ReGammend: A method for personalized recommendation of gamification designs

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Abstract

Gamification personalization has been increasingly investigated as an avenue to improve the effects of gamification. While currently, empirical data exist to start making evidence-based gamification design, current guidelines and methods to bridge the gap of evidence and design is lacking. To start facing this challenge, we outline a point of departure proposing the recommendation system ReGammend (recommendation system for gamification designs). The system tailor gamification design based on users' traits, contextual factors, goals, and other relevant moderating factors. The recommendation system uses information from the previous literature to recommend gamification designs with multiple game elements aiming to positively affect the positive outcomes stemming from gamification. The proposed system contributes to researchers and practitioners, providing a practical way to personalize gamification designs.

Keywords

Gamification design, recommendation system, user experience, user-centered design, user modeling

1. Introduction

In the last decade, gamification (*i.e.*, the design approach of products, activities, services and systems to create similar motivational experiences as games usually create [1]), has increasingly become an important research topic in different contexts [2]–[5]. The application of gamification in contexts such as education [6], health [7], and government services [8], in general, seeks to affect the user behavior, engaging them during the use of gamified environments [9].

Different studies indicated that applying gamification could have positive results in the users, as students having better learning outcomes [10], the raise of users' participation in fitness courses [11], or the increase of the efficacy of persuasive health strategies [12]. Despite the positive results that studies have reported over the years, a considerable number of negative or mixed results have highlighted that gamification could not affect all users in the same way [1], [10], [13]. With that, researchers started to search for ways to personalize gamification and create gamified environments that would be more suitable for the different users' profiles and preferences [3], [14].

Nowadays player and user typologies are the most investigated users' characteristic in personalized gamification, with indications that the user preference over gamification designs depends on their user types [15]. Prior research has also indicated that the user types are dynamic [16], what would demand from designers and researchers a constant personalization of the

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gamified systems based on these user types. This process would be easier with the automation of the personalization, however, albeit the considerable number of studies that sought to personalize gamification over the years, the automation of this process still remains a lack in the field [3].

One prominent possibility to make the process of personalization easier for researchers and designers could be the use of recommendation systems (RS). RS uses prior information to create a more suitable suggestion for the users, and have been used especially in the e-commerce and entertainment industry [17]. The recommendations provided by a RS can be done based on several aspects, such as user demographic information or purchases historic [18] and would help the user to find what best suits its preferences between all the items available [19].

Thus, in the field of personalized gamification, RS can be a useful tool to recommend personalized designs, since they can indicate to users the gamified activities that would better fit to their preferences [17]. Thus, automation of personalized gamification with RS also could help designers implement gamification to users who have no previous experience in the usage of gamified systems, create a more efficient personalization, as well as avoid asking the user about their preferences constantly.

Albeit some studies have started to seek how to implement RS in the gamification context [17], [20], proposals of how to implement RS to define the gamification design remains a lack in the field. To start to face this challenge, in this paper we present a novel approach that is an evidence-based RS that provide recommendations of which would be the most suitable gamification design for each user type, according to the users' traits. The RS proposed in this paper can be adapted and plugged-in different kind of gamified systems, thus, allowing designers and researchers to provide automatic recommendations for gamification design. At the same time, our work generates insights for future studies about dynamic recommendation of gamification designs in terms of graphical user interface (GUI).

2. Background and related works

In this section, we present the main topics addressed in this paper (*i.e.*, personalized gamification and RS in gamification), and the main related works. Personalization of gamification has shown through recent research that people have different orientations and preferences regarding gamification design [15], and therefore are affected differently according to the type of gamification design they need to use [21, 22]. Based on these results, studies have sought to identify the most suitable gamification designs for each user, considering different users' aspects (*e.g.*, user type, age, and demographic data) [3]. Overall, studies on gamification personalization are focused on *i)* identifying the relationships between different types of game elements and the user profile [23], *ii)* evaluating the effects of gamification personalization on the user experience [24, 25], or *iii)* proposing theoretical/conceptual models to personalize the gamification [26].

