Personalized gamification: A literature review of outcomes, experiments, and approaches

Luiz Rodrigues
Institute of Mathematics and Computer Science
University of São Paulo
São Carlos, São Paulo, Brazil
lalrodrigues@usp.br

Armando M. Toda
Institute of Mathematics and Computer Science
University of São Paulo
São Carlos, São Paulo, Brazil
armando.toda@usp.br

Paula T. Palomino
Institute of Mathematics and Computer Science
University of São Paulo
São Carlos, São Paulo, Brazil
paulatpalomino@usp.br

Wilk Oliveira
Institute of Mathematics and Computer Science
University of São Paulo
São Carlos, São Paulo, Brazil
wilk.oliveira@usp.br

Seiji Isotani
Institute of Mathematics and Computer Science
University of São Paulo
São Carlos, São Paulo, Brazil
sisotani@icmc.usp.br

ABSTRACT

Personalized gamification has gained substantial interest due to the expectation that it can improve gamification's success. Considering some secondary studies on this topic, they lack to present the characteristics of empirical studies and some aspects on how personalization approaches were designed. In this paper, we present a literature review based on previous research to address these gaps. Based on our analysis, our results provide: insights on how experiments to compare personalized gamification and non-personalized gamification are designed and evaluated; evidence on the effectiveness of personalized gamification found in primary studies; and an overview of how personalization approaches were designed. Our analysis converged in possible guidelines and a research agenda revealing five main needs: i) empirical studies comparing one size fits all and personalized gamification; ii) qualitative user studies; iii) personalization approaches that consider contextual characteristics as well as iv) rely on a broader, unambiguous set of game elements; and v) a benchmark of established resources to increase research reproducibility.

CCS CONCEPTS

• **Applied computing** ~ Education ~ Interactive learning environments • **Human-centered computing** ~ Human computer interaction (HCI) ~ Interaction techniques

KEYWORDS

Gamification, personalization, tailoring, literature review

ACM Reference format:

Rodrigues et al. 2020. Personalized Gamification: A literature review of outcomes, experiments, and approaches. In *Proceedings of the International Symposium on Gamification and Games for Learning (GamiLearn'20). ACM, Salamanca, Spain, 8 pages.* https://doi.org/to-be-defined

1 Introduction

It has been argued that, for gamified applications, one size does not fit all [41]. Given that the same gamification design is unlikely to work for all users, researchers started to investigate personalized gamification. That is, tailoring game elements based on information about the users aiming to improve gamification's effectiveness [59]. This approach is based on the fact that people with different characteristics have different preferences, perceptions, and experiences [47, 51, 61]. Consequently, by offering gamification designs tailored to users' characteristics, providers expect to improve their experiences and, thus, gamification's success [59].

Due to such expectations, personalized gamification has substantially attracted researchers' attention. A significant number of studies have been published, which have been recently summarized in a few literature reviews (e.g., [1, 27, 28]). However, two points were not addressed in previous research. First, despite some literature reviews analyzed the results from empirical studies [1,19], *they do not present a broad analysis of how personalized gamification's impact was assessed*. That is, aspects such as the control group that personalized gamification was compared to and the sample sizes, which would provide a valuable understanding of the validity of those experiments. Hence, although primary studies mostly report positive outcomes, as indicated in Hallifax et al. [19], whether using personalization improves one size fits all gamification remains unknown. To fill this gap, this paper investigates ***how empirical studies employing personalized gamification have been conducted to answer whether personalization improves one size fits all gamification effectiveness***.

Second, *some issues related to how personalization approaches were designed have not been discussed in previous research*. In this regard, none of the secondary studies discuss how the game elements at a given personalization approach were selected. This aspect is important because self-selection might lead the approach to ignore some game elements or use different names to represent elements with the same goal (e.g., both medals and trophies provide acknowledgment), leading to ambiguity in the experience they will provide to users. To illustrate such limitations, one might consider a personalization approach that uses game elements from the literature review by Nah et al. [42]. Although systematic, using this source would lead to an approach that does not consider the Collaboration game element, while featuring badges, prizes, and rewards, all of which have highly similar goals [58].

Additionally, the approach's development method is another relevant aspect that is discussed in a single related work. Klock et al. [27] discusses the algorithms used in that process (e.g., linear regression and factor analysis) as well as how those were evaluated, where survey and questionnaires were used most often. To provide a complementary point of view, we discuss whether those were developed based on theory or data. That is, whether they are theory- or data-driven. A clear understanding on which of those approaches has been used is important to shed light on development trends, especially considering the novelty of data-driven gamification, which has been advocated to enable the development of more tailored gamification designs than theory-driven alternatives [35]. To fill these gaps, this paper investigates ***how approaches for personalizing gamification have been developed, especially focusing on development choices, such as personalization criteria, the kind of source each approach relied on to select the game elements it uses, and whether it is theory- or data-driven.***

Therefore, our main objective is to conduct an exploratory study, through a literature review process, to expand the current body of knowledge on the impacts, approaches, and insights adopted to design personalized gamification systems. To achieve this goal, our study focuses on answering the following questions (RQ): (**RQ1**) *How empirical studies employing personalized gamification have been conducted?* (**RQ2**) *Does personalized gamification improve one size fits all gamification effectiveness?* and (**RQ3**) *How approaches for personalizing gamification have been developed?*. Thus, our main contributions are:

- Revealing the impact of personalized gamification;
- Showing an overview of how empirical studies have been conducted in this context; and
- Providing insights on how personalization approaches were developed.

Furthermore, we answer our RQ by extracting information from the studies included in previous literature reviews as they were recently published, a context in which conducting a new systematic process would be of little benefit [16]. Thereby, speeding up the process of communicating our findings while answering new research questions based on a state-of-the-art view.

