation, and decrease amotivation, compared to a single adaptation only based on learner motivation.

Finally, Oliveira et al. (2020) investigated whether there was a significant difference in the students' flow experience when using a personalized system for the student's profile (i.e., gamer type) in comparison with a traditional, not personalized gamified system design. The results showed that there was no significant difference in the students' flow experience (Oliveira et al., 2020). Table 1 presents a summary of the related works.

In summary, the empirical studies conducted in the field of education, in general, are concentrated only on the implementation or evaluation, not covering recent player types, (e.g., *BrainHex* or Hexad), neither did they provide empirical evaluations of the proposed solution. Most of the studies also did not provide an evaluation either, in terms of student's learning aspects, (e.g., user's flow experience). Especially, as highlighted in the study conducted by Klock et al. (2020), one of the main limitations of studies on personalized gamification is the lack of studies that compare students' experience in personalized and non-personalized gamified systems.

Table 1 Related works comparison

Study	PM	EA	SS	CE	CS	R
Monterrat et al. (2014b)	–	–	–	Not	Not	–
Monterrat et al. (2014a)	BrainHex	–	–	Not	Not	–
Lavoué et al. (2018)	BrainHex	Motivation	266	Yes	Yes	Personalization positively affects students' motivation
Sajjadi et al. (2014)	–	Engagement and flow experience	–	Not	Not	–
Gil et al. (2015)	–	–	–	Not	Not	–
Marinho et al. (2019)	Bartle's	Flow	18	Yes	Not	No significant difference
Stuart et al. (2020)	Hexad	Motivation and engagement	258	Yes	Yes	Personalization positively affects students' experience
Oliveira et al. (2020)	BrainHex	Flow	121	Yes	Yes	No significant difference
Our study	BrainHex	Enjoyment, gamification perception, motivation, and flow experience	121	Yes	Yes	Varied

PM, player model; EA, Experience analysis; SS, Sample size; CE, Controlled experiment; CS, comparative study; R, Result

According to the results of the systematic literature reviews conducted by Oliveira et al. (2018) and Klock et al. (2020), to the best of our knowledge, our study is the first experimental study to compare a personalized with a non-personalized version of a gamified educational system in terms of students' enjoyment, gamification perception, motivation, and flow experience. As far we know, our study also is the first to be conducted considering elementary school students as subjects.

Experimental design

The experiment conducted in this study is classified as a blocking factorial experiment with one independent variable and with ten possible values or "levels" (Wohlin et al., 2012; Van Solingen & Berghout, 1999). We followed a within-subjects design, where all participants take part in every condition (i.e., personalization conditions). The study was approved by the University of Saskatchewan Behavioral Research Ethics Board (Project BEH#16-142). The experiment used the Goal/Question/Metric (GQM) method (Caldiera & Rombach, 1994; Wohlin et al., 2012), which is an approach to define software metrics. This method assumes that for an organization to measure in an accurate way it must (Wohlin et al., 2012):

1. Specify the goals for itself and its projects;
2. Trace those goals to the data that is intended to define those goals operationally; and
3. Provide a framework for interpreting the data regarding the goals that were established.

Personalization process

To personalize the system we used the personalization process proposed by Oliveira and Bittencourt (2019c), describing gamification designs suitable for each BrainHex gamer type. The personalization process identifies some demographic information (e.g., age

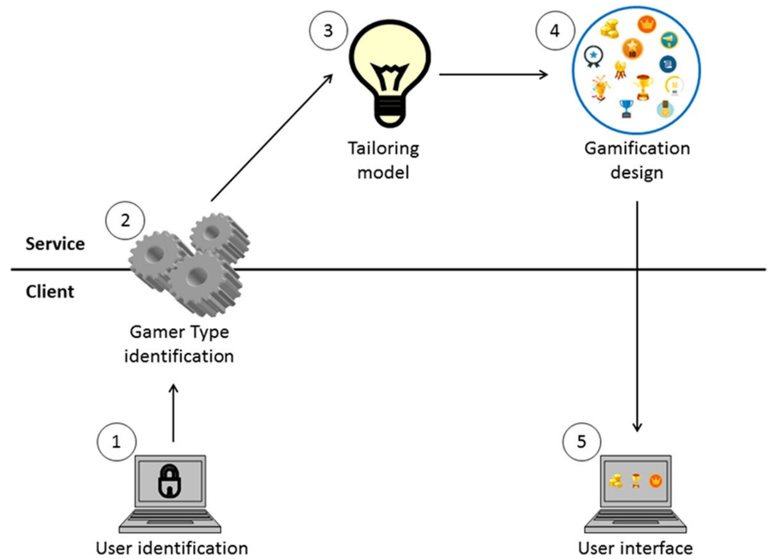

Fig. 1 General view of process [adapted from Oliveira and Bittencourt (2019c)]

and gender), identifies the student's gamer type (using the BrainHex questionnaire) and then provides a personalized interface (including appropriate gamification elements) for students. The process is composed of five different steps and presented in detail in Oliveira and Bittencourt (2019c). Figure 1 synthesizes this process. For further details regarding the personalization process (i.e., how and why each gamification elements were associated with each gamer type, see Oliveira and Bittencourt (2019c)).

1. **User identification:** the system allows students to create an account and provide demographic information;
2. **Gamer type identification:** the system provides the *BrainHex* questionnaire to identify the students' gamer types;
3. **Tailoring model:** responsible for personalizing the system interface in terms of gamification elements according to the previously identified students' gamer type;
4. **Gamification design:** generates the personalized interface;
5. **User interface:** personalized interface that appears for each student.