Albeit the different users' characteristics that have been investigated, the player and user typologies have received major attention [3]. Over the years, researchers have worked on how different patterns could be grouped and therefore indicate different player/user types in games and gamification systems. These player/user types normally are grounded in motivational or psychological theories [27], player experiences [28], or even neurobiological research [29]. The choice of the player/user typology that would be used in a personalized gamified system, can be one major factor on the user motivation [30], and therefore, should be an important aspect to be considered in the development of gamified personalized systems.

One way that has recently started to be discussed to improve the personalization of gamification is the use of RS [17], which in short are systems/algorithms capable of identifying aspects of individual users and provide dynamic recommendations (*e.g.*, design recommendations) [31]. RS can be classified into different categories: *i)* personalized, *ii)* collaborative, *iii)* content-based, *iv)* knowledge-based, and *v)* evidence-based [32].

The **personalized recommendation systems** use user profiles and some contextual parameters of users to provide personalized recommendations [32]. The **collaborative recommendation systems** use user-profile, some contextual parameters, and data of the community to which the user belongs. It recommends a similar product to a user which other users of their community are buying [32]. The **content-based recommendation systems** use the user-profile, contextual parameters as well as features of the product. Based on this, it recommends the product to the user which has the same feature as the product he has already purchased before [32]. The **knowledge-based recommendation systems** use the user profile, contextual parameters, product features, and knowledge models which keeps track of certain event in users' demographics and accordingly do the recommendations (*e.g.*, birthday recommends a certain product) [32]. **Evidence-based recommendation systems** use the user profile and previews evidence collected (*e.g.*, results of research) [32]. Evidence-based recommendation systems were of particular interest to us as it allowed us to use previous acknowledgement from the literature to provide recommendations.

Over the years, different approaches have been used to provide dynamic adaptation of GUI in different areas [32]–[34]. In the field of gamification, some studies involving recommendation also have been conducted. Khoshkangini *et al.* [20] designed and implemented a fully automated system for the dynamic generation and recommendation of challenges, which are personalized and contextualized based on the preferences, history game status, and performances of each player. They conducted a long-running open-field experiment (12 weeks) involving more than 400 active participants, however, they focused on proposing recommendations for challenges in gamified systems without proposing recommendations for gamification design itself.

Herpich *et al.* [35] proposed a digital picture frame that interleaves a picture display mode with a recommender mode to promote a healthy lifestyle and to increase well-being of elderly people. Although they used gamification as a means to increase user appreciation of the system, the authors also did not provide recommendations directly related to gamification designs.

Su *et al.* [36] proposed an adaptative path RS for the teaching of geometry. The authors also proposed and evaluated a gamified prototype within the system. The results indicated that personalized recommendations are important [36], however, the authors also did not provide recommendations related to gamification design.

Tondello *et al.* [17] proposed a general framework for personalized gameful applications using RS (*i.e.*, a framework to design RS for gamified applications). The framework proposed by Tondello *et al.* [17] does not provide a RS per se, but it helps the community to create RS for gamified systems.

Santos *et al.* [15] investigated how Hexad user types (*i.e.*, Achiever, Disruptor, Free Spirit, Philanthropist, Player, and Socialiser) are associated with the preference and perceived sense of accomplishment from different gamification designs (Performance, Ecological, social, Personal, and Fictional). The study conducted by Santos *et al.* [15] provides insights into which gamification designs are suitable for each user type, however, does not provide practical approach to implement this personalization in gamified systems.

In summary, studies on the recommendation in gamified systems focus on personalizing system attributes (*e.g.*, challenges and tasks), however, do not focus on personalizing the gamification design, and at the same time do not present how to automate the personalization process. At the best of our knowledge, this is the first evidence-based RS for gamification design. Table 1 present a comparison between the related work.

Table 1
Related works comparison

S	Y	UT	UTR	GD	EB
[20]	2021	No	No	No	No
[35]	2017	No	No	No	No
[36]	2017	No	No	No	No
[17]	2018	Yes	No	No	No
[15]	2021	Yes	Yes	Yes	No

Key: S: study; Y: year of the study; UT: used a user typology for gamification; UTR: provide the recommendations based on user' traits; GD: provide recommendations for the gamification designs; EB: provide an evidence-based RS.

3. Recommendation system

In this section, we present the RS proposed in this work. The system aims to provide recommendations of gamification designs according to the user's types. In summary, the RS receives as *input* the user type and provide as *output*, a recommendation of gamification design for the user. An example of implementation is presented.