3 Method

To achieve the objectives of this study, we opted to conduct an exploratory study since this kind of study is conducted to delve deep into an existing problem aiming to explicit it [32]. We choose to analyze existing works on the field that were found in previous literature reviews on the subject, since the studies were published recently [1, 19, 27, 28] and there is no need for updating the existing reviews [16]. Based on the exposed, we analyzed points that previous studies did not (i.e., how empirical studies have been conducted and how personalization approaches have been conducted).

To conduct this literature review, we defined two steps that are commonly encountered in other literature review processes, such as Kitchenham [26] and PRISMA checklist [64]: Studies selection and Data extraction. The first encompasses the process of selecting our studies based on predefined criteria, while the second step consists in defining and extracting information to answer our research questions.

3.1 Studies Selection

Figure 1 summarizes the study selection process. For study selection, our main criterion was secondary studies focused on personalized gamification. That is, we relied on recent secondary studies rather than conducting another systematic literature review. The secondary studies on personalized gamification that we screened have been published between three months and two years before the time of writing, covering state-of-the-art research on this topic. In addition, those have been published in varied venues, ranging from general human-computer studies [27] to the perspective of learning technologies [19]. Given that context, conducting a new systematic process would be of little benefit [16]. Thereby, our approach speeds up the process of communicating our findings while answering new research questions based on a state-of-the-art view.

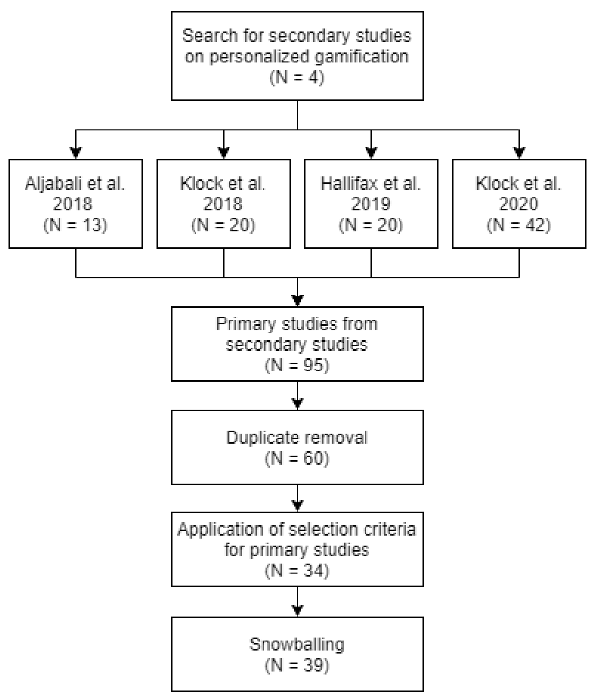

Figure 1. Study selecion process. N represents the number of studies selected after each step.

Based on the secondary studies' results, our selection criteria for primary studies were that they should either i) present an empirical study employing personalized gamification or ii) present an approach for personalizing gamification; that is, providing recommendations/guidance on how to tailor gamification designs to some specific criteria. Nevertheless, we also included other primary studies through snowballing, by verifying which studies cited the analyzed study, allowing us to collect some recent studies that were recently published and, therefore, could not be added in previous literature reviews. Thus, primary studies included in this paper are those meeting the aforementioned inclusion criteria and either found during our literature searches or included in the following secondary studies, which were selected in an ad-hoc manner: [1, 19, 27, 28].

3.2 Data Extraction

We extracted data from the included studies following the categorization presented before (i.e., empirical studies and recommendations). Figure 2 summarizes data extracted from each study of each category, which are further described next.

In reviewing recommendations, we focus on four main characteristics. The *first* characteristic is the personalization criteria, which we further split in two: user (e.g., demographics) and context (e.g., gamified task). This is important to demonstrate if approaches are exploring all kinds of characteristics known as relevant for gamification success.

The *second* is how the recommendation was developed, which might be theory- (e.g., linking game elements to some characteristics based on theories behind those) or data-driven (e.g., exploring data from users' behavior, opinions, or preferences to determine the recommendations). This is important to understand which development approach has been used more or less.

Third, we consider how the recommendation's game elements were selected (e.g., from a literature review or some taxonomy). The relevance of this choice is avoiding selection bias as well as preventing the recommendation of ambiguous game elements.

The *fourth* characteristic is to which domain the recommendation was built for (e.g., education or general; that is, no specific domain), which is important as the domain is another aspect that needs to be considered when designing gamified systems.

In reviewing empirical studies on the use of personalized gamification, we follow two main perspectives. One is analyzing the effect of personalized gamification overall, as well as that of different personalization approaches. To that end, we extracted the kind of outcome analyzed and whether personalization was positive, null, mixed, or negative for each kind. The other perspective concerns understanding how such experiments have been conducted, aiming to identify best practices and perspectives needing to be tackled. Then, we extracted the condition personalization was compared to, the personalization criteria, the number of game elements in each condition, the intervention duration, the sample size, the data analysis form, and the study context.

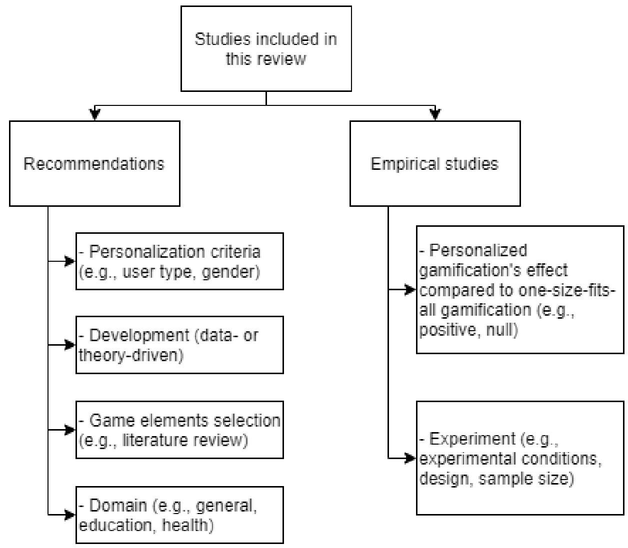

Figure 2. Data extracted from selected studies depending on their type. Recommendations provide guidance on how to personalize gamification whereas empirical studies perform user studies applying personalized gamification.