Implementation

The tailoring model was implemented in a gamified educational system called *MeuTutor* (Oliveira & Bittencourt, 2019a), chosen by convenience because it was considered more geographically accessible and implements the nine most used gamification elements in gamified intelligent educational system (Points, Levels/Stages, Badges, Leaderboards, Prizes and Rewards, Progress bars, Storyline, and Feedback), as identified by Nah et al. (2014), Koivisto and Hamari (2019), and Klock et al. (2020), avoiding some validity threats. The system provides different kinds of educational tasks (e.g., quiz and mini essays). In the default version, we presented all gamification elements available in the system (i.e., Points (XP), Levels/stages, Badges/ Trophies, Ranking/ Leaderboards, Progress bars, Storyline, Feedback, Background history, and Avatar). In the Figs. 2, 3,

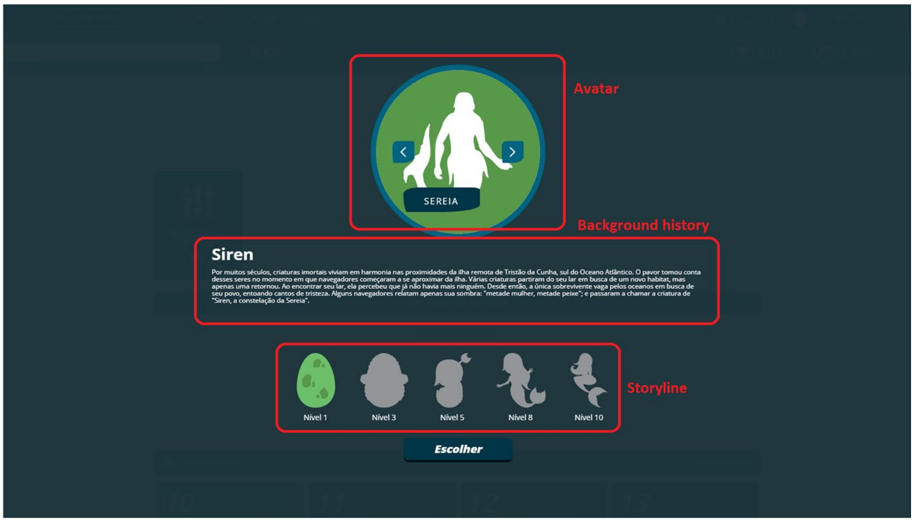

Fig. 2 *MeuTutor* default version (Avatar selection)

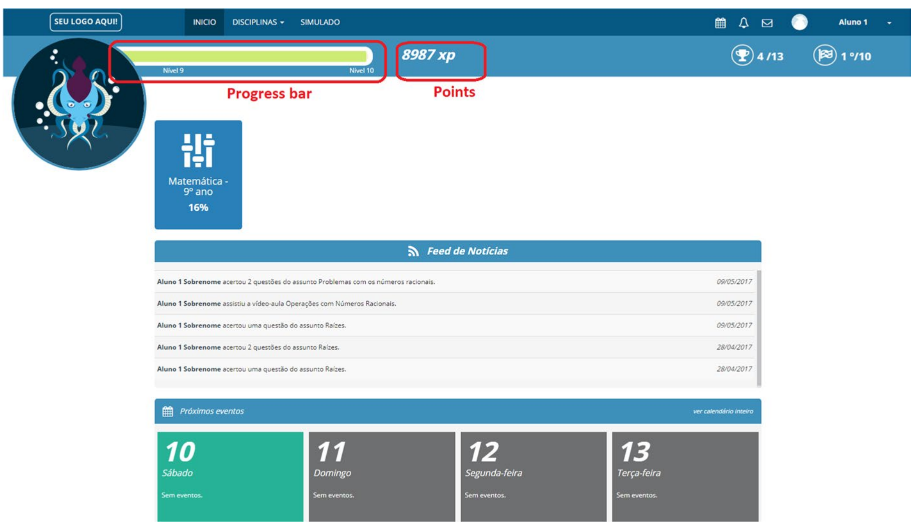

Fig. 3 *MeuTutor* default version (Homepage)

and 4 we present some examples for the default version of the system. In the Achiever version, we present Points and Badges/Trophies. In the Figs. 5 and 6 we present some examples for the Achiever version. Details about how each version was personalized (i.e., its gamification elements) can be found in Oliveira and Bittencourt (2019d). Details about the system and the figures with all versions of the system (i.e., personalized version) can be found in Oliveira and Bittencourt (2019a).

Objective and hypotheses

The main goal of the study was to compare the effectiveness, in terms of students' flow experience, gamification perception and motivation, of the non-personalized version of the system with the gamified educational system personalized according

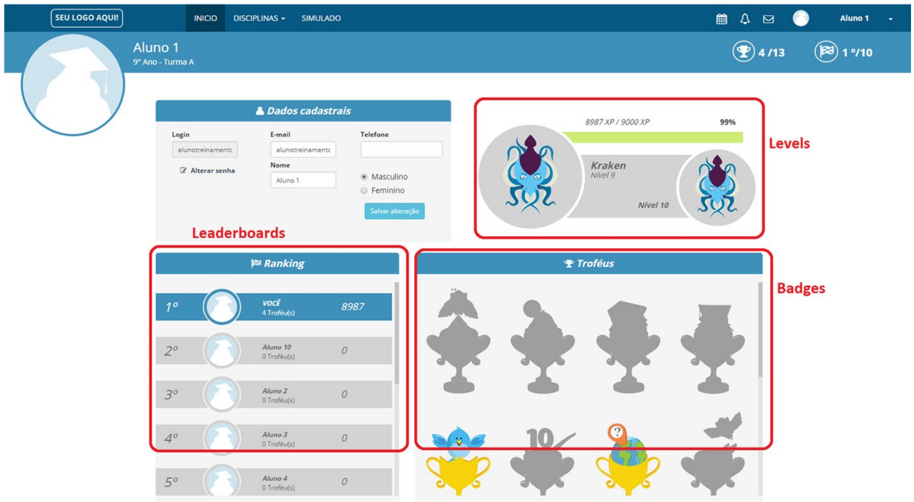

Fig. 4 *MeuTutor* default version (Student profile)