3.1. Materials and method

To design the general architecture of the RS, we used the framework proposed by Tondello *et al.* [17]. This framework defines the general inputs, processes, and outputs to implement recommendation in gamified applications. Tondello's framework was of our interest because, as far we know, is the only framework to implement RS in gamified systems and can be adapted for different contexts.

To define/identify the users' types, in the example of implementation presented in our paper, we used the Hexad framework [27], which defines different orientations of users according to their preferences related to interaction with gameful applications. The Hexad framework defines six different user types that a given user can be (*i.e.*, Achiever, Disruptor, Free Spirit, Philanthropist, Player, and Socialiser). Hexad was of special interest in our work because it is (as far as we know) the only model for user types identification for the gamification domain. At the same time, it has already been validated in several languages and is widely used in academia and industry [37]–[39]. However, in future uses of our RS, Hexad can be replaced by another framework that better adapts to the application context.

To define the gamification designs to be recommended, in our example if implementation, we used the taxonomy proposed by Toda *et al.* [40]. Toda's taxonomy defines five gamification designs that are organized according to motivation types and can be used to personalize gamified environments. The taxonomy proposed by Toda *et al.* [40] was especially used in our work because it is, as far as we know, the only taxonomy focused on proposing gamification designs, as well as because it is already widely used in field studies. Also, in future uses of our RS, the taxonomy can be replaced by another that better fits the application context.

Finally, to provide recommendations for gamification designs, in our example of implementation, we followed an evidence-based recommendation model, using the study conducted by Santos *et al.* [15], who identified how the different gamification designs proposed in the taxonomy of Toda *et al.* [40] affect the perceived sense of accomplishment and preference of users according to their Hexad user type. We used the study conducted by Santos *et al.* [15] as a basis for our recommendations for being, as far as we know, the only study that related Hexad user types with the gamification designs proposed by Toda *et al.* [40].

The work was organized in two general steps: *i)* RS design (general architecture) and *ii)* RS implementation (example of implementation). In the *first step*, the general idea of the RS was planned according to the materials previously described. In the *second step*, an example of implementation was provided, so that it could be used in different types of gamified systems.

3.2. Recommendation system design

Initially, the general RS was modeled according to Tondello's framework [17]. The framework defines that a RS for gamification should have four Inputs (User profile, Items, Transactions, and Context), a Recommendation model, and a Rating [17].

The **user profile** should represent the user information that will be taken into account during the personalization process [17]. In our example, we used the Hexad profile of users [37]. **Items** must represent the system attributes that were used in the personalization process [17]. In our implementation example, we used the gamification design types proposed by Toda *et al.* [40].

The **Transactions** must represent how the personalization will be defined [17]. In our implementation example, transactions are the crossover between user types (Hexad) and gamification designs, defined according to the model by Santos *et al.* [15]. The **Context** must represent the definitions made at the user level of the system [17]. In our implementation example, we use information from the system administrator, who can make settings related to the type of personalization they want (accomplishment-based recommendation or preference-based recommendation).

The **Recommendation** must be the algorithm itself, where personalization is processed [17]. In our implementation example, we used an evidence-based algorithm to provide the gamification design recommendation according to the results of the study by Santos *et al.* [15]. Finally, **Ratings** are the recommendations generated by the algorithm [17]. In our implementation example, ratings are the gamification design recommendations that should appear in the user interface. Despite the examples used/suggested in this study (*e.g.*, Hexad [27], Toda's framework [40], and Santos's recommendations [15]), the proposed RS is independent of these examples and can be adapted according to different needs. Figure 1 presents the general structure for our RS.

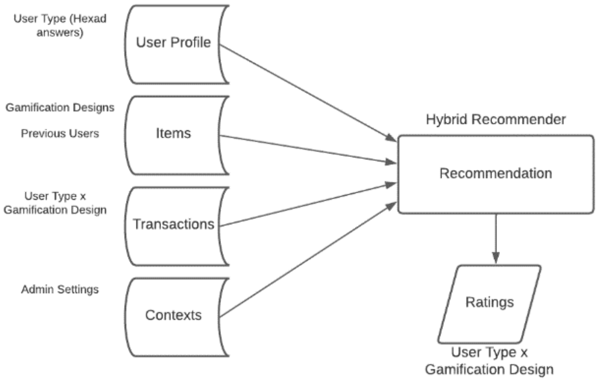

Figure 1: Inputs and outputs of the recommendation system (adapted from Tondello *et al*. [17]).