4 Results and Discussion

This section presents and discusses the results of each RQ.

4.1 RQ1: How empirical studies employing personalized gamification have been conducted

Table 1 summarizes the empirical studies included in this review[1]. A key point to understanding those studies is the condition to which personalized gamification was compared. Frequently, the baseline comparison was random gamification; that is, randomly selected game elements [38, 53, 56]. There were also comparisons to no gamification [23, 25, 31, 38]. Additionally, there were cases in which comparisons were made to counter-tailored gamification; that is, when users receive the game element they (are expected to) prefer the less [31, 36, 38]. The main problem of such approaches is that personalized gamification emerged as a means to improve one size fits all gamification's effectiveness, and comparing it to random, counter-tailored, or no gamification does not contribute to understanding whether that objective was met.

On the other hand, some studies indeed compared personalized to one size fits all gamification. Hassan et al. [21] is one of these works, however, their experimental condition featured adaptive learning as well as gamification. Similarly, the personalization approach in Daghestani et al. [9] influenced the content's difficulty as well as the help (e.g., guidance on further readings) users received. Such approaches limit the understanding of whether personalized gamification was the source of the results as it was not experimentally controlled. Differently, three studies controlled personalized gamification experimentally, comparing it

[1] [56] appears three times because authors compared three personalization strategies to a control condition.

Table 1. Overview of empirical studies included in this review.

Ref	Compared to	Personalization Criteria	# GE	Intervention Duration	Sample size	Measured Outcome	Data analysis	Context
[9]	OSFA	Gamer type*	21/2-2	?	76	M~, C+	Qt	Undergraduate class
[44]	OSFA	Gamer type	9/?	<1 day	121	M~	Qt	Elementary students
[17]	OSFA	Likes	3/2-3	2 months	2102	B+/-	Qt	Social network users
[39]	OSFA	User type	?/2-3	14 weeks	81	B+/-, M+/-	Qt	Undergrad online class
[21]	OSFA	Learning style*	5/2-5	?	175	B+, M+	Qt	Undergrad class
[38]	OSFA, NG, CT, R	Gamer type	0-3/1	<1 day	59	B+/-, M+/-	Qt	Middle school
[23]	NG, Cmp, Col	Performance	0-1/2	<1 day	54	B+/-	Mx	Primary class
[53]	R	Motivation style	?/2-3	1 month	100	B+	Qt	Undergrad class
[56]	R	User type	1/1	6 weeks	258	B+/-, M~	Qt	Daily children
[56]	R	IM	1/1	6 weeks	258	B~, M+/-	Qt	Daily children
[56]	R	User type and IM	1/1	6 weeks	258	B+/-, M+/-	Qt	Daily children
[36]	CT	Gamer Type	2/2	3 weeks	280	B+, M+/-	Qt	Daily adults
[31]	NG, CT	Gamer type	2/2	3 weeks	266	B+/-, M+/-	Qt	Daily adults
[25]	NG	Age*	1/1	<1 day	40	B+/-	Qt	Primary class
* Personalized gamification was not controlled experimentally								
#GE = Number of game elements in personalized/baseline condition; OSFA = one size fits all; NG = no gamification; Cmp = competitive gamification; Col = collaborative gamification; CT = counter-tailored gamification; R = random gamification; IM = Initial motivation; ? = information undefined in the study; M = motivational; C = cognitive; B = behavioral; + = positive; +/- = mixed; ~ = null; Qt = quantitative; Mx = mixed.								

to one size fits all gamification in terms of students' flow experience [44], undergraduate learners' motivation and behavior [39], and social network users' behavior [17]. Note that there is a condition studied in Monterrat et al. [38] that might be considered one size fits all: providing all three game elements deliberately selected during the study. However, authors do not compare this condition to the one with tailored gamification.

Concerning the empirical setups, most studies experimented with few elements in both the personalized and the baseline conditions (i.e., around one and three game elements in each), with a few exceptions [9, 21, 44]. Furthermore, few interventions lasted less than a day [23, 25, 38, 44], while the majority lasted between three and eight weeks (or two months), most sample sizes ranged from 40 to 280, with a case of studying a social network that featured over 2000 participants [17], and the application contexts were varied, including primary, elementary, middle, and undergraduate classes, social networks, and adults and children daily tasks. This overview demonstrates empirical studies were conducted in varied settings, mostly using few game elements in both conditions and with sample sizes and time frames (interventions duration) comparable to overall gamification studies [2, 30, 54].

Another point is that all but one study employed a quantitative data analysis approach. As personalized gamification is a recent field [27, 62], performing qualitative analyses could substantially contribute to the field by shedding light on users' perceptions of personalized gamification designs. Those insights are likely to help designers to better understand how to personalize as well as reasons for unexpected findings.

Concerning the personalization criteria, all studies considered either user's characteristics, such as Brainhex gamer types [40] (e.g., [9, 44]) and Hexad user types [34, 63] (e.g., [39, 56]), or interactions (e.g., [17]). Hence, demonstrating a predominant focus on user characteristics. This predominance reveals a gap in studying the impact of personalization approaches exploring contextual criteria (e.g., [3, 5]), despite the literature has acknowledged and recommended research should explore this vein [19,30, 33, 52].

