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► **To cite this version:**

Elise Lavoué, Baptiste Monterrat, Michel Desmarais, Sébastien George. Adaptive Gamification for Learning Environments. *IEEE Transactions on Learning Technologies*, 2019, 12 (1), pp.16 - 28. 10.1109/TLT.2018.2823710 . hal-01784233

**HAL Id: hal-01784233**

**<https://hal.science/hal-01784233>**

Submitted on 22 May 2018

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# Adaptive Gamification for Learning Environments

Élise Lavoué, Baptiste Monterrat, Michel Desmarais, Sébastien George

**Abstract**— In spite of their effectiveness, learning environments often fail to engage users and end up under-used. Many studies show that gamification of learning environments can enhance learners’ motivation to use learning environments. However, learners react differently to specific game mechanics and little is known about how to adapt gaming features to learners’ profiles. In this paper, we propose a process for adapting gaming features based on a player model. This model is inspired from existing player typologies and types of gamification elements. Our approach is implemented in a learning environment with five different gaming features, and evaluated with 266 participants. The main results of this study show that, amongst the most engaged learners (i.e. learners who use the environment the longest), those with adapted gaming features spend significantly more time in the learning environment. Furthermore, learners with features that are not adapted have a higher level of amotivation. These results support the relevance of adapting gaming features to enhance learners’ engagement, and provide cues on means to implement adaptation mechanisms.

**Index Terms**— Educational games, Adaptation to user profiles, Adaptive and intelligent educational systems

## 1 INTRODUCTION

Two different approaches are currently used to make computer-based learning more engaging: learning games and gamification. Learning games refer to the use of games for learning purposes [1], while gamification is based on the use of game design elements integrated in learning environments without turning the activity into a game [2]. The main purpose of these approaches is to foster learners’ participation and motivation to use the learning environment with a gamification approach.

The concept of gamification has earned a strong interest in the research community at least since early 2010. This concept has been used in many areas such as marketing [3], crowdsourcing [4] and health [5]. The work presented in this paper applies in particular to the educational domain [6]. Gamification is now widely used in education and has even been presented by Bíró [7] as a new educational theory, such as behaviorism, constructivism, cognitivism, and connectivism.

However, little is known on the impact of the adaptation of gaming features to a learner’s profile. While learners have different types of motives when interacting with games [8], most gamified systems integrate game elements under a “one size fits all” approach, without taking into account users’ individual preferences. Yet, akin to the strong positive impact of individualized tutoring on learning [9], we can reasonably argue that adapting gamification to the individual can generate substantial gains in engagement, and consequently increase learning gains.

Also, while some contributions have been made toward adaptation of learning games, with respect to both their educational properties and their game mechanics [10], few works have so far considered the creation of adaptive gamification systems [11], [12].

In this paper, we propose a model to automatically adapt gaming features to learner player types in learning environments. This model has been applied to an existing web-based learning environment named *Projet Voltaire*, developed by the Woonoz company specialized in memorization software. The environment aims to teach French spelling and grammar. As memorization is generally based on repetition, learning tasks are often perceived as boring [13]. Woonoz observes that many learners quickly drop out of the environment, in spite of its efficiency. The company thus launched a gamification project, in collaboration with our research team, to increase learners’ motivation to use the learning environment. In this context, we developed five gaming features corresponding to different player types. Adaptation of these features was based on the judgment of six gamification experts and on the use of the BrainHex questionnaire to identify the learner player types.

We conducted an experiment in a real world setting over a period of three weeks to investigate the impact of our proposed adaptive gamification approach on learners’ participation and motivation to use the learning environment. This experiment involved a broad spectrum of 266 participants. The first group of participants had the two most adapted features integrated in their learning environment, while the second group had the two features least adapted to their profile, and the third group had no gaming features at all. We analyzed the time spent on the environment and the learners’ answers to a questionnaire concerning their motivation and their enjoyment of the gaming features. The results show that the adapted gaming features’ condition has a greater number

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of highly engaged users, as measured by time spent within the learning environment. We also show that adaptation of gaming features can maintain low levels of amotivation. These results support the claim that an adaptive gamification environment can be more engaging than a non-adaptive environment for enhancing learners' participation in learning environments.

We review in section 2 the related research on gamification and gaming features. We also focus on player typologies and existing approaches for adaptation in learning environments. In section 3, we propose an implementation of gaming features and a model for adapting these features to player types. We then present in section 4 the design of the experiment we conducted to study the impact of adaptation on learners' participation and motivation to use the learning environment. Section 5 is dedicated to the detailed results of the experiment. We finally discuss in section 6 our findings, the limitations of the study, and the research impacts. We conclude with research avenues on dynamic adaptation of gaming features.

## 2 RELATED WORKS

In this section, we review previous studies on gamification of learning environments together with the various types of gamification elements that we have chosen to ensure adaptation of gaming features. We also review various player typologies and adaptation techniques that can be used to link these gamification features to player types.

### 2.1 Impact of gamification on learning processes

Gamification generally relies on the integration of game mechanics in existing environments. In recent years, a number of studies have been conducted on the effects of gamification on learning processes through the integration of many game elements in the learning environment [14], [15]. However, since the observed outcomes of the gamification approach are not related to a particular feature, it is not possible to determine which feature is better suited to learners' preferences.

Some studies evaluate more specifically the impact of the integration of one particular gaming feature on the learning process. For instance, Landers, Bauer and Callan [16] studied the impact of leaderboards on task performance and highlighted the interest of this gaming feature in supporting goal setting. Boyce [17] proposes a "deep gamification" approach, combining both game-based and play-based elements and showed that integration of points and achievements generates learning gains. The study conducted by Hanus and Fox [18] showed that integration of a leaderboard and badges induces a lower level of motivation and lower final exam scores for students, thereby showing a negative effect of this gamification feature. Hamari [19] focused his study on the use of badges to increase learner activity. Da Rocha Seixas, Gomes and de Melo Filho [20] were also interested in the impact of badges on learners' performances, and the results indicate that their performances were increased. The

inconsistency of these results reveals the complexity of the effects of specific gaming features on learners' performances and participation.

Nowadays it is well recognized that gaming mechanisms that motivate some learners (e.g. competition) may be detrimental to others [21]. In this perspective, we conducted a first exploratory study that showed the potential of the adaptation of gaming features for enhancing learners' motivation [22].