Finally, the RS was defined in nine components: *i)* User, *ii)* Admin, *iii)* User profile, *iv)* User modeling unit, *v)* User model, *vi)* System database, *vii)* Admin settings, *viii)* Content managing unit, and *ix)* User object (UO):

User: the user is the person who will use the gamification system. The system can identify the trait, for instance, the user can answer a questionnaire (Hexad in our example) to provide their user type to the system (as input) and will receive the personalized system with the most appropriate gamification designs for their profile (as output).

- **Admin**: The admin is responsible for managing the gamification system. It chooses which parameter to take into account when recommending a design. In the example of implementation provided in our work, the admin may choose between "user preference" or "user perceived sense of accomplishment" to the algorithm provide the recommendation.
- **User profile**: The user profile consists of the answers to the questionnaire.
- **User modeling unit**: The user modeling unit is the unit responsible for processing the user's answers provided in the questionnaire. It returns the scores for each user type (*e.g.*, Disruptor, Free Spirit, Achiever, Player, Socialiser, and Philanthropist) when using Hexad.
- **User model**: The user model is responsible to stores the information returned by the User modeling unit. Therefore, it contains the scores of each user type.
- **System database**: The system database contains data about previous study' users so that the collaborative RS can compare them to the current user. Also contains the results obtained from the previous study and the variety of possible gamification designs.
- **Admin settings**: The admin settings store information about which parameter the admin wants to use for recommending gamification designs.
- **Content managing unit**: The content managing unit manages all the information coming from the User Model, System database, and Admin settings. It processes data to provide a rating for each possible gamification design. Returns the best design rating for the UO.
- **User object (UO):** Contains the recommended gamification design for the current user.

All of the RS components can be changed as per system needs. In other words, where we use Hexad as a framework to identify user types, another framework that is more appropriate for each context type can be used (*e.g.*, BrainHex [29], Bartle's Archetypes [28]). Where we are using Toda's taxonomy to define gamification designs [40], other more context-appropriate taxonomies can be used. Where we are using the study by Santos *et al*. [15] to define transactions, other evidence-based information can be used. Figure 2 present the general RS architecture.

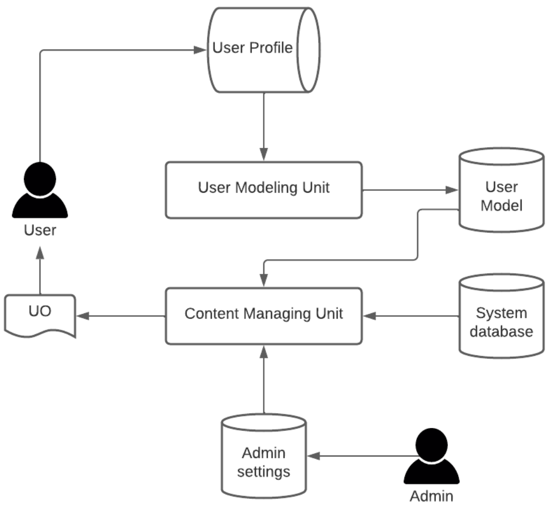

Figure 2: RS architecture

3.3. Example of implementation

To provide a RS easily interpretable and incremental, we implemented an example for the RS in JavaScript (programming language highly compatible with different types of web systems). The system was register National Institute of Industrial Property of Brazil. The current version of the system can be found in a GitHub repository with a commercial license[2].

Initially, following the architecture presented in Figure 2, the User Modeling Unit was implemented. Each user type is represented in an array. Another array is created to represent possible choices as to the type of recommendation (*i.e.*, accomplishment-based or preference-based recommendation). Another array is created to represent each dominant user's type. Finally, the last array is created to represent the recommendations possibilities (*i.e.*, the available designs to be recommended). The User Modeling Unit is presented in the Code 1.