4.2 RQ2: Effectiveness of Personalized gamification compared to one size fits all gamification

Primary studies suggest personalized gamification's effects are mixed. Overall, outcomes are mixed in terms of positive with null (e.g., [9, 25, 39]), although in some cases both positive and negative results have been reported (e.g., [17, 38]). In other cases, the reported findings were overall null [44, 56] or positive [21]. As shown in Table 1, these mixed findings appear to hold regardless of analyzing motivational, behavioral, or cognitive outcomes. Nevertheless, the baseline comparison for those findings was varied. Therefore, one can only assure that, for instance, personalized gamification is more effective than counter-tailored or random gamification. However, in seeking to understand how personalized gamification compares to one size fits all gamification, these results must be analyzed with caution. As discussed before, only three studies compared personalized and one size fits all gamification through a proper experimental setting. In this context, Oliveira et al. [44] found personalization did not affect elementary students' flow experience. Mora et al. [39] found positive but statistically insignificant results from personalization use based on undergraduate learners' motivation and behavior. Outside the educational context, Hajarian et al. [17] found both positive (e.g., in time-in-system) and negative (e.g., in gamification usage) results for their like-based personalization approach for social networks. Thereby, demonstrating that the few studies that contribute to understanding whether personalized gamification improves one size fits all gamification show inconclusive results. Thus, at the current point, the literature has insufficient evidence to confirm if available approaches for personalized gamification improves the general one size fits all approach.

4.3 RQ3: How approaches for personalizing gamification have been developed

Table 2 summarizes research on recommendations for personalizing gamification included in this review. Predominantly, these recommendations rely on user data criteria. More specifically, these criteria are user typologies [14, 15, 18, 22, 29, 36, 43, 47, 57, 60, 61, 63], personality [4, 6, 8, 10, 12, 15, 24, 46], demographics [11, 45, 49], and in-system behavior [7]. In contrast, the number of recommendations that consider contextual factors (i.e., four; [3, 5, 48, 50]) is substantially smaller compared to those considering some user aspect. Hence, demonstrating recommendations for personalizing gamification rarely consider contextual factors, which might explain the lack of empirical studies involving this kind of criteria.

Concerning recommendations’ development, data-driven approaches were most often adopted than the theory-driven ones. On one hand, recommendations build from theoretical concerns are commonly inspired by definitions behind criteria and game elements’ definitions, using those to link one to another (e.g., users with specific player type are more likely to enjoy specific game elements; [3, 6, 14, 15, 22, 37, 57]). On the other hand, data-driven development procedures are mostly based on surveys, asking users to indicate their preferences based on game elements definitions, storyboards, and prototypes (e.g., [5, 10–12, 18, 47, 60, 61]), as well as exploring users’ interactions to implicitly identify which are likely to be the best game elements for them (e.g., [4, 7, 29]). There is also the recommendation by [63], which relies on both perspectives; that is, exploring both user data and theoretical foundations. This context demonstrates most approaches have been developed based on data, such as user preference. Thereby, showing that personalization approaches are mainly embracing the recent perspective of data-driven gamification [35].
In terms of the game elements selection, studies explored games literature [3, 15, 29], gamification literature [5, 7, 22, 60, 63], informal [4, 10–12, 14, 18, 61] and systematic [24, 43] literature reviews, and, in other cases, deliberately made self-selections [6, 8, 36, 57]. In addition, there were cases in which the recommendations were to personalize persuasive [45–47] and

Table 2. Recommendations/guidelines for personalizing gamification included in this review.

Ref	Game elements selection	User Criteria	Context Criteria	Development	Domain
[47]	Persuasive strategies	User type	None	Data-driven	General
[60]	Marczewski work	User type, personality trait, age, gender	None	Data-driven	General
[61]	Informal literature review	User types, personality traits, age, and gender	None	Data-driven	General
[18]	Informal literature review	User type, gamer type, personality trait	None	Data-driven	General
[63]	Marczewski work	User type, personality traits	None	Mixed	General
[22]	Marczewski work	User type	None	Theory-driven	Education
[8]	Self-selected	Personality trait	None	Data-driven	Education
[10]	Informal literature review	Personality trait	None	Data-driven	Education
[12]	Informal literature review	Personality trait	None	Data-driven	Education
[24]	Gamification literature review	Personality trait	None	Data-driven	General
[6]	Self-selected	Personality trait	None	Theory-driven	General
[46]	Persuasive strategies	Personality trait	None	Data-driven	Health
[15]	Games literature	Bartle's player type and personality trait	None	Theory-driven	General
[14]	Informal literature review	Bartle's profile	None	Theory-driven	Education
[57]	Self-selected	Bartle's profile	None	Theory-driven	Education
[29]	Games literature	Bartle's profile	None	Data-driven	Education
[36]	Self-selected	Gamer type	None	Theory-driven	General
[43]	Gamification literature review	Gamer type	None	Data-driven	Education
[45]	Persuasive strategies	Gender	None	Data-driven	Health
[11]	Informal literature review	Age, Gender, gaming frequency	None	Data-driven	Education
[49]	Social Influence Strategies	Age, Gender	None	Data-driven	General
[4]	Informal literature review	Player role	None	Theory-driven	Education
[7]	Gamification literature	Motivational and gameplay strategy	None	Theory-driven	Education
[48]	Social Influence Strategies	Gender, Age	Culture	Data-driven	General
[50]	Social Influence Strategies	None	Culture	Data-driven	General
[3]	Games literature	Personality traits and learning style	LAT	Theory-driven	Education
[5]	Gamification literature	User type	Moodle's LA	Data-driven	Education

social influence strategies [48–50]. This context suggests most recommendations are built upon a set of game elements that was deliberately selected (e.g., self-selecting elements from games literature) or from literature reviews that summarize game elements used in, for instance, previous gamification research. A limitation is that these summaries are prone to featuring ambiguous game elements due to the lack of validation (e.g., experts assessing similarities) and might fail to consider less common ones because they are rarely studied. Thus, available recommendations likely will suffer from similar limitations.