### 2.2 Gaming Features

Gamification generally relies on the integration of game mechanics in existing environments. Vassileva [23] reviewed the literature on game mechanics that can be applied to develop game-like elements in digital applications. She groups several mechanics: ownership (such as points, tokens, badges), achievements (a virtual or physical representation of having accomplished something), status (displaying a rank or level of achievement), community collaboration, and quests (challenges related to time-limit or competition). Kapp [6] also lists typical game elements like goals, rules, competition, cooperation, time, rewards, levels (player, game, difficulty), feedback, storytelling (hero's journey), aesthetics (harmony). More recently, Robinson and Bellotti [24] proposed a taxonomy of gamification elements comprising an objective, a social feature, an incentive, and a resource. Based on a systematic literature review, Antonaci *et al.* [25] identified 21 game elements suitable for MOOCs.

In order to determine the level at which adaptation of gaming elements should be conducted, we studied more particularly the classifications distinguishing the different levels of abstraction of gamification. Deterding *et al.* [2] propose a classification of game elements in five levels of abstraction. The authors consider the *interface elements* to be the most concrete ones, such as badges, leaderboards and levels. These elements reify the *game design patterns and mechanics* level. Examples given are time constraints and limited resources. The third level is the *game design principles and heuristics*, also described as guidelines for approaching the design problem. Such guidelines include setting various game styles and setting clear goals, such as managing the balance between the level of challenge and the skills of the players in order to lead them to the state of flow [26]. The fourth level groups the *game models*: conceptual models of the game components, such as curiosity and fantasy. Finally, *game design methods* belong to the most abstract type of elements. It includes for example playtesting and playcentric design.

Gamification elements are also often classified through the MDA model (Mechanics, Dynamics and Aesthetics). This framework was developed by Hunicke, LeBlanc and Zubeck [27], and applied to the design of educational games [28] and to gamification [29]. In this framework, *mechanics* refer to game elements in the user interface and the related algorithms. *Dynamics* are at a higher level of abstraction and refer to the interactions between the interface elements and the player. Then, *aesthetics* describe the emotional response of the player to the dynamics experienced. We can also classify game elements through the

DMC framework (Dynamics, Mechanics and Components) from the most abstract to the most concrete elements. Just as in the MDA framework [27], *Dynamics* describe the gaming experience at a high level. However, *Mechanics* refer to generic concrete elements, while *Components* refer to implementation of game mechanics for a specific software.

Our approach is based on the design of game elements that can be added to or removed from the user interface of the learning environment. Adaptation of gaming features can be conducted by integrating removable elements without disrupting the learning activity. Thus, adaptable gaming features should be defined at the most concrete level of abstraction of gamification: the interface elements defined by Deterding *et al.* [2], the mechanics according to the MDA framework, and the components according to the DMC model. In this perspective, we define gaming features as *an indivisible set of game design elements reifying a set of game dynamics*. As an example, we can consider a leaderboard comparing users' scores and rewarding the winner with a trophy. The leaderboard and trophy are the game design elements, while the main game dynamic that it reifies is competition. Such elements can be integrated in the interface for some users, and removed for other users without directly affecting the learning activity.

### 2.3 Player Typologies

Learners have different emotional responses to game mechanics. The diversity of players' expectations and behaviors is illustrated by player typologies, which can be used as a basis for adaptation.

Bartle's classification of players in four types (*killer, achiever, explorer* and *socializer*) is one of the most widely used in the gaming domain [30]. This typology was used as a basis by many others [31, 32, 11]. Based on an empirical study, Yee [33] identified three categories of motivational components: achievement, social interaction and immersion. However, these player typologies are bound to a specific game genre (Role Playing Games), and they may not work if applied in other contexts [34], such as gamification.

To address this problem, Kallio, Mäyrä and Kaipainen [35] developed a player type heuristic independent from the game genre. However, they focused on the relationship between the player and the gaming activity, and their typology cannot be applied to gamification. Another player typology applicable to various contexts was developed by Heeter *et al.* [36]. However, their typology is focused on mastery and achievement, and does not consider other game dynamics such as socializing and exploring. Another recent contribution in this area is the BrainHex gamer typology [37], [38]. This classification comprises seven player types:

- the *Seeker* enjoys discovery and exploration,
- the *Survivor* enjoys escaping and feeling fear,
- the *Daredevil* enjoys playing on the edge and taking risks,
- the *Mastermind* enjoys solving puzzles and devising strategies,

- the *Conqueror* enjoys defeating difficult opponents,
- the *Socializer* enjoys interacting with other players,
- the *Achiever* enjoys completing tasks.

The BrainHex types were investigated in relation to the players' behavior. Orji *et al.* [39] found significant correlations between BrainHex and determinants of a healthy behavior. Rogers, Kamm and Weber [40] found interesting relations between some player types and players' in-game behavior. For example, players whose dominant type was Seeker explored more than other player types.

We decided to use the BrainHex typology for adaptation to player types as it offers various advantages. First, it is not specific to a context (as Bartle's typology is specific to role-playing games) and considers a wide range of game mechanics. Secondly, BrainHex does not confine each player to one archetype, but represents them as a complete set of values indicating their interest in each type of mechanics. Finally, BrainHex is the only typology that is associated with a simple questionnaire that can be used to identify users' player types.

### 2.4 Adaptation of Games and Gamification

While there is currently very little research on adaptation of gamification, considerable research has been devoted to adaptation in serious games (and learning games in particular). Most methods propose a way to adjust the level of difficulty, for example by adapting the help given to players [41], the training intensity [42], or the educational scenario [43]. Besides these contributions to the "serious aspect" of the game, some proposals focus on making games more entertaining, for example by adapting the circuit of a car racing game [44] or the width of the gaps in a platform game [45]. However, none of these examples change the dynamics of the game.

Only a few approaches really adapt the game dynamics. Thue *et al.* [46] worked on adaptive storytelling. They adapt the *events* that will occur and then affect the gameplay. Natkin *et al.* [47] adapt the *quests* that are presented to the players. The quests are sufficiently varied to assume they create different game dynamics, like defeating other players or solving puzzles. Göbel *et al.* [48] adapt the scenes of a serious game to suit players' preferences.