Code 1

User Modeling Unit representation

```
const userSchema = Schema({

     userTypes: Array,

    choiceRecommendationType:
Array,
      dominantTypes: Array,

      recommendation: Array
   });
```

To implement the recommendations (based on Santos *et al.* [15]), two three-dimensional matrixes were created, representing the ß-value and the *P*-value, accordingly to the following indexation: `recommendationTable[UserType][Criterion][Design]`. In an example, considering the Code 2, to get the ß-value of the Philanthropist's preference for the social design, we have following processing, `BTable[0][1][4]`.

Code 2

Content Managing Unit representation

```
const createRecommendation = async
(req, res) => {
       const user = await
userModel.findById(req.params.user_id
); // The User Model of a specific
user is taken

       const accomplishment = []
       const preference = [] // Two
arrays are created to store the
recommendations for both criteria
       for (userType of
user.dominantTypes) {
           let
recommendation_based_accomplishment =
maxIndexBPTable
(recommendationModel.BTable[userType]
[0],
recommendationModel.PTable[userType][
0]);
           let
recommendation_based_preference =
maxIndexBPTable(recommendationModel.B
Table[userType][1],
recommendationModel.PTable[userType][
1]);
accomplishment.push(recommendation_ba
sed_accomplishment);

preference.push(recommendation_based_
preference); // Add recommendation
to respective arrays
       }

       const recommendation =
[accomplishment, preference]
       return recommendation;
   }
```

Finally, the function `maxIndexBPTable` get the indexes which the value of ß-value is maximum, get the most significant p-value and provide the recommendation.

[2] Link to access the code: https://github.com/kibonusp/rs-gamification-design

4. Agenda for future studies

In this section, we present the work limitations, as well, an agenda for further studies. Our work contributes to the field of gamification design, providing a RS able to be adapted and plugged in general gamified systems. However, we have some limitations, which create the possibility to propose future studies that would further the knowledge in the field. Firstly, in our work we did not evaluate the RS. Therefore, future studies should evaluate the system in terms of recommendation effects (considering users preference and perceived sense of accomplishment), as well as plug the RS in different systems and evaluate its efficacy in provide the personalized gamification. Future studies also can compare the users' experiences when using a personalized (with the RS) and a non-personalized (without the RS) version of the gamified system.

Recent studies have pointed out that using one single user characteristic to personalize gamification might not be sufficient to create a suitable gamified system for the users [30], since they have different characteristics that could influence the use of the gamified system [3]. Other aspects such as demographic information, gaming habits or personality traits can be addressed in future studies about RS, to investigate how the multiple user characteristics (besides only user traits) can be combined into different recommendations for gamification designs.

Different studies have pointed out that the use of questionnaires to assess the user type present some limitations, as for example random responses [41] or missing data [3]. Also, measuring the user type only in the first system use, might not be the best option since their profile can change over time [16], [28]. Future studies can adapt the RS to predict the user type based on user behavior data or their first answer to the questionnaire. In this way, the RS could provide recommendations that would be adapted to the user changes.

Table 2
Summary of the agenda for future studies

Study proposal	Motivation	Type of study	Contribution
Studies to evaluate recommendation effects	Validation of the RS	Experimental	Generation of evidences that automation of gamification could be done through RS
Studies comparing the personalized and not personalized recommendation	Validation of the RS	Experimental	Generation of evidences that automation of gamification could be done through RS
Improvement of the RS to create personalization based on multiple users' characteristics	Improvement of the recommendations	Exploratory and empirical	Further the literature on how to create RS to automation of gamification
Studies adapting the RS to predict the user type	Improvement of the recommendations	Exploratory and empirical	Further the literature on how to create RS to automation of gamification
Studies about the impact of the context in the recommendations	Improvement of the recommendations	Exploratory and surveys	Further the literature on how to create RS to automation of gamification
Improvement of the RS to create recommendations for game elements	Improvement of the recommendations	Exploratory	Further the literature on how to create RS to automation of gamification

In this version of the RS, we also did not consider the context of application, creating a RS that could be used regardless domain. The context can play an important role in the effectiveness of gamification [30], and prior research have indicated that studies about how the context impact the success of the implementation of gamification strategies, are a gap in the field [1], [3], [16]. Future studies can use and adapt the RS to specific domains and evaluate if the recommendations fit the user preferences, and therefore, positively affecting their behavior.