Lastly, recommendations to only two specific domains were found. These are health [45, 46] and education [3–5, 7, 8, 10–12, 14, 22, 29, 43, 57]. The remaining ones did not target specific domains [6, 15, 18, 24, 36, 47–50, 60, 61, 63]. Although the general view from these recommendations is valuable to allow them to be used in any domain, the lack of specificity might be seen as limiting, though. It has been argued that gamification should consider not only the user but the context and the domain (e.g., [33]). Accordingly, recommendations for personalizing gamification that focus on a specific domain are expected to be more beneficial to that domain, compared to generic ones. From this perspective, the health and education domains are one step ahead as recommendations for them have been developed, while other domains would have to rely on the general approaches.

5 Research Agenda

This section delineates five lines of research yet to be addressed based on our findings.

Comparing personalized and one size fits all gamification: Perhaps the most important step towards advancing the personalized gamification field is conducting empirical studies comparing personalized and one size fits all gamification. As the main goal of the former is to improve the effectiveness of the latter, such comparisons are of utmost importance. However, as we demonstrated, most studies compare personalized gamification to other conditions (e.g., counter-tailored and random gamification). Therefore, future studies should perform such comparative analyses to reveal which personalization approaches achieve the goal of personalized gamification. The planning of those studies can follow the characteristics revealed in this review (e.g., the number of game elements per condition and sample size).

Developing personalization approaches that consider contextual characteristics: Several researchers agree that gamification's success depends not only on user characteristics but also on contextual factors (e.g., [13, 18, 20, 33]). Accordingly, personalization approaches should also consider contextual aspects as personalization criteria. However, as we have shown, few approaches explore those characteristics. Therefore, we call for future research to expand beyond the use of user characteristics as personalization criteria, exploring contextual factors as well (e.g., culture). In doing so, the work by Savard and Mizoguchi [55] might provide valuable guidance in understanding and operationalizing the context.

Performing qualitative user studies: Personalized gamification is a recent field study, in which a deeper understanding of users' experiences would certainly contribute to shedding light on positive and negative aspects of personalization approaches available, as well as help to achieve a better understanding of the effectiveness of subjective, rarely used game elements such as storytelling and narrative. Performing qualitative analyses (e.g., interviews) is a way to gather such knowledge, however, our findings reveal that studies are predominantly based on quantitative data. Therefore, we urge for research capturing qualitative feedback to reveal users' subjective experiences with personalized gamification and, consequently, insights into how to improve personalization approaches. Such studies could be performed similarly to the quantitative studies analyzed in this paper. The difference would be in terms of data collection, though, capturing participants' feedback through structured interviews, focal groups, and/or observation. Consequently, it will be possible to analyze personalized gamification's impact based on the context of use, through subjects' emotions/perceptions, which is unfeasible through common quantitative approaches, such as questionnaires/scales and data log [32].

Building personalization approaches from validated taxonomies of game elements: When designing gamification, using well-defined game elements that provide the expected affordances is necessary. Accordingly, one expects that personalization approaches will be able to recommend game elements with the purposes that best suit a user/circumstance (e.g., providing performance feedback, immersing the user in a ludic experience [58]) while preventing the suggestion of two or more of those that feature the same goal (unambiguity). As we found, most personalization approaches recommend game elements selected deliberately or from systematic studies, which makes them prone to such limitations as some elements might not be included or different names might be used for the same end. Therefore, we call for future research to develop personalization approaches upon validated taxonomies of game elements aiming to ensure a broader set of unambiguous game elements.

Providing and establishing resources to be reused in future empirical studies. To increase research reproducibility, the field study would benefit from a toolkit featuring resources such as systems and validated questionnaires to enable the execution of empirical studies in more similar conditions. For instance, a system that can be used to experiment with personalized gamification designs is presented by Tondello [59]. Therefore, we call for future research to develop, disclose, and discuss such resources towards establishing a benchmark for empirical studies on personalized gamification.

6 Conclusions and Limitations

Personalized gamification emerged as a means to improve the effectiveness of one size fits all gamification. It has attracted the attention of several researchers, and much research has been conducted to understand how to personalize as well as to reveal its impact. In this paper, we presented a literature review that answered three RQ regarding personalized gamification.

We answered our first RQ by founding that most studies compare personalized gamification to counter-tailored and random gamification, use few game elements in both the experimental and baseline conditions, analyze quantitative data collected in classrooms and *in the wild*, and rely on sample sizes and time frames comparable to general gamification studies. For the second RQ, we found that the existing literature provides inconclusive evidence on how personalized and one size fits all gamification compare as few studies performed such comparison. In the third RQ, we found that approaches were mainly developed based on data (i.e., data-driven) rather than theory, using literature reviews and deliberate choices for selecting the game elements to consider, predominantly focusing on user characteristics and with few approaches focused on specific domains.

By answering those RQ, this study helps to fill up some previously cited gaps by providing a broader understanding of how empirical studies employing personalized gamification have been conducted, as well as the approach’s impact, along with an overview of how personalization approaches have been developed. Thus, contributing by revealing the impact of personalized gamification, showing an overview of how empirical studies have been conducted in this context, and providing insights on how personalization approaches were developed.