These studies rely on different player typologies and use different adaptation methods. Thue *et al.* [46] rely on Laws' typology [49] and associate each event directly to one of the player types. Natkin *et al.* [47] rely on the Five-Factor Model. Their system represents both players and quests as vectors of player types, where the selection is made by identifying the shortest distance between vectors. Göbel *et al.* [48] rely on Bartle's typology [30]. They also use a vector representation for the players and game scenes. Despite their differences, these three approaches rely on a matrix associating the game components (*events, quests* or *scenes*) with the player types. Our proposal for gamified learning environments is inspired by this approach.



### 3 IMPLEMENTATION OF ADAPTIVE GAMIFICATION IN A WEB-BASED LEARNING ENVIRONMENT

In this section we propose a model for adaptive gamification according to learners' player types. We then present an implementation of this model in an existing web-based learning environment.

#### 3.1 Adaptation Model

In order to adapt gaming features to the learner's player profile, we propose a linear model to estimate the adequacy of gaming features for the player typology factors. This model estimates the preference for a feature by a weighted sum of personality traits.

The general principle is similar to a widely used approach in recommender systems, where a matrix of users' votes (preferences) for items (films, for example) is factorized into the product of two matrices: a matrix that represents users' preferences for latent factors (film genres) and another representing the degree to which the item (film) belongs to these factors [50]. This approach has also been used to model student skills mastery and to predict the success of a specific student for a given item [51]. For example, if a student possesses the skills required by an item, the product of the student and item skills vectors will be 1 and a successful outcome is expected.

The player model we propose relies on a matrix factorization model. Assume we have  $f$  gaming features developed in a system that is accessed by  $u$  users, and assume a player model comprising  $p$  player types. We represent the users' profiles in a matrix  $\mathbf{B}$  of size  $u \times p$ , giving a value for all player types to each player. The way in which each gaming feature matches the given player types is represented in a matrix  $\mathbf{A}$  of size  $p \times f$ . Finally, the way each gaming feature is adapted to a player is represented in a matrix  $\mathbf{R}$  of size  $u \times f$ .  $\mathbf{R}$  can be simply obtained by the product of the other matrices:  $\mathbf{R} = \mathbf{B} \mathbf{A}$ .

We provide an example of this model in Figure 1. This example considers a set of four users, three gaming features, and a hypothetical player model with two types: Competitor (C) and Socializer (S). In this example, the players' profiles (in  $\mathbf{B}$ ) reveal that user  $u1$  enjoys competition considerably, while user  $u2$  prefers social mechanics. Furthermore, the gaming feature representation (in  $\mathbf{A}$ ) shows that feature  $f1$  is highly competitive, while feature  $f3$  is social. Therefore, matrix  $\mathbf{R}$  shows that feature  $f1$  has the highest relevance value for user  $u1$ , and that feature  $f3$  has the highest relevance value for user  $u3$ .

The range of values within matrix  $\mathbf{B}$  is determined by the chosen player typology. In this work, we rely on the BrainHex typology (see part 2.2), which represents users

as a vector of values in  $[-10, 20]$  for each player type. The number of columns is also determined by the player typology: matrix  $\mathbf{B}$  has seven with the BrainHex typology. We propose to use only values contained in  $[0, 1]$  for matrix  $\mathbf{A}$ . This ensures that the relevance values in  $\mathbf{R}$  will be kept in the same order of magnitude as the values in  $\mathbf{B}$ . Since there can be negative values in matrix  $\mathbf{B}$ , negative values can also appear in matrix  $\mathbf{R}$ . These values indicate a negative impact of the gaming feature on users' motivation.

#### 3.2 Gamification of the Learning Environment

We developed five gaming features for an existing online learning environment named *Projet Voltaire*. This environment is used to teach French spelling and grammar to French-speaking people. Its main learning activity is based on reading incorrect sentences and pointing out where the mistake is. After a wrong answer, learners can read the grammar rule corresponding to their mistake. Two screenshots of the learning environment are presented in Figure 2, the first before the learner's answers, and the second after them. The learners' activity is analyzed by a didactic engine, responsible for adjusting difficulty and providing them with the most relevant items for effective learning.

Adaptation of the learning environment is based on two separate engines developed independently, one for didactic content adaptation and the other for gamification adaptation [52]. The didactic engine chooses the learning items to be presented to the learner, whereas the gamification engine adapts the gaming features displayed on the interface according to learners' profiles. In this paper, we only focus on the gamification engine.

The five gaming features were integrated in the environment in such a way that they can be toggled on or off independently from the didactic content engine and the general workflow (for more details see [52]). Although the user interface with the five features activated would be overloaded and counterproductive, it is still simple to use when one or two features are activated. Partial views of the gaming features are presented in Figure 3.

The first gaming feature is a set of *stars* that learners can earn for each grammar rule once they have mastered it. The second feature is a relative *leaderboard*. The score is based on the best number of correct consecutive answers that the learners can give. It does not show the best performers but the learners' neighbors, i.e. it shows a within reach goal consisting in surpassing the person just before rather than surpassing the best one. The third feature is tips that aim at enhancing social interactions by providing learners with a means of helping each other.

$$\begin{array}{ccc|c|c|ccc}
 & f1 & f2 & f3 & & C & S & & f1 & f2 & f3 \\
 \mathbf{u1} & 10 & 00 & 05 & & \mathbf{u1} & 10 & 00 & \mathbf{C} & 1 & 0 & \frac{1}{2} \\
 \mathbf{u2} & 00 & 06 & 12 & = & \mathbf{u2} & 00 & 12 & \mathbf{S} & 0 & \frac{1}{2} & 1 \\
 \mathbf{u3} & 06 & 03 & 09 & & \mathbf{u3} & 06 & 06 & & & & \\
 \mathbf{u4} & -08 & 03 & 02 & & \mathbf{u4} & -08 & 06 & & & & 
 \end{array}$$

Fig. 1. An example of linear model  $\mathbf{R} = \mathbf{B} \mathbf{A}$ . This example comprises 4 users ( $u1$ - $u4$ ), 3 gaming features ( $f1$ - $f3$ ) and a 2-factor player model: competition (C) and social (S). The matrix  $\mathbf{R}$  represents the estimated preferences of users for features.