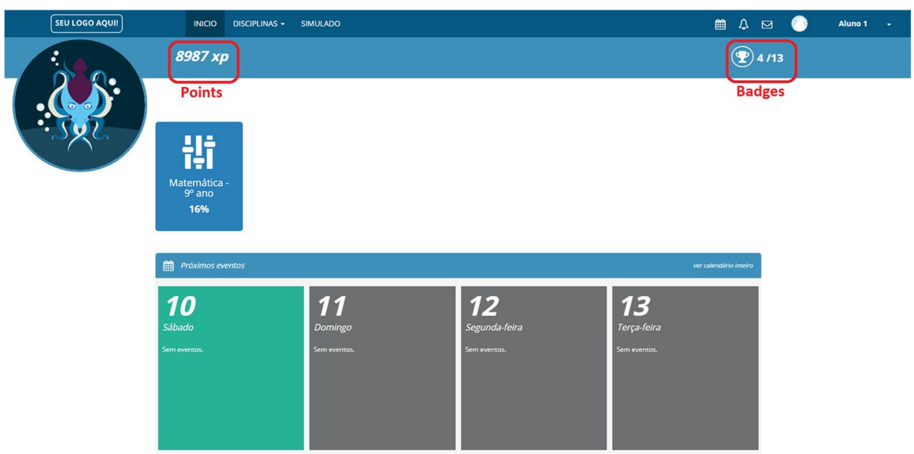

Fig. 5 *MeuTutor* achiever version (Homepage)

to the students' gamer types. For many years, personalization has been studied in different areas (Riecken 2000; Blom 2000; Fan & Poole, 2006). The studies identified that the use of personalized systems tends to affect users' experiences (Klock et al., 2020). In gamified systems, recent studies have also shown that the personalization of the gamification (according to different aspects, for instance, gender, user' types, and pedagogical tasks), can affect (positively or negatively) the users' experiences (Hallifax et al., 2019; Klock et al., 2020; Rodrigues et al., 2020). Given the results of recent studies on the effects of personalization, we hypothesize that the **personalization of gamification (based on gamer types) affects the students' experience (*i.e.*, students' flow experience, enjoyment, perception of gamification and motivation) in a gamified system**.

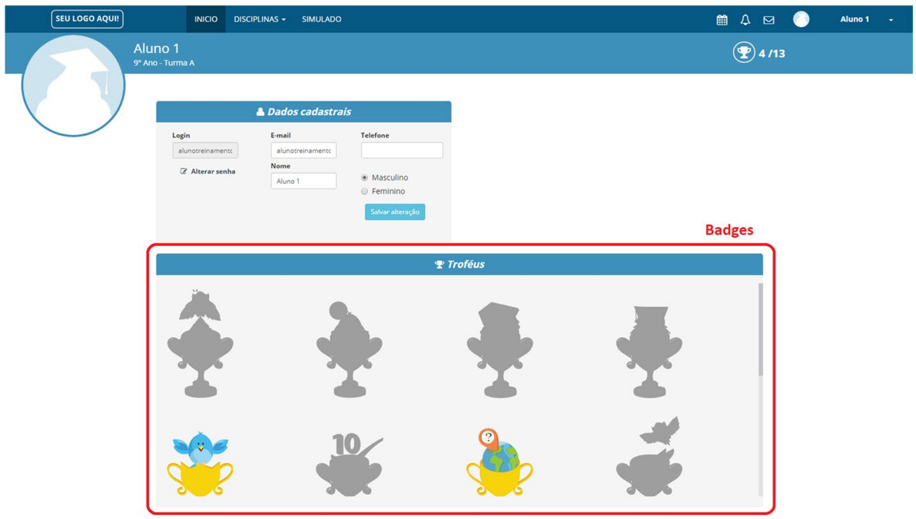

Fig. 6 *MeuTutor* achiever version (Student profile)

Materials

To conduct the experiment, we used a static version (i.e., a prototype) of a system called *MeuTutor*, presented in the "section Implementation". To identify the students' flow experience level during the system usage, we used the Dispositional Flow Scale-2 (DFS-2) (Jackson & Eklund, 2002). The DFS-2 scale was proposed and validated by Jackson and Eklund (2002) and consists of the nine flow dimensions defined by Csikszentmihalyi (1997). The used scale was also empirically validated for the gamification domain by Hamari and Koivisto (2014). To identify students gamer types, we used the BrainHex player model (Nacke et al., 2014), it includes 28 questions about the respondent game experiences and preferences to classify participants into their dominant gamer types (Nacke et al., 2014; Orji et al., 014; Lavoué et al., 2018). To collect the students' enjoyment, gamification perception and motivation, we used a non-validated questionnaire (developed by the authors themselves) in a five-point Likert scale (Albaum 1997). We asked the students with the following questions:

- The system looks good and pleasant to use to learn;
- The gamification elements of the system make me enjoy studying in the system;
- The gamification elements motivate me to study in the system.

Procedure

In the *Step 1*, the participants answered the *BrainHex* survey (Nacke et al., 2014) to identify their gamer type. Scores from each gamer type were summed to find the player's dominant gamer type (primary type) and sub-types (following Orji 2014). In the *Step 2*, students were randomly distributed into seven different groups according to their gamer types, inside each gamer type group. Each group of students was randomly divided into two different groups, one group to use first the personalized system (called "group A") and the other to use first the non-personalized system (called "group B"). In the *Step 3*,

Table 2 Sample of experiment

Gamer type	Sample	Male	Female
Achiever	48	18	30
Conqueror	28	15	12
Daredevil	6	5	1
Mastermind	3	0	3
Seeker	16	5	11
Socializer	9	5	4
Survivor	12	4	8
Total	121	52	69

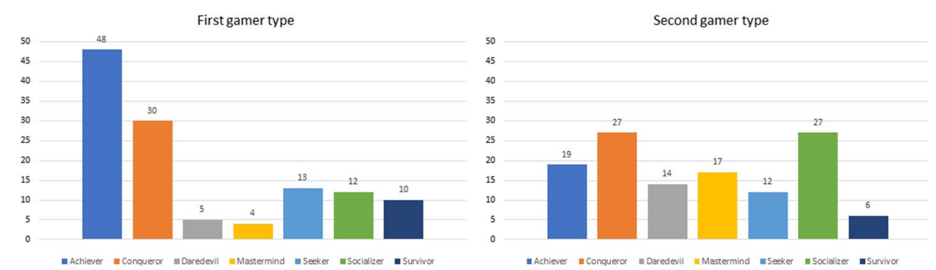

Fig. 7 Students' gamer types distribution

the students of the "group A" used the personalized version (according to the student' gamer type) for their gamer type and in the sequence responded the DFS-2. At the same time, the "group B" used the non-personalized version (one-size-fits-all approach) and also responded the DFS-2. Next, the groups were inverted, so the "group A" used the non-personalized version and "group B" used the personalized version (to then respond to the DFS-2 again). In each usage section, the students used the system for at least 30 minutes, where they studied the subject Basic Operations (Mathematics) and then answered different questions on the subject. In *Step 4*, the students' answers were organized by the researchers and the data was analyzed.