The implications from our contribution are twofold. First, it provides a general overview of different approaches for personalizing gamification. Hence, one can use this overview as a starting point towards understanding how gamification has been personalized. Second, we provide guidelines of how future empirical research on this field might be conducted by showing previous studies’ settings. Thereby, one can follow those guidelines to plan future research. Furthermore, we presented a research agenda with five gaps to be addressed in future studies, which emerged from our findings, guiding researchers on tracks needing attention.

Nevertheless, this paper has a main limitation that must be considered in interpreting our findings: the lack of following a systematic procedure for study selection. Studies were selected from a set of literature reviews published recently, reviews that were determined based on our described steps. While this jeopardizes future replications from this paper, it improves the chances of selecting a broader range of relevant primary studies as we exploited the selection process from four systematic studies. However, this does not exclude the limitations from the systematic procedures those studies followed, such as failing to find relevant studies due to string and search engine selection or not including a study due to interpretation or coding problems.

ACKNOWLEDGMENTS

The authors are thankful to the funding provided by CNPq, CAPES, and FAPESP (Projects 2016/02765-2; 2018/11180-3; 2018/15917-0; 2018/07688-1).

REFERENCES

[1] Rasha Najib Aljabali and Norasnita Ahmad. 2018. A Review on Adopting Personalized Gamified Experience in the Learning Context. In 2018 IEEE Conference on e-Learning, e-Management and e-Services (IC3e). IEEE, 61–66.

[2] Shurui Bai, Khe Foon Hew, and Biyun Huang. 2020. Is gamification “bullshit”? Evidence from a meta-analysis and synthesis of qualitative data in educational contexts. Educational Research Review (2020), 100322.

[3] Johan Baldeón, Inmaculada Rodríguez, and Anna Puig. 2016. LEGA: A LEarner-centered GAmification Design Framework. In Proceedings of the XVII International Conference on Human Computer Interaction (Salamanca, Spain) (Interacción ’16). ACM, New York, NY, USA, Article 45, 8 pages. https://doi.org/10.1145/2998626.2998673

[4] Simone S Borges, Riichiro Mizoguchi, Vinicius HS Durelli, Ig I Bittencourt, and Seiji Isotani. 2016. A link between worlds: Towards a conceptual framework for bridging player and learner roles in gamified collaborative learning contexts. In Advances in Social Computing and Digital Education. Springer, 19–34.

[5] Klaudia Bovermann and Theo J Bastiaens. 2020. Towards a motivational design? Connecting gamification user types and online learning activities. Research and Practice in Technology Enhanced Learning 15, 1 (2020), 1–18. https://doi.org/10.1186/s41039-019-0121-4

[6] Charles Butler. 2014. A framework for evaluating the effectiveness of gamification techniques by personality type. In International Conference on HCI in Business. Springer, 381–389.

[7] Geiser Chalco Challco, Dilvan A Moreira, Riichiro Mizoguchi, and Seiji Isotani. 2014. An ontology engineering approach to gamify collaborative learning scenarios. In CYTED-RITOS International Workshop on Groupware. Springer, 185–198.

[8] David Codish and Gilad Ravid. 2014. Personality based gamification-Educational gamification for extroverts and introverts. In Proceedings of the 9th CHAIS Conference for the Study of Innovation and Learning Technologies: Learning in the Technological Era, Vol. 1. 36–44.

[9] Lamya F Daghestani, Lamiaa F Ibrahim, Reem S Al-Towirgi, and Hesham A Salman. 2020. Adapting gamified learning systems using educational data mining techniques. Computer Applications in Engineering Education 28, 3 (2020), 568–589.

[10] Mouna Denden, Ahmed Tlili, Fathi Essalmi, and Mohamed Jemni. 2017. Educational gamification based on personality. In 2017 IEEE/ACS 14th International Conference on Computer Systems and Applications (AICCSA). IEEE, 1399–1405.

[11] M. Denden, A. Tlili, F. Essalmi, and M. Jemni. 2017. An investigation of the factors affecting the perception of gamification and game elements. In 2017 6th International Conference on Information and Communication Technology and Accessibility (ICTA). IEEE, Muscat, Sultanate of Oman, 1–6. https://doi.org/10.1109/ICTA.2017.8336019

[12] Mouna Denden, Ahmed Tlili, Fathi Essalmi, and Mohamed Jemni. 2018. Does personality affect students’ perceived preferences for game elements in gamified learning environments?. In 2018 IEEE 18th International Conference on Advanced Learning Technologies (ICALT). IEEE, 111–115.

[13] Christo Dichev and Darina Dicheva. 2017. Gamifying education: what is known, what is believed and what remains uncertain: a critical review. International journal of educational technology in higher education 14, 1 (2017), 9.

[14] Fernando Timoteo Fernandes and Plinio Thomaz Aquino Junior. 2016. Gamification aspects in the context of electronic government and education: A case study. In International Conference on HCI in Business, Government, and Organizations. Springer, 140–150.

[15] Lauren S Ferro, Steffen P Walz, and Stefan Greuter. 2013. Towards personalised, gamified systems: an investigation into game design, personality and player typologies. In Proceedings of The 9th Australasian Conference on Interactive Entertainment: Matters of Life and Death. ACM, 7.

[16] Paul Garner, Sally Hopewell, Jackie Chandler, Harriet MacLehose, Elie A Akl, Joseph Beyene, Stephanie Chang, Rachel Churchill, Karin Dearness, Gordon Guyatt, et al. 2016. When and how to update systematic reviews: consensus and checklist. bmj 354 (2016), i3507.

[17] Mohammad Hajarian, Azam Bastanfard, Javad Mohammadzadeh, and Madjid Khalilian. 2019. A personalized gamification method for increasing user engagement in social networks. Social Network Analysis and Mining 9, 1 (2019), 47.