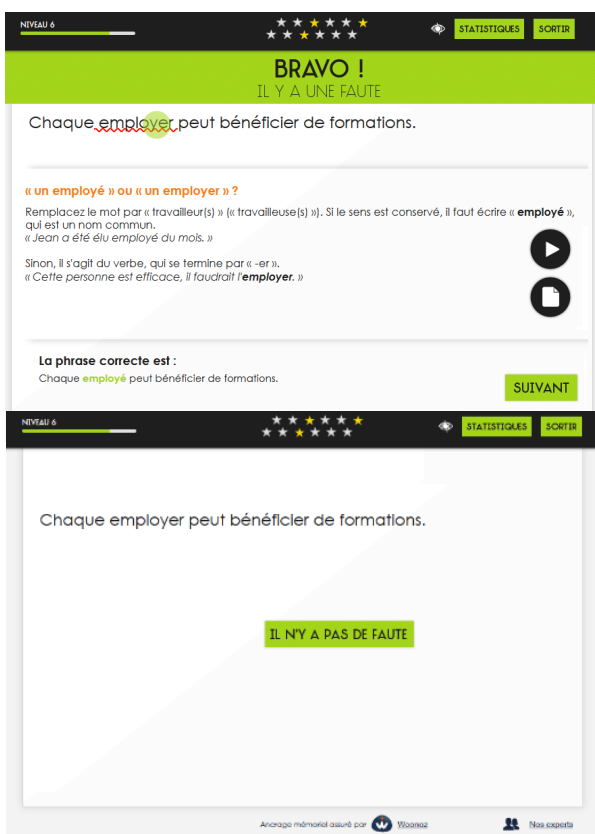


Fig. 2. The learning environment named Projét Voltaire. First interface: the learner has to read the sentence and point out the mistake. Second interface: after answering, the learner can see detailed explanations concerning the correct answer.



Fig. 3. Gaming features (1: stars, 2: leader board, 3: tips, 4: walker, 5: timer)

Each learner can propose a tip on how to remember a grammar rule, and obtains as feedback the number of learners interested in this tip. The fourth feature named *walkers* represents a walker progressing in a mountainous landscape. Each time the learner gives a correct answer, the walker takes another step. The gradient of the path is generated randomly, thus creating mountains with new shapes in order to arouse the learner's curiosity. At some points, the walker passes a flag and the learner can access a short story on the origin of a word. The fifth feature is a

*timer* that encourages the learner to repeat an exercise faster than the previous time. Finishing an exercise quickly leads to a reward (one, two or three cups).

### 3.3 Estimating the A-matrix

Whereas matrix **B** can be directly obtained from the answers to the BrainHex questionnaire over the 7 traits of the gamer profile, matrix **A** must be derived by some other means. In a previous study, we compared an A-matrix given by experts and an A-matrix extracted empirically from users' preferences [53]. As the expert-derived A-matrix was more accurate, we shall base ourselves on it for the adaptation process. We detail below the construction of this A-Matrix.

We relied on six experts to build the A-matrix. The experts are academics specialized in serious games and gamification. First, the experts read the description of the BrainHex player types in order to understand them. Second, they used the learning environment for roughly one hour. The five gaming features were activated during this use. They were then able to fill a matrix with values relating the seven player types to the five gaming features. They were asked to pick the values out of the following:

- No match: 0
- Weak match: 0.25
- Medium match: 0.5
- Strong match: 0.75
- Very strong match: 1

For each of the 35 positions in the A-matrix (5x7), we took the median of the six values proposed by the experts. We chose the median instead of the mean because it is less influenced by an extreme value that could have been left by just one of the experts. The resulting A-matrix is presented in Table 1. We used the IntraClass Correlation (ICC) [54] to measure the experts' agreement. The result obtained is 0.43, a value considered to be moderate, but high enough to confirm the agreement.

### 3.4 Interpretation of the A-matrix

The values in the A-matrix identify the degree to which game features match player types. This work is based on the description of the player types. For example, the description of the Conqueror type includes "*Players fitting the Conqueror archetype enjoy defeating impossibly difficult foes, struggling until they achieve victory, and beating other players (...)*" [37]. This description suggests these types of

TABLE 1  
EXPERTS A-MATRIX

	Stars	Leader board	Tips	Walker	Timer
Seeker	0.5	0	0.75	<b>0.88</b>	0
Survivor	0.13	0.5	0	0	0.38
Daredevil	0.63	0.63	0	0.13	<b>0.88</b>
Mastermind	0.63	0.63	0.38	0.25	0.25
Conqueror	0.75	<b>1</b>	0.13	0.38	0.75
Socializer	0.13	0.13	<b>1</b>	0.25	0
Achiever	<b>1</b>	0.75	0.13	<b>0.88</b>	<b>1</b>

Columns: gaming features. Rows: BrainHex player types.

The values higher to 0.8 are in bold type.

players enjoy competition. As the leaderboard implements competition, it has been linked more strongly to the Conqueror type. The stars present a set of items that can be obtained by completing a set of exercises. Therefore this feature was mainly related to the Achiever player type. The tips are the only feature that allows social interactions and thus was mainly linked to the Socializer type. Learners who propose a tip help other learners, and acquire a form of recognition when other learners select their tip. The walker feature was strongly related to the Seeker type as it offers exploration of visual landscape and discovery of word-related stories. It is also closely related to the Achiever type, probably because learners may look for the end of the landscape to “complete the path”, even if there is no end. Finally, the timer was strongly related to the Daredevil type due to the pressure exerted by the seconds left to complete an exercise. It was also related to the Achiever type as a result of the cups that can be earned by faster learners.

## 4 DESIGN STUDY

We conducted an experiment to evaluate the impact of adaptive gamification on learners’ participation, motivation and enjoyment of gaming features. The main question we addressed is “Can adaptation of gamification features based on implementation of our model enhance users’ participation and motivation to use the learning environment?” More precisely, we derive three research hypotheses:

- H1: Learners with adapted gaming features spend more time in the learning environment than learners with counter-adapted features or without gaming features.
- H2: Learners with adapted gaming features enjoy them more than learners with counter-adapted features or without gaming features.
- H3: Learners with adapted gaming features have a higher level of motivation to use the learning environment than learners with counter-adapted features or without gaming features.

### 4.1 Participants

A call for volunteers was broadcast on the Facebook page of the learning environment nine days before the start of the experiment. The volunteers had to answer the BrainHex survey and to provide their email in order to apply for participation in the experiment. The only reward for participants was the opportunity to use the environment for free throughout the experiment. 338 people volunteered for the experiment and filled in the player types questionnaire. After they received their login credentials, 266 of them actually used the learning environment. The participants were 210 women and 56 men, ranging in age from 18 to 75 (M = 40.3 years old, SD = 9.8 years). Among these participants, 178 answered the final questionnaire on motivation and enjoyment (see section 4.2). Participants were divided into three experimental groups:

- AF group (n=112): participants had adapted gaming features.