Participants

The participants were 121 Brazilian elementary school students, in which 52 are self-reported as male and 69 are self-reported as females, aged between 11 and 13 years. Table 2 summarize our sample.

According to different studies (Bentler & Chou, 1987; Hair et al., 1998), our sample size adequate for this kind of experiment. Bentler and Chou (1987) states there must be a minimum ratio of 5 respondents per 1 construct in the model. Hair et al. (1998) suggests the same rule for factorial analyses. Therefore, as we have seven constructs (i.e., the seven BrainHex gamer types), we have an adequate sample for all. Only for the masterminds (were solely three participants were identified) the sample is not considered adequate. Therefore, we removed these participants from the analysis.

About the *BrainHex* data, initially, the Fig. 7 present the students gamer types distributions (comparing the first gamer type (also presented in the Table 2) and second gamer type of the students participants). The results indicate that the most common second

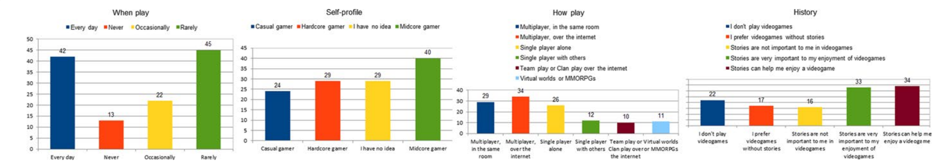

Fig. 8 *BrainHex* analysis

Table 3 Internal reliability for the DFS-2

	CSB	MMA	G	F	C	CTRL	LSC	T	A
Non-personalized version									
α	.693	.778	.769	.650	.654	.731	.706	.629	.776
Personalized version									
α	.690	.629	.733	.684	.654	.673	.692	.722	.766
Personalized and non-personalzied version (together)									
α	.691	.712	.753	.668	.653	.700	.699	.677	.770

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

gamer types are conquerors and socializers. In our analysis for this article, however, we only considered the first gamer type of the participants. We also collected additional information about playing habits and preferences (Fig. 8).

Results

Initially, to guarantee the reliability of the results, (i.e., the consistency among the items for a same construct in the scale), we analyzed it for each of the flow experience subscales. We considered the responses for the non-personalized and personalized versions of the system separately and also together. The results show that in both phases the α values were similar, and not all scales showed significant internal consistency. Table 3 present the internal reliability for the DFS-2. The internal reliability for the overall flow experience was .902.

To define the most suitable statistical test, following the recommendation of Wohlin et al. (2012), we calculated the data normality through the Shapiro-Wilk test (Razali & Wah, 2011). Hence our data are **normal** for measured aspects ($p \leq 0.05$), as well as, in our study we have one independent variable (i.e., the gamer types) with different dependent variables (the flow experience dimensions and the other students' experience), following the recommendation of Wohlin et al. (2012), we used uni-factorial ANOVA (Miller 1997) to analyze the effects of personalized gamification on students experience. Table 4 presents the result of our analysis. In summary, **the personalized gamification did not affected the students experience**, thus rejecting our hypothesis.

Data mining

For the data mining analyses, we initially decided to consider the set of all the information obtained during our study (i.e., all data from *BrainHex* questionnaire: gender ("Female", "Male", "Other", or "I prefer to not inform'), when they play ("Never",

Table 4 Students experience analysis (uni-factorial ANOVA)

	Mean	SD	Mean Square	*f*-value	*p* value
CSB	3.618	0.876	0.668	0.864	0.591
MMA	3.331	0.944	0.959	1.081	0.377
G	3.760	0.884	0.501	0.629	0.829
F	3.662	0.861	0.732	0.987	0.465
C	3.681	0.848	0.843	1.184	0.292
CTRL	3.625	0.903	1.120	1.402	0.159
LSC	3.505	0.939	1.178	1.362	0.179
T	3.443	0.894	0.680	0.845	0.613
A	3.619	0.995	0.774	0.773	0.688
Flow	3.583	0.679	0.397	0.856	0.600
Enjoyment	5.09	1.773	2.690	0.849	0.608
Perception	4.81	1.733	3.338	1.119	0.344
Motivation	4.77	1.718	1.470	0.485	0.932

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

"Rarely", "Occasionally", "Every week", or "Every day"), self-profile ("Midcore gamer", "Hardcore gamer", "Casual gamer" or "I have no idea!"), how they prefer to play ("Single player alone", "Virtual worlds or MMORPGs", "Multiplayer, over the internet", "Multiplayer, in the same room", "Virtual worlds or MMORPGs", "Single player with others" or "Team play or Clan play over the internet"), opinion about the importance of stories in a game ("Stories are not important to me in videogames", "Stories can help me enjoy a videogame", "I prefer video games without stories", "I don't play video games" or "Stories are very important to my enjoyment of video games"), first gamer and second gamer type. We also included all flow experience dimensions of each user, in both the personalized and non-personalized versions of the gamified educational systems). We conducted the experiment in a controlled environment (i.e., computer lab with personal computers).

To perform data mining analyzes, we also needed to provide structured information about our data set. We analyzed the five-number summary (FNS) for each flow experience dimension. This summary consists of the five most important sample percentiles: the sample minimum (smallest observation); the lower quartile or first quartile; the median (the middle value); the upper quartile or the third quartile; the sample maximum (largest observation) (Shi et al., 2018). Table 5 presents these results. The generated groups were also used to transform numerical data into nominal data to execute data mining (association rules).