Finally, in this work we propose a RS based on gamification designs. To provide these recommendations it was possible to find only one study in the literature that related the Hexad user types with gamification designs [15]. Therefore, it was not possible to provide individual game elements recommendations for the users or create recommendations based in different studies. Since there is a large number of studies that relates the Hexad user types with the game elements individually (see [3] for a review), future studies can improve our RS using prior research to provide recommendations for individual game elements for the users. These evaluations and comparisons studies would provide the field with more evidence-based that the RS could be an option to personalize gamification. Table 2 summarize the agenda for future studies.

5. Final remarks

In this study, we propose a RS for gamification designs, capable of recommending gamification designs according to the user type. Thus, we contribute to academia and to the industry. In future work, we aim to improve the RS, provide recommendations based on other user characteristics.

6. References

[1] J. Koivisto and J. Hamari, "The rise of motivational information systems: A review of gamification research," *International Journal of Information Management*, vol. 45. Elsevier Ltd, pp. 191–210, Apr. 01, 2019. doi: 10.1016/j.ijinfomgt.2018.10.013.

[2] M. Trinidad, M. Ruiz, and A. Calderon, "A Bibliometric Analysis of Gamification Research," *IEEE Access*, vol. 9, pp. 46505–46544, 2021, doi: 10.1109/ACCESS.2021.3063986.

[3] A. C. T. Klock, I. Gasparini, M. S. Pimenta, and J. Hamari, "Tailored gamification: A review of literature," *International Journal of Human Computer Studies*, vol. 144, Dec. 2020, doi: 10.1016/j.ijhcs.2020.102495.

[4] J. Majuri, J. Koivisto, and J. Hamari, "Gamification of education and learning: A review of empirical literature," in *Proceedings of the 2nd International GamiFIN Conference*, 2018, pp. 11–19. Accessed: Feb. 15, 2022. [Online]. Available: http://ceur-ws.org/Vol-2186/paper2.pdf

[5] D. Johnson, S. Deterding, K. A. Kuhn, A. Staneva, S. Stoyanov, and L. Hides, "Gamification for health and wellbeing: A systematic review of the literature," *Internet Interventions*, vol. 6. Elsevier B.V., pp. 89–106, Nov. 01, 2016. doi: 10.1016/j.invent.2016.10.002.

[6] L. Rodrigues *et al.*, "Personalization Improves Gamification: Evidence from a Mixed-methods Study," in *Proceedings of the ACM on Human-Computer Interaction*, Sep. 2021, vol. 5, no. CHIPLAY. doi: 10.1145/3474714.

[7] M. Altmeyer, P. Lessel, S. Jantwal, L. Muller, F. Daiber, and A. Krüger, "Potential and effects of personalizing gameful fitness applications using behavior change intentions and Hexad user types," *User Modeling and User-Adapted Interaction*, vol. 31, no. 4, pp. 675–712, Sep. 2021, doi: 10.1007/s11257-021-09288-6.

[8] S. K. Bista, S. Nepal, C. Paris, and N. Colineau, "Gamification for online communities: A case study for delivering government services," *International Journal of Cooperative Information Systems*, vol. 23, no. 2, 2014, doi: 10.1142/S0218843014410020.

[9] J. Hamari, "Gamification," in *The Blackwell Encyclopedia of Sociology*, Oxford, UK: John Wiley & Sons, Ltd, 2019, pp. 1–3. doi: 10.1002/9781405165518.wbeos1321.

[10] S. Bai, K. F. Hew, and B. Huang, "Does gamification improve student learning outcome? Evidence from a meta-analysis and synthesis of qualitative data in educational contexts," *Educational*

Research Review, vol. 30. Elsevier Ltd, Jun. 01, 2020. doi: 10.1016/j.edurev.2020.100322.