TABLE 2  
MEAN VALUE OF EACH PLAYER PROFILE IN THE THREE USER GROUPS (AF, CF AND NF)

	SEEK	SURV	DARE	MAST	CONQ	SOCI	ACHI
AF	12.8	-0.5	6.1	14.0	10.2	13.8	13.4
CF	12.4	0.4	5.1	12.5	10.4	14.9	12.6
NF	12.9	-0.2	5.5	14.1	9.8	12.8	13.9

Rows: experimental groups. Columns: gaming features (SEEK: seeker; SURV: survivor; DARE: daredevil; MAST: mastermind; CONQ: conqueror. SOCI: socializer; ACHI: achiever)

- CF group (n=111): participants had counter-adapted gaming features.
  - NF group (n=43): participants had no gaming features.
- The player profiles were rather equally distributed among the three groups as shown in Table 2.

### 4.2 Material and Data

The experiment included two surveys: the first to initialize players’ profiles, and the second to evaluate learners’ motivation.

#### 4.2.1 Player Type Survey

To initialize players’ profiles, we used the BrainHex questionnaire translated into French. It comprises 28 items: 4 are related to each of 7 player types. The given result is a list of values in [-10; 20] for each player type. The validity of the BrainHex typology and its associated questionnaire was investigated recently. Busch *et al.* [55] measured the internal consistency of each of the seven factors underlying the test with Cronbach’s Alpha (n = 592). They found acceptable reliability coefficients.

#### 4.2.2 Motivation Survey

Learners’ motivation to use the learning environment was evaluated using the Situational Motivation Scale (SIMS) [56] (see Appendix). This questionnaire is used to evaluate intrinsic motivation, identified regulation, external regulation and amotivation, with four items for each motivational component. “*Intrinsic motivation refers to performing an activity for itself.*” “*Identified regulation occurs when a behavior is valued and perceived as being chosen by oneself.*” “*External regulation occurs when behavior is regulated by rewards or in order to avoid negative consequences.*” Finally, amotivation refers to “*a lack of contingency between user’s behaviors and outcomes*”. Identified regulation and external regulation are subcomponents of extrinsic motivation. As we did not offer rewards for participation, the items evaluating external regulation were ignored in order to reduce questionnaire size.

#### 4.2.3 Enjoyment Survey

Enjoyment of gaming features was assessed through a questionnaire. We asked learners to rate each gaming feature in the user interface according to the statement “I enjoyed this feature”. Possible answers were: 1 = no, not at all, 2 = not very much, 3 = a little, 4 = moderately, 5 = rather yes, 6 = yes, 7 = absolutely yes.

#### 4.2.4 Interaction Traces

We collected data on the duration of learners’ sessions.

TABLE 3  
DISTRIBUTION OF ACTIVATED GAMING FEATURES

	Stars	Leader board	Tips	Walker	Timer	Total
AF	20	45	54	60	45	224
CF	17	56	49	46	54	222
Total	37 (8%)	101 (23%)	103 (24%)	106 (24%)	99 (22%)	

Columns: gaming features. Rows: experimental groups.

We can measure the total time spent in the learning environment and the detail for each session. The environment could also collect data on learning activities and outcomes. However, as the system dynamically adapts the level of difficulty to each learner, it could be difficult to compare results. We thus choose not to use this information in our analysis.

### 4.3 Procedure

The learners filled in the player type questionnaire (BrainHex) before using the learning environment. We then computed learners' preferences for each feature ( $\hat{\mathbf{R}}$ ), as  $\hat{\mathbf{R}} = \mathbf{B} \mathbf{A}$ , the product of experts' mapping of player types to features ( $\mathbf{A}$ ) by players' answers to the BrainHex questionnaire ( $\mathbf{B}$ ). Normalization was conducted in order to balance the probability of each gaming feature to be selected. To this end, each value in matrix  $\hat{\mathbf{R}}$  is divided by the mean value of the row.

Volunteers were randomly assigned to an experimental group. For members of the group with adapted conditions (AF), the two gaming features with the highest score in  $\hat{\mathbf{R}}$  were activated. For the group with counter-adapted conditions (CF), the two gaming features with the lowest score in  $\hat{\mathbf{R}}$  were activated. NF group members used the environment without gaming features. Distribution of gaming features is presented in Table 3.

The stars gaming feature were selected less frequently in the process than the other gaming features. As the values in matrix  $\hat{\mathbf{R}}$  were very high for the stars feature for all users, these values were the most affected by the normalization process with a high decrease. However, it ensures that each feature is rather equally distributed in the two groups.

Once the system was initialized, participants received their password to log into the web site. They were told they could use their access as much as they wanted. After 3 weeks, we sent them the motivation survey (SIMS) and the enjoyment survey to evaluate the gaming features they had used for the AF and CF groups.

## 5 RESULTS

### 5.1 Learners' Participation

The 266 users spent on average 2 hours and 15 minutes in the learning environment. Over the three-week period, participants with adapted gaming features (AF) spent on average 42 minutes more than participants with counter-adapted features (CF) and 43 minutes more than participants without gaming features (NF) (see Table 4). We

TABLE 4  
TIME SPENT ON THE LEARNING ENVIRONMENT

	N	M	SD	Wilcoxon	Student t-	Likeli-
				test with	test with	hood test
				AF	AF	with AF
AF	112	2h36	3h54	N.A.	N.A.	N.A.
log(AF)		0h10	0h00			
CF	111	1h54	2h11	p = 0.875	p = 0.945	p = 0.015
log(CF)		0h09	1h01			
NF	43	1h53	2h54	p = 0.378	p = 0.265	p = 0.198
log(NF)		<0h01	1h22			

N = number of participants, M = mean, SD = standard deviation. Student t-test and Likelihood ratio test were conducted on log transformed data.

conducted several tests on the log of the time spent. The log-transform of time is used because it fits well with normally distributed data, contrary to raw times. We compare group AF with groups CF and NF that lead to inconsistent results. The Wilcoxon test and the Student t-test on log-transformed data yield non-significant results. However, we also performed a test to compare distributions based on likelihood ratios. We used the Normal distribution to fit the log of the data for the different conditions and computed the likelihood ratio, over which a Chi-square test can be applied. This leads to a significant difference between groups AF and CF ( $p = 0.015$ ,  $p < 0.05$ ). These contradictory results could be explained by the fact that the likelihood ratio test is a more powerful test under some assumptions [57]. They lead us to go further into the distributions of time spent by group.