Next, we analysed data using Association Rule Mining (ARM) (Agrawal et al., 1993), which is a method for discovering interesting relations between variables in large databases, using some measures of interestingness (Piatetsky-Shapiro 1991).

Through this technique, we identified a series of *if-then* patterns in our data. To carry out these tests, we transformed the numerical data referring to the data log obtained into nominal values based on its FNS. This choice is since we obtain a homogeneous division of the groups according to their characteristics. Following the

Table 5 Five number summary

	CSB	MMA	G	F	C	CTRL	LSC	T	A	Flow
Non-personalized version										
Min.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1st Quart.	3.062	2.750	3.312	3.250	3.250	3.000	3.000	2.750	3.000	3.118
Median	3.750	3.500	4.000	3.500	3.750	3.750	3.500	3.500	3.750	3.556
Mean	3.633	3.383	3.805	3.627	3.674	3.609	3.512	3.412	3.623	3.587
3rd Quart.	4.250	4.250	4.500	4.250	4.250	4.250	4.188	4.000	4.500	4.076
Max.	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	4.861
Personalized version										
Min.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1st Quart.	3.000	2.750	3.250	3.250	3.062	3.000	3.000	3.000	3.000	3.167
Median	3.500	3.250	3.750	3.750	3.750	3.500	3.500	3.500	3.750	3.625
Mean	3.611	3.301	3.707	3.711	3.691	3.645	3.506	3.486	3.641	3.589
3rd Quart.	4.250	4.000	4.438	4.250	4.250	4.438	4.250	4.000	4.438	4.076
Max.	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000	5.000

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

literature recommendations (Huang et al., 2000; Yuan & Huang, 2005), we used the criteria support, confidence and lift to identify the most important relationships. To execute the the analysis, we used the *Apriori* algorithm, one of the most popular algorithms to discover frequent *itemsets* from a data set and derive association rules (Wu et al., 2008). We run our tests using the R programming language[2] within the *RStudio* software[3]. We used the native packages "Arules" and "arulesViz". All the codes used in our analyzes, as well as our data set, can be found in the supplementary materials.

Initially, after the *Apriori* algorithm execution, we obtained a total of 6852 rules and after using the "Pruning" technique (Ahmed et al., 2011) the list of rules decreased to 5532. In the sequence, we defined some parameters (rules with a support less than 0,100; confidence less than 0,900 (90% confidence level); and lift less than 1,300) as recommended by Huang et al. (2000) and Yuan and Huang (2005). After this treatment (indices filtering) we obtained 244 rules. Furthermore, we also analyzed each of the 244 rules individually (human filtering) in order to remove obvious rules (i.e., obvious rules given the nature of the study, e.g., *if* CT-CSB *is* medium *and* T-A *is* medium *then* T-Flow *is* medium) and meaningless rules (i.e., rules that don't make sense or are outside the scope of the analysis, e.g., *if* CT-G *is* medium *and* T-Flow *is* medium *then* CT-Flow *is* medium). After these analysis, we obtained 12 rules. Fig. 9 summarize this process.

Gender-related rules

In this section, we present the rules found showing patterns related to the gender of the students. In total, eight rules were found. Table 6 presents the rules.

[2] https://www.r-project.org/

[3] https://rstudio.com/

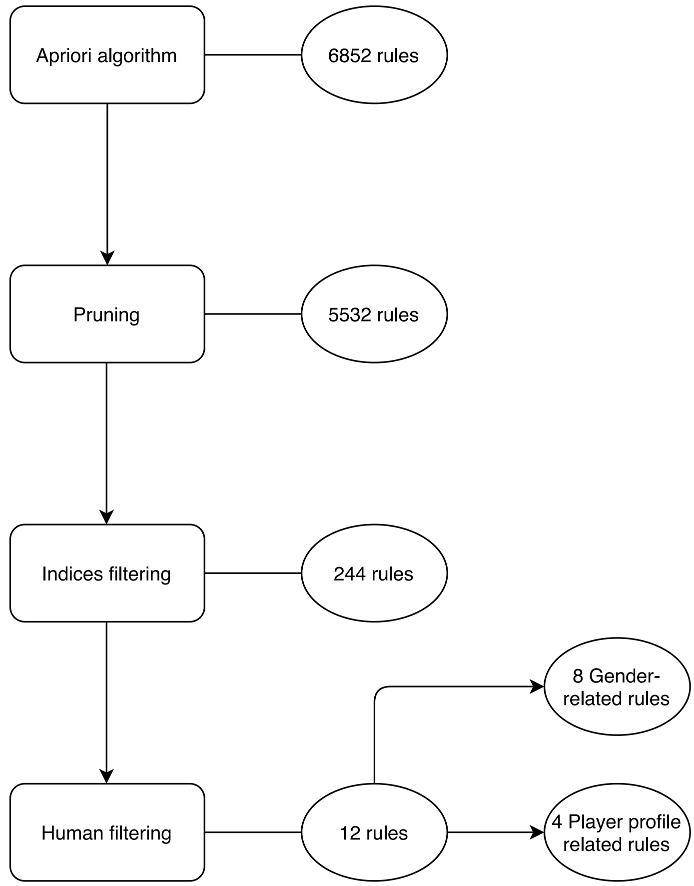

Fig. 9 Data mining process

Table 6 Gender-related rules

Id	Rules	Support	Confidence	Lift
1	*if* NP_G *is* very_high *and* SeflProfile *is* Hardcore gamer *then* Gender *is* Male	0.107	1.000	2.14
2	*if* WhenPlay *is* Never *then* Gender *is* Female	0.107	1.000	1.877
3	*if* SeflProfile *is* I have no idea! *and* HowPlay *is* Single player alone *then* Gender *is* Female	0.107	1.000	1.877
4	*if* History *is* I don't play videogames *then* Gender *is* Female	0.172	0.955	1.792
5	*if* SeflProfile *is* I have no idea! *and* History *is* I don't play videogames *then* Gender *is* Female	0.131	0.941	1.767
6	*if* P_C *is* high *and* History *is* Stories are very important to my enjoyment of videogames *then* Gender *is* Male	0.107	0.929	1.987
7	*if* NP_Flow *is* medium *and* History *is* I don't play videogames *then* Gender *is* Female	0.107	0.929	1.743
8	*if* NP_Flow *is* medium *and* P_CTRL *is* medium *and* WhenPlay *is* Rarely *then* Gender *is* Female	0.107	0.929	1.743

NP_G, clear goals in the non-personalized system; P_C, concentration in the personalized system; NP_Flow, flow experience in the non-personalized system; P_CTRL, sense of control in the personalized system

Player profile related rules

In this section, we present the rules found showing patterns related to the students' player profile. In total, four rules were found. Table 7 organize the rules.