[11] M. Altmeyer, M. Schubhan, A. Krüger, and P. Lessel, "A long-term investigation on the effects of (personalized) gamification on course participation in a gym," in *Proceedings of the 5th International GamiFIN Conference*, 2021, pp. 60–69. Accessed: Feb. 15, 2022. [Online]. Available: http://ceur-ws.org/Vol-2883/paper7.pdf

[12] R. Orji, G. F. Tondello, and L. E. Nacke, "Personalizing persuasive strategies in gameful systems to gamification user types," in *Conference on Human Factors in Computing Systems - Proceedings*, Apr. 2018, vol. 2018-April. doi: 10.1145/3173574.3174009.

[13] A. M. Toda, P. H. D. Valle, and S. Isotani, "The dark side of gamification: An overview of negative effects of gamification in education," in *Communications in Computer and Information Science*, 2018, vol. 832, pp. 143–156. doi: 10.1007/978-3-319-97934-2_9.

[14] L. Rodrigues, A. M. Toda, P. T. Palomino, W. Oliveira, and S. Isotani, "Personalized gamification: A literature review of outcomes, experiments, and approaches," in *PervasiveHealth: Pervasive Computing Technologies for Healthcare*, Oct. 2020, pp. 699–706. doi: 10.1145/3434780.3436665.

[15] A. C. G. Santos *et al.*, "The relationship between user types and gamification designs," *User Modeling and User-Adapted Interaction*, vol. 31, pp. 907–940, 2021, doi: 10.1007/s11257-021-09300-z.

[16] A. C. G. Santos, W. Oliveira, J. Hamari, and S. Isotani, "Do people's user types change over time? An exploratory study," in *Proceedings of the 5th International GamiFIN Conference*, Jun. 2021, pp. 90–99. Accessed: Feb. 15, 2022. [Online]. Available: http://ceur-ws.org/Vol-2883/paper10.pdf

[17] G. F. Tondello, R. Orji, and L. E. Nacke, "Recommender systems for personalized gamification," in *UMAP 2017 - Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, Jul. 2017, pp. 425–430. doi: 10.1145/3099023.3099114.

[18] H. Tan, J. Guo, and Y. Li, "E-learning Recommendation System," in *International Conference on Computer Science and Software Engineering*, Dec. 2008, pp. 430–433. doi: 10.1109/csse.2008.305.

[19] J. Davidson *et al.*, "The YouTube video recommendation system," in *RecSys'10 - Proceedings of the 4th ACM Conference on Recommender Systems*, 2010, pp. 293–296. doi: 10.1145/1864708.1864770.

[20] R. Khoshkangini, G. Valetto, A. Marconi, and M. Pistore, "Automatic generation and recommendation of personalized challenges for gamification," *User Modeling and User-Adapted Interaction*, vol. 31, no. 1, pp. 1–34, 2021, doi: 10.1007/s11257-019-09255-2.

[21] L. Hassan, J. Rantalainen, N. Xi, H. Pirkkalainen, and J. Hamari, "The relationship between player types and gamification feature preferences," in *Proceedings of the 4th International GamiFIN Conference*, 2020, vol. 2020, pp. 11–20. Accessed: Feb. 16, 2022. [Online]. Available: http://ceur-ws.org/Vol-2637/paper2.pdf

[22] M. Altmeyer, M. Schubhan, P. Lessel, L. Muller, and A. Krüger, "Using Hexad User Types to Select Suitable Gamification Elements to Encourage Healthy Eating," in *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, 2020, pp. 1–8. doi: 10.1145/3334480.3383011.

[23] W. Oliveira and I. I. Bittencourt, "Selecting the Most Suitable Gamification Elements for Each Situation," in *Tailored Gamification to Educational Technologies*, Springer, 2019, pp. 55–69.

[24] S. Hallifax, E. Lavoué, and A. Serna, "To tailor or not to tailor gamification? An analysis of the impact of tailored game elements on learners' behaviours and motivation," *International Conference on Artificial Intelligence in Education*, no. May, 2020, doi: 10.1007/978-3-030-52237-7_18.

[25] W. Oliveira *et al.*, "Does Tailoring Gamified Educational Systems Matter? The Impact on Students' Flow Experience," in *Hawaii International Conference on System Sciences*, 2020, pp. 1226–1235. doi: 10.24251/hicss.2020.152.