Figure 4 shows the distribution of the participants over the three groups according to the time spent in the environment. This figure reveals a similar behavior among all three groups for the first 75% of users, and different results among the groups for the 25% of users who used the environment the longest. Considering the 25% of the most active participants in each group (over two hours), there is a large difference between members who had adapted features and the two other groups. Table 5 reports an

TABLE 5  
TIME SPENT BY PARTICIPANTS ON THE ENVIRONMENT FOR THE 75% LESS ENGAGED VS. 25% MOST ENGAGED

	75% less engaged users			25% most engaged users			
	N	M	SD	N	M	SD	
AF							(1) Wilcoxon test
log(AF)	84	1h02	0h46	28	7h18	5h29	(2) Student t-test
					1h46	0h37	(3) Likelihood test with AF
CF							(1) p = 0.004
log(CF)	83	1h01	0h40	28	4h28	2h58	(2) p = 0.008
					1h22	0h26	(3) p = 0.001
NF							(1) p = 0.010
log(NF)	32	0h53	0h41	11	4h45	4h39	(2) p = 0.053
					1h19	0h36	(3) p = 0.014

N = number of participants, M = mean, SD = standard deviation. Student t-test and Likelihood ratio test were conducted on log transformed data.



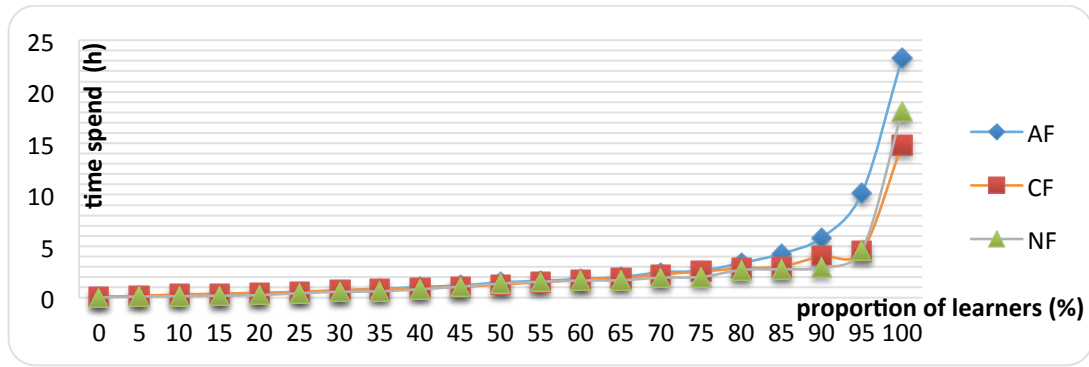


Fig. 4. Time spent (in hours) on the environment on the y-axis, cumulative percentage of students on the x-axis.

TABLE 6  
ENJOYMENT OF THE GAMING FEATURES

	(1) Stars			(2) Leader board			(3) Tips			(4) Walker			(5) Timer			Total	
	N	M	SD	N	M	SD	N	M	SD	N	M	SD	N	M	SD	M	SD
AF	11	3.5	1.8	29	4.6	1.4	39	4.7	1.8	41	4.3	1.8	26	4.5	1.7	4.4	1.7
CF	10	4.8	1.7	38	4.3	1.7	33	4.0	1.6	30	4.0	2.0	39	4.6	1.6	4.3	1.8

*N* = number of answers on the feature, *M* = mean, *SD* = standard deviation

analysis on this specific group of more active learners. The Wilcoxon test, the Student t-test and the likelihood ratio test on log transformed data performed on these users shows highly significant differences for the group with adapted features compared to the group with counter-adapted features and the group without features.

These results provide partial evidence for accepting the H1 hypothesis, as participants who spent over two hours with the learning adaptation and who were presented with adapted gaming features spent significantly more time on PV than the other participants. However, no effect is significant for less than two hours of use. This could be the result of a migration of otherwise average- or even low-engaged users- to high-engaged ones..Or else it could be the result that only highly engaged learners are affected. Further studies will be required to elucidate this question.

The roughly equal time spent by users with counter-adapted features (CF) and users without features (NF) is another important result. It suggests that gaming features may not impact users' participation when they counter-match their player profile. However, this result is obtained with two gaming features added to the environment and cannot be generalized to any gamification process.

## 5.2 Learners' Enjoyment of the Assigned Features

We asked learners the degree to which they enjoyed their gaming features. The mean values obtained for each feature are presented in Table 6.

Participants with adapted features and counter-adapted features gave a similar mean value for their enjoyment of the gaming features. The only feature with a difference greater than one point is the stars gaming feature, but there are insufficient participants with this feature to draw a conclusion (see Table 3). With a mean value at 4.4 for the AF group and 4.3 for the CF group, we

observe that users with adapted features enjoyed the features just as much as the group with counter-adapted features. This result led us to reject hypothesis H2: enjoyment of gaming features does not seem to be dependent on their adaptation to users' player profiles.

## 5.3 Learners' Motivation

The SIMS questionnaire was used to evaluate intrinsic motivation, identified regulation, and amotivation of all groups. All results are contained in a range from 4 to 28 (4 questions per motivation component, scored from 1 to 7 each, see Appendix). 178 participants answered the final questionnaire. They report on average a value of 21.4 for intrinsic motivation, 24.1 for identified regulation, and 5.6 for amotivation. These high motivation results reflect the fact that all users volunteered and were interested in learning French spelling and grammar. Table 7 presents the detailed results for the three groups of participants.

We conducted several tests to compare the level of motivation of group AF with groups CF and NF (see Table 7). Regarding intrinsic motivation, a student t-test leads to significant results between learners with adapted features (AF) and learners without gaming features (NF). However, the Wilcoxon and likelihood ratio tests yield non-significant results, although the rather low p-values obtained tend to confirm these observations. Amotivation of users with counter-adapted features (CF) is significantly higher than for users with adapted features (AF) with both the t-test and the likelihood ratio test. This means that CF group members have less motivation to continue using the environment than AF group members. This difference is not observed for participants with no gaming features. We observe no significant difference in identified regulation between the three groups of participants.