Table 7 Player profile related rules

Id	Rules	Support	Confidence	Lift
1	*if* P_T *is* high *and* SeflProfile *is* Hardcore gamer *then* P_Flow *is* high	0.107	1.000	2.103
2	*if* P_A *is* high *and* SeflProfile *is* Hardcore gamer *then* P_Flow *is* high	0.107	0.929	1.953
3	*if* P_Flow *is* medium *and* HowPlay *is* Multiplayer *and* over the internet *then* NP_Flow *is* medium	0.115	0.933	2.233
4	*if* NP_Flow *is* high *and* HowPlay *is* Multiplayer *and* over the internet *then* P_Flow *is* high	0.107	0.929	1.953

P_T, sense of transformation of time in the personalized system; P_Flow, flow experience in the personalized system; P_A, *autotelic* experience in the personalized system; NP_Flow, flow experience in the non-personalized system

Discussions and implications

This article has presented thus far the most comprehensive look on studies in personalized gamification; a field that has seen noteworthy increases in the past few years, however, that continues with an open question about how gamer types-based personalization affects the students' flow experience and other perceptions (e.g., motivation and enjoyment). The results presented in this article, above all, allowed us to realize that personalization, as implemented in the *MeuTutor* system and investigated in our study, did not present a significant difference under the aspect of the students' flow experience. However, it also revealed some aspects that may have contributed to these results, and that can be considered in new studies in the domain of personalized gamified educational systems.

In summary, our main conclusions are: *i)* personalization of gamification based on gamer types did not significantly affect the students' flow experience, perception of gamification and motivation; *ii)* students with some gamer types (e.g., Achiever' and Socializer) had a better enjoyment in the non-personalized system; *iii)* people who play more have a greater tendency to have positive results with gamification; and *iv)* participants who have indicated that they never play are female. Based on the conclusions and the comparison of our results with the results of other recent studies, we can advance the literature on some points.

Our results show that for Achievers, the best experience in both measured aspects has always occurred in the non-personalized system, similar to the Seekers and Socializers, where also, the study's participants have always indicated a better experience in the non-personalized version. This result shows that the best experience in the non-personalized system was not only in terms of the users' flow experience but also in the other aspects evaluated. Such result is contrary to many of the studies cited in the related works section (Lavoué et al., 2018; Marinho et al., 2019; Stuart et al., 2020), which in general show that there was no difference between the versions of the system or that the personalized version provided better results.

For Conquerors participants, enjoyment was higher in the non-personalized system, however, the perception regarding the gamification elements was higher in the personalized system, while the motivation was the same in both versions of the system. For Daredevil participants, enjoyment was greater in the personalized version, however, the perception of gamification and motivation was greater in the non-personalized system. Finally, for Survivors, the perception of gamification and motivation was greater in the personalized system, while enjoyment was the same (see Table 4).

These results indicate that there was no unanimity between the different profiles regarding the personalized and non-personalized versions, similar to the results regarding the students' flow experience, reinforcing for example the results of the study conducted by Oliveira et al. (2020). However, there was no significant difference in carrying out the hypothesis test, indicating that compared to other studies (Lavoué et al., 2018; Marinho et al., 2019; Stuart et al., 2020), our results can be seen as surprising.

Also, no rules were found related to differences in the flow experience when students used a personalized version for their gamer type or a non-personalized version. However, other significant rules related to different participants' characteristics were found. We organized all of our rules into two groups (rules related to the **gender of participants** and rules related to **player characteristics**). These results implies that personalization did not work as expected for the participants of this study, as presented by Oliveira and Bittencourt (2019c), this may have occurred due to some points:

- **Low-level personalization**: this concerns the fact that the personalization (which in our study focused on the gamification elements) could be not enough to alter a deeper user experience (such as the flow experience). At the same time, the general gamification design may not be good enough to affect users' deeper experiences;
- **Concentration in the first player type**: this concerns the fact that personalization was based only on the main gamer type profile of each player, without considering the secondary profile of the player. This may have been a weak personalization strategy, unable to achieve all aspects of personalization necessary for each individual;
- **Use of a player model for games**: this concerns the fact that the study used a player model focused on games (i.e., BrainHex), and not on gamified systems;
- **Gender and age of participants**: this concerns the fact that personalization focused only on the most suitable gamification elements for each profile, without considering the age, gender, demographic aspects, type of activities and context of these participants, which may leave out important characteristics for personalization.

About the gender related rules, the rule 1 indicates that when the experience in the dimension of "clear goals" was "very high" (5 in the Likert scale) and the participants declared themselves as a "hardcore gamer", then the gender was male (see Table 6). This rule shows that even when it comes to a gamified system (and not exactly a game), participants who play more might have a greater tendency to have positive results with gamification, including having a better flow experience. This may also be because they had a clear understanding ("clear goals" was "very high") of the activities they were doing.

The rule 2 shows that the participants who have indicated that they never play are female (see Table 6). This result can confirms that in some places, the culture of playing video games is not yet fully distributed among the genders, being more common in the male audience. This rule is confirmed by rules 4 and 5 (see Table 6), which show that concerning the importance of history in games, most girls indicated that they do not play video games and that they have no idea of their profile as a player (in the question about “the importance of history in games”, have an option to indicate that “do not play games”).