[26] G. F. Tondello, R. R. Wehbe, L. Diamond, M. Busch, A. Marczewski, and L. E. Nacke, “The gamification user types Hexad scale,” in *CHI PLAY 2016 - Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play*, Oct. 2016, pp. 229–243. doi: 10.1145/2967934.2968082.

[27] A. Marczewski, *Even Ninja Monkeys Like to Play: Gamification, Game Thinking and Motivational Design*. CreateSpace Independent Publishing Platform, 2015.

[28] R. Bartle, “Hearts, clubs, diamonds, spades: Players who suit MUDs,” 1996.

[29] L. E. Nacke, C. Bateman, and R. L. Mandryk, “BrainHex: A neurobiological gamer typology survey,” *Entertainment Computing*, vol. 5, no. 1, pp. 55–62, 2014, doi: 10.1016/j.entcom.2013.06.002.

[30] S. Hallifax, A. Serna, J. C. Marty, G. Lavoué, and E. Lavoué, “Factors to consider for tailored gamification,” in *CHI PLAY 2019 - Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, Oct. 2019, pp. 559–572. doi: 10.1145/3311350.3347167.

[31] N. Idrissi and A. Zellou, “A systematic literature review of sparsity issues in recommender systems,” *Social Network Analysis and Mining*, vol. 10, no. 1, pp. 1–23, 2020, doi: 10.1007/s13278-020-0626-2.

[32] G. Vaibhavi Subhash and P. Ramanuj, “Optimizing Recommender System: Literature Review,” *Turkish Journal of Computer and Mathematics Education*, vol. 12, no. 10, pp. 3934–3939, 2021.

[33] G. Ghiani, M. Manca, and F. Paternò, “Dynamic user interface adaptation driven by physiological parameters to support learning,” *EICS 2015 - Proceedings of the 2015 ACM SIGCHI Symposium on Engineering Interactive Computing Systems*, pp. 158–163, 2015, doi: 10.1145/2774225.2775081.

[34] T. Alves, J. Natálio, J. Henriques-Calado, and S. Gama, “Incorporating personality in user interface design: A review,” *Personality and Individual Differences*, vol. 155, p. 109709, 2020, doi: 10.1016/j.paid.2019.109709.

[35] M. Herpich, T. Rist, A. Seiderer, and E. André, “Towards a gamified recommender system for the elderly,” *ACM International Conference Proceeding Series*, vol. Part F1286, pp. 211–215, 2017, doi: 10.1145/3079452.3079500.

[36] C. H. Su, “Designing and developing a novel hybrid adaptive learning path recommendation system (ALPRS) for gamification mathematics geometry course,” *Eurasia Journal of Mathematics, Science and Technology Education*, vol. 13, no. 6, pp. 2275–2298, 2017, doi: 10.12973/EURASIA.2017.01225A.

[37] G. F. Tondello, A. Mora, A. Marczewski, and L. E. Nacke, “Empirical validation of the Gamification User Types Hexad scale in English and Spanish,” *International Journal of Human Computer Studies*, vol. 127, pp. 95–111, Jul. 2019, doi: 10.1016/j.ijhcs.2018.10.002.

[38] A. Manzano-león *et al.*, “Adaptation and validation of the scale of types of users in gamification with the spanish adolescent population,” *International Journal of Environmental Research and Public Health*, vol. 17, no. 11, pp. 1–10, Jun. 2020, doi: 10.3390/ijerph17114157.

[39] N. Taşkın and E. Kılıç Çakmak, “Adaptation of modified gamification user types scale into Turkish,” *Contemporary Educational Technology*, vol. 12, no. 2, pp. 1–17, 2020, doi: 10.30935/cedtech/7942.

[40] A. M. Toda *et al.*, “A taxonomy of game elements for gamification in educational contexts: Proposal and evaluation,” in *International Conference on Advanced Learning Technologies*, 2019, vol. 2161–377X, pp. 84–88. doi: 10.1109/ICALT.2019.00028.

[41] R. Kimpen, R. de Croon, V. vanden Abeele, and K. Verbert, “Towards predicting hexad user types from mobile banking data: An expert consensus study,” in *CHI PLAY 2021 - Extended Abstracts of the 2021 Annual Symposium on Computer-Human Interaction in Play*, Oct. 2021, pp. 30–36. doi: 10.1145/3450337.3483486.