We conclude that hypothesis H3 can be partially accepted. The lower amotivation of members with adapted features suggest they are more willing to continue using

TABLE 7  
RESULTS OF THE SIMS MOTIVATION QUESTIONNAIRE

	Intrinsic motivation					Identified regulation					Amotivation					
	N	M	SD	T-test	Wilcoxon	Likelihood	M	SD	T-test	Wilcoxon	Likelihood	M	SD	T-test	Wilcoxon	Likelihood
AF	73	21.2	3.8	N.A.	NA	N.A.	24.3	2.7	N.A.	N.A.	N.A.	5.1	1.4	N.A.	N.A.	N.A.
CF	75	21.1	4.2	0.929	0.892	0.718	23.6	3.5	0.285	0.673	0.734	6.1	2.7	0.035	0.127	0.026
NF	30	22.9	2.6	0.033	0.117	0.176	25.0	2.9	0.432	0.179	0.334	5.2	1.5	0.830	0.698	0.987

*N* = number of answers, *M* = mean, *SD* = standard deviation. *P*-values are given for each test in comparison with raw data of AF group.

the environment than users with counter-adapted features. However, intrinsic motivation tends to be higher when participants do not have a gamified environment and amotivation is at the same level. These results are consistent with findings from other studies and are discussed in section 6.3.

#### 5.4 Impact of Assigned Gaming Features on Learners' Participation and Amotivation

To study in more detail the influence of the various gaming features, we repeated the previous measurements with subgroups possessing the same combinations of features. Only a subset of all possible feature combinations contains large enough samples to allow statistical hypothesis testing. Among the participants, 31 members of the AF group and 38 members of the CF group had features 2 (leaderboard) and 5 (timer). Meanwhile, 38 members of the AF group and 32 members of the CF group had features 3 (tips) and 4 (walker). These two combinations of features are the most frequent and the only ones with significant results, presented in Table 8. We focus on the time spent in the environment by learners over the three weeks and their level of amotivation.

With features 2 and 5 (leaderboard and timer), participants for whom these features are adapted spent far more time in the environment than the other participants (1h20 on average; +68%). However, this result is not statistically significant -we notice that the *p*-value obtained with the likelihood ratio test is rather low-, and the level of amotivation of the two groups is relatively similar.

Concerning features 3 and 4 (tips and walker), the results are very different. On the one hand, participants for whom these features are adapted spent slightly more time in the environment than the other participants (26 minutes on average; +21%). On the other hand, they present a very great and significant difference in their level of amotivation, as participants with adapted features are

less amotivated.

Participants with adapted and counter-adapted features can have a significant difference in amotivation while having exactly the same gaming features. These results confirm that the differences observed in users' amotivation according to adaptation (and counter-adaptation) of their features were not due to variations in gaming feature distribution (see Table 3) but in fact rather to the adaptation process itself. These results also tend to show that the impact of gaming features on users' motivation and participation depends on the gaming features themselves: features 2 and 5 tend to increase users' participation, while features 3 and 4 have an impact on users' amotivation. This suggests that each feature can have a specific target behavior (e.g. motivation, retention, concentration). This is an exploratory study, and more investigations are required to explore the impact of various game features on learners' behavior.

## 6 DISCUSSION

### 6.1 Main Findings

Concerning our first hypothesis (H1), the results show that 1) learners with counter-adapted features spent on average the same time in the environment as learners without features, and 2) the adaptive features apparently only affect the most engaged users. We find little to no difference for the majority of users who spend less than two hours, but for the top quartile we find a significant trend that suggests these more involved users get even more involved, or else that otherwise average or low involved migrate towards the high involved group when presented with adapted features.

Regarding the second hypothesis (H2), the results do not show any difference in learners' enjoyment of the gaming features. This result is quite surprising as we observe a significant impact of adaptation with indirect

TABLE 8  
TIME SPENT AND AMOTIVATION OF SUBGROUPS WITH SIMILAR COMBINATIONS OF FEATURES

	Time spent						Amotivation						
	Features 2 & 5			Features 3 & 4			Features 2 & 5			Features 3 & 4			
	N	M	SD	N	M	SD	N	M	SD	N	M	SD	
AF	32	3:18	3:10	38	2:28	1:49	AF	20	5.8	2.2	28	4.4	0.6
CF	43	1:58	1:29	32	2:02	1:29	CF	31	5.9	2.5	21	7.0	3.3
T.test (log)	p = 0.472			p = 0.850			T-test	p = 0.938			p = 0.012		
Wilcoxon	p = 0.583			p = 0.538			Wilcoxon	p = 0.745			p = 0.005		
Likelihood (log)	p = 0.078			p = 0.905			Likelihood	p = 0.991			p < 0.001		

*N* = number, *M* = mean, *SD* = standard deviation. Student *t*-test and Likelihood ratio test were conducted on log transformed data on time spent.

measurements: the time spent by engaged users and the level of amotivation declared in the questionnaire. This point suggests that learners' enjoyment of gaming features does not depend on the impact of the features on their motivation and participation. This result is in line with a previous study that showed that the adaptation process might have a negative impact on the perceived usefulness and fun of adapted gaming features [58]. This observation has strong implications on the adaptation process, as it indicates that adaptation should not be based on explicit learners' choices.

With respect to the third hypothesis (H3), an important result from the motivation survey is that adaptation of gaming features is a means of keeping learners' amotivation relatively low: at the same level as for learners without gaming features. We also observe that intrinsic motivation tends to be lower with use of a gamified learning environment than with a non-gamified one. This result is similar to other studies such as in [18]. For learners that are intrinsically motivated by the learning activity – as in our study - integration of gaming features could lead to a decrease in this motivation component.

Finally, we observe significant differences in levels of amotivation and participation according to the assigned features. This suggests that the impact of the implemented features differs across their game mechanics: some have a direct impact on motivation to use the learning environment, others on the time spent. For example, the timer encourages learners to start over the current level to beat their best time, and then to practice for a longer period. As another example, the tips provide learners with a means of helping other learners, thus making the activity more meaningful.

## 6.2 Limitations of the Study

A first limitation stems from the difficulty of demonstrating the impact of gamification on learners' performances. It would be interesting to measure the impact of adapted gamification not only on motivation and participation, but also directly on learning outcomes. This could generally be observed through the rate of correct answers and the time taken to respond [59]. However, this was not possible within this experiment because the didactic content engine dynamically adapted the level of difficulty, and led to similar good answer rates in all groups.