The rule 3 indicates that those who have no idea about their profile as a gamer and prefer to play alone, are female (see Table 6). This result is important because it highlights that in addition to females in general not playing as much as males, they prefer to play alone. This type of aspect can be fundamental to provide better personalization in gamified educational systems. For instance, the activities-based personalization (in groups or alone, collaborative or competitive) must be considered according to each gender.

The rule 6 shows that when a participant had a high concentration in the personalized system and indicated that stories are very important to their enjoyment of video games, these participants, in general, were male (see Table 6). The rule may be indicative that if, on the one hand, female participants do not play as much as males, in the other hand, the history of the game or the gamification system can be important for males and help to have a higher level of concentration.

The rule 7 highlights that when the flow experience was “medium” (three in the Likert scale) in the non-personalized version and does not play video games, they are female (see Table 6). This corroborates the rules previously presented and shows that participants who do not play video games (in the case of our female participants), may have a kind of difficulty in accepting gamification and have a better experience in this type of system, especially when it is not personalized. This rule is corroborated by rule 8.

About the player profile related rules, rules 1 and 2 support what was already presented in the previous section (see Table 7), indicating that possibly, people who have more interaction with games (people who claim to be hardcore gamers) may easier achieve a higher flow experience in personalized versions.

Rules 3 and 4 indicate that when the flow experience of those who prefer to play multiplayer and over the internet was medium in the personalized version, in the non-personalized version the flow experience was also medium and when it was high in one, it was also high in another (see Table 7). This rule may indicate that people who play online and therefore have more direct interaction in solving missions with other players have greater difficulty in achieving a flow experience in gamified systems, even when the system has personalization features for their profile, or that personalization based solely on the gamification elements makes no difference to people in that profile.

Limitations

In this section, we present some limitations that should be considered in future replications of this study. In general, we seek to mitigate the limitations generated in the study. Because it was a controlled experiment conducted in a classroom, external factors (e.g., noise and interference from colleagues) may have affected the students’ experience. We mitigate this limitation by asking students to focus on activities and avoiding teacher interference during the experiment. The students used the system for more than 30 minutes before responding to the survey, so, they may have been tired when responding to the survey. At the same time, perhaps this time is not enough for students to achieve the flow experience. In this way, some experiences measured in our study (e.g., flow experience) can be difficult to measure. To mitigate this limitation, whenever possible, we used a previews validated instrument (e.g., DFS-2). However, not all instruments used in the study are validated instruments (e.g., BrainHex). Specifically, the player model used in our study (i.e., BrainHex) may be unreliable and have issues with its psychometric properties (Fortes Tondello et al., 2018). Thus, we also recommend future replications of our study using others different player models (e.g., Hexad).

In our study, the data allows us to identify the main gamer types of each student. However, recent studies show that just the main game type is not enough to customize gamified systems. Future studies should collect data to identify the percentage of all gamer types for each participant. Our sample size was composed of 121 participants. To mitigate possible limitations regarding the sample size, we conducted a blocking factorial experiment (following a within-subjects design), where participants from the same group used both version of the system. Additionally, subjects of this evaluation should be expanded to other academic settings to obtain more generic results. The system used in this experiment has an interface design (in terms of gamification elements), so the students' experience in the system can be influenced by the system design beyond the gamification elements. At the same time, the general quality of the system can also influence the student's experience and need to be observed in futures replication for this experiment.

Research agenda proposal

Initially, in our study, as well as in related studies (e.g., Monterrat et al., 2015; Lavoué et al., 2018; Oliveira et al., 2018), gamification personalization is usually based only on gamification elements. Recent secondary studies (e.g., Böckle et al., 2017; Koivisto & Hamari, 2019; Hallifax et al., 2019) show that not only in studies related to education but in other domains (e.g., Health and Crowdsourcing), in general, personalization focuses on identifying the users' gamer types (or in some cases users' gender) and providing different gamification elements for each profile. This approach is important because, in games studies (base for gamification) (Rapp et al., 2019), the players' types and their preferences regarding the game elements have been investigated for many years (Bartle 1996). However, other aspects can influence the preferences of the participants concerning the gamified systems (Hallifax et al., 2019; Böckle et al., 2017; Oliveira & Bittencourt, 2019c).

Likewise, in addition to other personal aspects that may influence preferences for gamification elements, it is important to remember that gamified systems are not formed only by gamification elements, but several other aspects (e.g., screen components and colors) (Oyibo & Vassileva, 2017). Thus, without isolating the gamification elements from these other components, it is difficult to know whether the students' perception has been influenced only by the gamification elements (the focus of the studies) or by other components of the interface. In this sense, we recommend that new studies aiming to evaluate the personalization of gamification can consider other related aspects, such as the gamification design as a whole (e.g., gamification elements colors and visual aspects, elements position (in the users' interface), the moment when the elements will appear to users, and how the elements will go when relating to system educational activities and other components' interface).

Similarly, in our study, we defined the personalization design, based only on the students' gamer types (and not on gender, age or demographic profiles). Likewise, other recent studies (e.g., Orji 2014; Monterrat et al., 2014a; Oliveira et al., 2018) also proposed the personalization based on only one aspect (e.g., gamer type or gender). However, the results of our study (and the other mentioned studies) call attention to the need to propose a personalization design that is based on more than one aspect at the same time.

Although personalization based on gamer types is a primary and fundamental approach to personalizing gamified systems (Orji et al., 2013; Lavoué et al., 2018; Oliveira & Bittencourt, 2019c), we know that several other personal aspects can affect our preferences about the different aspects in a information system (Greene & Gynther, 1995; Karniol 2011; Vail et al., 2015). Thus, we recommend conducting new studies that can investigate different aspects of people's preferences for elements of gender, age, demographic data of users, and types of activities.

Another important factor is that the results obtained may have occurred due to considering only the first gamer type of each participant, which, according to recent studies (e.g., Hallifax et al., 2019), may be a negative aspect. This is because studies have shown that we do not have a single profile but a composition of profiles resulting from different characteristics and influenced in different ways in our preferences and perceptions (Tondello et al., 2017). Likewise, until today there are no studies that show whether people change their profile (gamer type) over time and if so, how often these changes can occur.