[18] Stuart Hallifax, Serna Audrey, Marty Jean-Charles, Lavoué Guillaume, and Lavoué Elise. 2019. Factors to Consider for Tailored Gamification. In CHI Play. ACM, Barcelona, Spain, 559–572. https://hal.archivesouvertes. fr/hal-02185647

[19] Stuart Hallifax, Audrey Serna, Jean-Charles Marty, and Élise Lavoué. 2019. Adaptive Gamification in Education: A Literature Review of Current Trends and Developments. In Transforming Learning with Meaningful Technologies, Maren Scheffel, Julien Broisin, Viktoria Pammer-Schindler, Andri Ioannou, and Jan Schneider (Eds.). Springer International Publishing, Cham, 294–307.

[20] Juho Hamari, Jonna Koivisto, Harri Sarsa, et al. 2014. Does Gamification Work?-A Literature Review of Empirical Studies on Gamification.. In HICSS, Vol. 14. 3025–3034.
[21] Muhammad Awais Hassan, Ume Habiba, Fiaz Majeed, and Muhammad Shoaib. 2019. Adaptive gamification in e-learning based on students' learning styles. Interactive Learning Environments (2019), 1–21.
[22] Barryl Herbert, Darryl Charles, Adrian Moore, and Therese Charles. 2014. An investigation of gamification typologies for enhancing learner motivation. In 2014 International Conference on Interactive Technologies and Games. IEEE, 71–78.
[23] Tomislav Jagušt, Ivica Botički, and Hyo-Jeong So. 2018. Examining competitive, collaborative and adaptive gamification in young learners' math learning. Computers & education 125 (2018), 444–457.
[24] Yuan Jia, Bin Xu, Yamini Karanam, and Stephen Voida. 2016. Personality-targeted gamification: a survey study on personality traits and motivational affordances. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. 2001–2013.
[25] Michael D Kickmeier-Rust, Eva-C Hillemann, and Dietrich Albert. 2014. Gamification and smart feedback: Experiences with a primary school level math app. International Journal of Game-Based Learning (IJGBL) 4, 3 (2014), 35–46.
[26] Barbara Kitchenham. 2004. Procedures for performing systematic reviews. Keele, UK, Keele University 33, 2004 (2004), 1–26.
[27] Ana Carolina Tomé Klock, Isabela Gasparini, Marcelo Soares Pimenta, and Juho Hamari. 2020. Tailored gamification: A review of literature. International Journal of Human-Computer Studies 144 (2020), 102495.
[28] Ana Carolina Tomé Klock, Marcelo Soares Pimenta, and Isabela Gasparini. 2018. A systematic mapping of the customization of game elements in gamified systems. Anais do Simpósio Brasileiro de Jogos e Entretenimento Digital (2018).
[29] Antti Knutas, Jouni Ikonen, Dario Maggiorini, Laura Ripamonti, and Jari Porras. 2016. Creating student interaction profiles for adaptive collaboration gamification design. International Journal of Human Capital and Information Technology Professionals (IJHCITP) 7, 3 (2016), 47–62.
[30] Jonna Koivisto and Juho Hamari. 2019. The rise of motivational information systems: A review of gamification research. International Journal of Information Management 45 (2019), 191–210. https://doi.org/10.1016/j.ijinfomgt.2018.10.013
[31] Elise Lavoué, Baptiste Monterrat, Michel Desmarais, and Sébastien George. 2018. Adaptive gamification for learning environments. IEEE Transactions on Learning Technologies 12, 1 (2018), 16–28.
[32] Jonathan Lazar, Jinjuan Heidi Feng, and Harry Hochheiser. 2017. Research methods in human-computer interaction. Morgan Kaufmann.
[33] De Liu, Radhika Santhanam, and Jane Webster. 2017. Toward Meaningful Engagement: A Framework for Design and Research of Gamified Information Systems. MIS quarterly 41, 4 (2017), 1011–1034.
[34] Andrzej Marczewski. 2018. Even Ninja Monkeys Like to Play: Unicorn Edition. Gamified UK (2018).
[35] Michael Meder, Till Plumbaum, and Sahin Albayrak. 2017. A Primer on Data-Driven Gamification Design. In Proceedings of the Data-Driven Gamification Design Workshop. CEUR-WS.org, 12–17.
[36] Baptiste Monterrat, Michel Desmarais, Elise Lavoué, and Sébastien George. 2015. A player model for adaptive gamification in learning environments. In International conference on artificial intelligence in education. Springer, 297–306.
[37] Baptiste Monterrat, Elise Lavoué, and Sébastien George. 2014. Toward an adaptive gamification system for learning environments. In International Conference on Computer Supported Education. Springer, 115–129.
[38] Baptiste Monterrat, Elise Lavoué, and Sébastien George. 2017. Adaptation of gaming features for motivating learners. Simulation & Gaming 48, 5 (2017), 625–656.
[39] A. Mora, G. F. Tondello, L. E. Nacke, and J. Arnedo-Moreno. 2018. Effect of personalized gameful design on student engagement. In 2018 IEEE Global Engineering Education Conference (EDUCON). 1925–1933. https://doi.org/10.1109/EDUCON.2018.8363471
[40] Lennart E Nacke, Chris Bateman, and Regan L Mandryk. 2014. BrainHex: A neurobiological gamer typology survey. Entertainment computing 5, 1 (2014), 55–62. https://doi.org/10.1016/j.entcom.2013.06.002
[41] Lennart E Nacke and Christoph Sebastian Deterding. 2017. The maturing of gamification research. Computers in Human Behaviour (2017), 450–454.
[42] Fiona Fui-Hoon Nah, Qing Zeng, Venkata Rajasekhar Telaprolu, Abhishek Padmanabhuni Ayyappa, and Brenda Eschenbrenner. 2014. Gamification of education: a review of literature. In International conference on hci in business. Springer, 401–409. https://doi.org/10.1007/978-3-319-07293-7_39