We also note that the participants in this experiment were all volunteers and interested in using the learning environment. This probably played a role in the motivation and participation outcomes. It would be interesting to conduct such an experiment in a context where learners do not engage in the activity through their own choice, such as in the study conducted in an undergraduate course by de Marcos *et al.* [60]. In this study, the participation rates and scores remained low with deployment of a gamification plugin in the learning management system.

The number of proposed gaming features is currently limited. We propose five different features and, even if this were a sufficient base to test the adaptation mechanism, a larger set of features could lead to other analyses.

It could be possible, for example, to evaluate which properties or combination of properties are effective for impacting motivation positively.

Finally, another limitation is the result of the number of participants who answered the final questionnaire on motivation and enjoyment of gaming features (only 178 answers from 266 participants initially). This could have led to a bias in the study results, as participants with greater motivation would answer the questionnaire. Nevertheless, comparisons between groups are not impacted by this sampling problem and our results are significant.

## 6.3 Implications of the Findings

To the best of our knowledge, our study is the first to propose implementation of gamification adaptation in a learning environment in ecological, real-life conditions.

First, based on our findings on learners' participation, it is our opinion that adaptation of gaming features can lead to an increase in participation only for the most active users, i.e. users who spend considerable time in the learning environment. This implies that other mechanisms would have to be determined for user retention at start of use.

Second, it appears that learners may not be aware of the gaming features that motivate them most to use the environment, as our findings on participation and motivation are not in line with those on enjoyment. This observation has strong implications on the adaptation process, as it indicates that adaptation should not be based on explicit learners' choices, but rather on indirect measurements through questionnaires or interaction traces.

Our findings on the components of learners' motivation also have strong implications on the gamification process. Regarding the impact on amotivation, our findings suggest that adaptation of gaming features can reduce this risk and maintain the learners engaged in the learning activity even if their intrinsic motivation is lower. However, gamification may also reduce intrinsic motivation due to a low level of acceptance of "non serious" elements within a serious environment, perceived as a disturbance by learners who are already intrinsically motivated.

Finally, we surmise that our preliminary findings on specific functionalities have implications on the way gaming features should be designed according to the expected impact on learners (e.g. motivation or participation). Further studies are needed to evaluate, for each type of feature, the impact it has on each component of learners' motivation and learning processes.

## 6.4 Generalization of the Adaptation Process

Our approach of adaptive gamification is generic and could be applied to learning environments using other learners' models, like the learning styles or personality traits. For instance, Buckley and Doyle [61] based their study on the Index of Learning Styles (ILS) [62] to identify that learners who are orientated towards active or global learning styles have a positive impression of gamification. They also investigated the personality traits according to the Ten Item Personality Measure (TIPI) [63] to show that



extraverted individuals like gamification, while conscientious individuals are less motivated by it. In the context of educational games, Hwang *et al.* [64] showed that both students' learning motivation and achievement were enhanced when they are presented with a game that matches their preference for either sequential or global learning. Adaptive gamification could thus rely on these results but more studies would be needed to identify more precisely which gaming feature suits the best to which learning style.

Our approach could also be applied to a wider range of activities. In particular, this gamification system could be applied to educational activities with repetitive tests and/or multiple-choice questions. These kinds of activities are popular in online learning platforms and MOOC. Moreover, such activities are the most appropriate for adapted gamification due to their low intrinsically motivating nature. Potential scenarios of use are:

1. Before the activity:
  - a. defining several game features according to the learning activity,
  - b. defining an adaptation matrix based on experts' opinions (A-matrix): gaming features  $\times$  player types (e.g. BrainHex).
2. During the activity:
  - a. defining the player type of each user with a questionnaire or from traces of use,
  - b. selecting adapted gaming features by considering the player type of the user: the proposed adaptation principles and algorithm are generic and could be re-used.

The choice of gaming features (1.a.) is a crucial step. We observed that some features influence the duration of use, while others reduce amotivation.

Another advantage of this approach is its scalability, as the previous steps do not require more work when there are more learners. On the contrary, if the system has gaming features that rely on user interactions, designers should be very careful when there are few users. They may have to implement a constraint to assign this feature to a minimum number of users, in order to maintain the competition or cooperation mechanics underlying the gaming feature.

A limitation to our approach in its current state is that users have to fill in a large questionnaire on game preferences. While this could be done in experimental conditions, it may not be appropriate in some learning contexts. As a solution, we could provide learners with access to the gamification settings of the environment, so that they can directly state their preferences. However, our findings suggest that learners' choices would not match the features that really motivate them for a given learning activity. This appears to be a major issue in the personalization of gamification.

## 7 CONCLUSION AND FUTURE WORKS

In this paper we presented an adaptive gamification model based on a linear model between player types (BrainHex) and gamification features. We also proposed

an implementation of this model based on the opinion of gamification experts. While serious games integrate the game mechanics at the core of the activity, our approach is based on independent gaming features and an adaptation that can be integrated to already existing learning environments. Moreover, while didactic adaptation and gaming adaptation cannot easily be combined in the context of serious games [44], our system based on gamification allows adaptation of gaming features without consequences on adaptation of the learning content and pedagogical scenario.

In recent years, many studies focused on the effectiveness of gamification with respect to learners' motivation and participation. However, these studies did not consider the relationship between the tested game mechanics and the player profile of the learners. We conducted an experimental study in ecological conditions, which shows that adaptive gamification (1) can significantly improve the participation of learners who use the environment the longest (top 25% in our study), and (2) can reduce learners' level of amotivation compared to counter-adaptive gamification. Furthermore, experimental results suggest that user motivation and user participation are two factors that can be influenced independently by different game features.

The proposed system selects gaming features by considering the player type of the user, but does not consider users who do not want to play. Accordingly, a further version of the system should consider the number of integrated gaming features as a variable for the adaptation process. It could then provide no features for a user who is already intrinsically motivated or who wants an uncluttered user interface, and three or more features for a user willing to play. This would also prevent a decrease in intrinsic motivation.

Currently, the player profile initialized through the BrainHex survey remains identical during the learning activity. In future works, we plan to experiment with a dynamic player profile adaptation based on user interaction traces. Indeed, users' actions could be interpreted in relation to their player types: for example, a learner frequently interacting with a competitive feature would have a high score for the "Conqueror" type. First, this dynamic profile could account for the evolution in players' preferences over time. Second, an incremental construction of the user profile could alleviate the issue of the preliminary BrainHex questionnaire.

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