In this context, when investigating users' preferences for gamification elements, as well as presenting different gamified interfaces for users of information systems (e.g., gamified educational systems), it may be important to seek to identify their profiles and subprofiles, as well as, the percentage of the profile for each user, in addition to providing personalization more focused on these individualities. Thus, we recommend for new studies to consider not only the first gamer type of each user but also to consider the percentages for each gamer type, looking for ways to automate the process of identifying the profile of the players and to personalize gamification in real-time.

In our study, we used the *BrainHex* player model, however, studies carried out more recently have identified that there are other player models more suitable for the gamification domain (Hallifax et al., 2019) and with better psychometric validation (e.g., Hexad Tondello et al., 2016, 2019). Hexad, for example, considers that we do not have a single profile, but a fusion of different profiles and provides a percentage of how much closer each individual is to each profile (Tondello et al., 2016). This can help for example to more suitable profile for a person and provide a more assertive personalization.

Thus, to update the use of instruments in this type of study, as well as to make a more appropriate identification of the profile of participants in new studies, we suggest that new studies may consider other player models such as Hexad (Tondello et al., 2019) when considering personalizing gamification based on gamer types. Further studies should be conducted, for example, to identify which gamification elements (and other design aspects of gamification) are most appropriate for each Hexad player type, as well as to evaluate new design proposals based on these profiles.

In our study, we did not consider a specific type of activity, without personalizing gamification according to some type of educational activity (e.g., video, questionnaire, reading, among others). Especially, in educational systems, the gamification elements, in general, are associated with the educational activities provided in the system (Werbach & Hunter, 2012; Rodrigues et al., 2019). Thus, according to recent studies (e.g., Baldeón

Table 8 Research agenda

Challenges/suggestions	Suggested research methods	Suggested references
Personalization based on different interface aspects (e.g., gamification elements colors and position, interface components and colors)	Surveys (to investigate which interface aspects can be personalized); Design science research (to provide test applications)	Monterrat et al. (2015), Böckle et al. (2017), Lavoué et al. (2018), Oliveira et al. (2018), Koivisto and Hamari (2019), Hallifax et al. (2019)
Personalization based on different user characteristics (e.g., gender, age, and demographic aspects)	Surveys (to investigate which user characteristics can influence their preferences); Design Science Research (to provide test applications); experiments/quasi-experiments, field studies, case studies and focus groups (to examine the users' preferences and evaluate proposed approaches)	Lavoué et al. (2018), Oliveira and Bittencourt (2019c), Hallifax et al. (2019)
Personalization considered multiple gamer types (e.g., second user gamer type or gamer types characteristics percentage)	Design Science Research (to provide test applications); experiments/quasi-experiments, field studies, case studies and focus groups (to evaluate proposed approaches)	Hallifax et al. (2019), Koivisto and Hamari (2019), Bai et al. (2020)
Personalization considering modern player models and appropriate to the gamification domain (e.g., Hexad)	Experiments/quasi-experiments, field studies, case studies and focus groups (to evaluate the users' preference based on these player models)	Hallifax et al. (2019), Oliveira and Bittencourt (2019c), Bai et al. (2020)
Personalization based on educational activities	Surveys (to investigate which most suitable gamification design for each type of activity); Design Science Research (to provide test applications); experiments/quasi-experiments, field studies, case studies and focus group (to evaluate proposed approaches)	Baldeón et al. (2016), Rodrigues et al. (2019), Bovermann and Bastiaens (2020)

et al., 2016; Rodrigues et al., 2019; Bovermann & Bastiaens, 2020), the association between the type of activity provided and the elements can alter the users' perception of the system experience, drawing attention to a new type of gamification customization based on the type of educational activity.

Thus, to provide a deeper adaptation focused not only on general aspects of educational systems but also on aspects related to the educational activities provided in the system, we suggest that new studies may also consider these aspects in personalization, initially, seeking to identify whether there are elements of gamification that can better adapt to each type of educational activity, and then propose and evaluate systems that offer these aspects of personalization. Table 8 presents a summary for the proposed research agenda.

Concluding remarks

In recent years, studies have been conducted to enhance existing gamified systems using different approaches. One of the most recently worked on approaches is the personalization of gamified educational systems, expecting to provide systems with the gamification design composed according to the users' characteristics. However, this approach still presents contradictory results, calling attention to the need for new studies that can bring more concrete results on the effectiveness of personalized gamification in educational systems.

To confront this challenge, we personalized an static version of a gamified educational system according to the students' gamer type (using the *BrainHex* player model) and then compared the personalized version with the non-personalized version of the system in terms of the participants' flow experience, enjoyment, gamification perception, and motivation. The results of this study indicated that there was no significant difference in the students' flow experience, gamification perception and motivation, however, was a significant difference in terms of students' enjoyment (for two different gamer types). Also, to obtain even more profound results, we conducted further analysis of the data through data mining techniques. The new results confirmed that there was no difference in terms of students' flow experience, however, they provide us insights that can indicate what led to these results and guide the conduct of new studies.

The results of the study allowed us to advance the state of the art, recognizing that, not always, personalizing the gamification will increase its effectiveness, especially in stimulating deeper user experiences (e.g., flow experience), suggesting that more studies are needed to evaluate new perspectives of personalization. As future work, we hope and suggest evaluating new perspectives for the personalization of gamification in educational systems, seeking to provide more complete personalization, based on both more sophisticated user models including for example, gender, richer personality models, culture etc and adapting not only on the game elements, but also other aspects, such as the system interface design and aesthetics, and the educational activities.

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Authors' contributions
WO: Conceptualization, Methodology, Formal analysis, Validation, Writing—review & editing. JH: Supervision, Methodology, Validation, Writing—review & editing. SJ: Conceptualization, Formal analysis. AMT: Conceptualization, Formal

analysis, Validation, Writing - review & editing. PTP: Conceptualization, Formal analysis, Validation, Writing—review & editing. JV: Supervision, Writing—review & editing. SI: Supervision. All authors read and approved the final manuscript.

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Original dataset available as supplementary material

Code availability
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Competing interests
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