[43] Wilk Oliveira and Ig Ibert Bittencourt. 2019. Tailored Gamification to Educational Technologies. Springer Nature.
[44] Wilk Oliveira, Armando Toda, Paula Toledo, Lei Shi, Julita Vassileva, Ig Ibert Bittencourt, and Seiji Isotani. 2020. Does Tailoring Gamified Educational Systems Matter? The Impact on Students' FlowExperience. In Proceedings of the 53rd Hawaii International Conference on System Sciences. ScholarSpace, 1226–1235.
[45] Rita Orji. 2014. Exploring the Persuasiveness of Behavior Change Support Strategies and Possible Gender Differences.. In BCSS@PERSUASIVE. 41–57.
[46] Rita Orji, Lennart E Nacke, and Chrysanne Di Marco. 2017. Towards personality-driven persuasive health games and gamified systems. In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems. 1015–1027.
[47] Rita Orji, Gustavo F Tondello, and Lennart E Nacke. 2018. Personalizing persuasive strategies in gameful systems to gamification user types. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. ACM, 435. https://doi.org/10.1145/3173574.3174009
[48] Kiemute Oyibo, Rita Orji, and Julita Vassileva. 2017. The influence of culture in the effect of age and gender on social influence in persuasive technology. In Adjunct publication of the 25th conference on user modeling, adaptation and personalization. 47–52.
[49] Kiemute Oyibo, Rita Orji, and Julita Vassileva. 2017. Investigation of the Persuasiveness of Social Influence in Persuasive Technology and the Effect of Age and Gender.. In PPT@ PERSUASIVE. 32–44.
[50] Kiemute Oyibo, Rita Orji, and Julita Vassileva. 2017. Investigation of the social predictors of competitive behavior and the moderating effect of culture. In Adjunct publication of the 25th conference on user modeling, adaptation and personalization. 419–424.
[51] Luiz Rodrigues, Robson Bonidia, and Jacques Duílio Brancher. 2020. Procedural versus human level generation: Two sides of the same coin? International Journal of Human-Computer Studies 141 (2020), 102465. https://doi.org/10.1016/j.ijhcs.2020.102465
[52] Luiz Rodrigues, Wilk Oliveira, Armando Toda, Paula Palomino, and Seiji Isotani. 2019. Thinking Inside the Box: How to Tailor Gamified Educational Systems Based on Learning Activities Types. In Proceedings of the Brazilian Symposium of Computers on Education. SBC, 823–832. https://doi.org/10.5753/cbie.sbie.2019.823
[53] Fatemeh Roosta, Fattaneh Taghiyareh, and Maedeh Mosharraf. 2016. Personalization of gamification-elements in an e-learning environment based on learners' motivation. In 2016 8th International Symposium on Telecommunications (IST). IEEE, 637–642. https://doi.org/10.1109/ISTEL.2016.7881899
[54] Michael Sailer and Lisa Homner. 2020. The Gamification of Learning: a Meta-analysis. Educ Psychol Rev 32 (2020), 77–112.
[55] Isabelle Savard and Riichiro Mizoguchi. 2019. Context or culture: what is the difference? Research and Practice in Technology Enhanced Learning 14, 1 (2019), 1–12.
[56] Hallifax Stuart, Elise Lavoué, and Audrey Serna. 2020. To tailor or not to tailor gamification? An analysis of the impact of tailored game elements on learners' behaviours and motivation. In 21th International Conference on Artificial Intelligence in Education.
[57] Bahar Taspinar, Werner Schmidt, and Heidi Schuhbauer. 2016. Gamification in education: a board game approach to knowledge acquisition. Procedia Computer Science 99 (2016), 101–116.
[58] Armando M Toda, Ana CT Klock, Wilk Oliveira, Paula T Palomino, Luiz Rodrigues, Lei Shi, Ig Bittencourt, Isabela Gasparini, Seiji Isotani, and Alexandra I Cristea. 2019. Analysing gamification elements in educational environments using an existing Gamification taxonomy. Smart Learning Environments 6, 1 (2019), 16. https://doi.org/10.1186/s40561-019-0106-1
[59] Gustavo Fortes Tondello. 2019. Dynamic Personalization of Gameful Interactive Systems. Ph.D. Dissertation. University of Waterloo.
[60] Gustavo F Tondello, Alberto Mora, Andrzej Marczewski, and Lennart E Nacke. 2019. Empirical validation of the gamification user types hexad scale in English and Spanish. International Journal of Human-Computer Studies 127 (2019), 95–111.
[61] Gustavo F Tondello, Alberto Mora, and Lennart E Nacke. 2017. Elements of gameful design emerging from user preferences. In Proceedings of the Annual Symposium on Computer-Human Interaction in Play. ACM, 129–142. https://doi.org/10.1145/3116595.3116627
[62] Gustavo F Tondello, Rita Orji, and Lennart E Nacke. 2017. Recommender systems for personalized gamification. In Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization. ACM, 425–430. https://doi.org/10.1145/3099023.3099114
[63] Gustavo F Tondello, Rina RWehbe, Lisa Diamond, Marc Busch, Andrzej Marczewski, and Lennart E Nacke. 2016. The gamification user types hexad scale. In Proceedings of the 2016 annual symposium on computer-human interaction in play. ACM, 229–243. https://doi.org/10.1145/2967934.2968082
[64] Andrea C Tricco, Erin Lillie, Wasifa Zarin, Kelly K O'Brien, Heather Colquhoun, Danielle Levac, David Moher, Micah DJ Peters, Tanya Horsley, Laura Weeks, et al. 2018. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Annals of internal medicine 169, 7 (2018), 467–473.