# Adaptive Gamification and its Impact on Performance

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**Abstract.** The objective of this work is to measure the effects that adaptive and counter-adaptive gamified applications have on individuals' performance. Researchers have sought to explore how individuals' player type can be used to tailor gamification. However, existing studies do not measure the impact that adaptive gamification has on individuals' performance since they tend to focus on exploring the relationship between individuals' player type and their game element preferences. Consequently, a designer may spend valuable resources creating a gamified application and yet, not see any positive effects or even see negative effects on individuals' performance. In light of this gap, a randomized experiment was conducted in which participants' performance on (i) an adapted gamified application, (ii) a non-adapted gamified application, (iii) a non-gamified application, and (iv) a counter-adapted gamified application was analyzed. In this work, the game elements in the adapted and counter-adapted gamified applications were selected based on individuals' Hexad player type dimensions. The results revealed that the performance of individuals who interacted with the adapted gamified application was greater than any other group. In contrast, the performance of individuals who interacted with the counter-adapted gamified application was worse than any other group. This work provides empirical evidence on the effectiveness of adaptive gamification. Moreover, the results highlight the need to consider individuals' player type when designing gamified applications and the latent detrimental effects of not doing so.

**Keywords:** Gamification; Hexad Player Type; Adaptation.

## 1 Introduction

The research community has gained increased interest in gamification to improve individuals' motivation [1–4]. In gamification, designers integrate game elements into their applications (e.g., Points, Leaderboards, Levels) to motivate individuals to perform a task or a series of tasks [5]. For example, in the health and wellness context, several studies have implemented gamification to motivate users to perform physical tasks in order to improve their physical fitness or health awareness [6–9].

Multiple studies indicate that the perception and preference of game elements differ at an individual level [10s–15]. Studies also suggest that a gamified application that motives an individual might not have the same effect on another individual [9,16]. These studies are in line with the Self-Determination Theory (SDT) and the Cognitive Evaluation Theory which indicate that the effects of a stimulus (e.g., game element) on an individual's motivation is mediated by his/her perception of the stimulus itself [17]. Because of these differences, researchers are exploring how individuals' game element preferences can be assessed using player type models [7,13,18–21]. Individuals' player type information can be used to adapt or personalize gamified applications [3,15]. The concepts of adaptation and personalization are closely related since their objective is to tailor an application to provide an improved user experience [22]. Personalization is defined as the process where "*the content is tailored by the system to individuals' tastes*" [23]. While adaptation is when an application is used to "*tailor the interaction to different users in the same context*" [24].

While researchers are gaining interest in adaptive gamification, a recent literature review found that most of the studies to date only explore user modeling for future adaptation and do not measure the impact of adaptive gamification [3]. The few studies that do not focus on user modeling, only provide conceptual frameworks or little empirical evidence of the impact that adaptive gamification has on individuals [3,13,19,21,22,25]. Hence, it still unclear if designers should spend valuable resources adapting an existing gamified application with the objective to improve an individual's performance. In light of the existing knowledge gap, a randomized between-subject experiment is conducted to explore the differences between participants' performance on (i) an adapted gamified application (i.e., an application that implements the game elements that are recommended for a given individual), (ii) a non-adapted gamified application (i.e., a *one-size-fits-all* application that implements all possible game elements), (iii) a non-gamified application (i.e., an application that does not implement any game elements), and (iv) a counter-adapted gamified application (i.e., an application that implements game elements that are not recommended for a given individual).

## 2 Literature Review

Research indicates that gamifying an application may not lead to increased motivation or behavioral changes in every condition [14,26,27]. Studies have also found that the perception and preference of game elements differ at an individual level [10,13]. Unfortunately, most of the existing gamification applications are designed with a "*one-size-fits-all*" approach (i.e., non-adapted).

According to the Self-Determination Theory (SDT), an individual will be motivated if his/her innate psychological needs for *Autonomy*, *Competence*, and *Relatedness* are satisfied. Nevertheless, how these psychological needs are fulfilled depends on individuals' perceptions [17]. Furthermore, the Cognitive Evaluation Theory indicates that the effect of extrinsic rewards (e.g., game elements) on an individual's innate psychological needs is mediated by their perception of these extrinsic rewards as controlling or informational [17]. A recent gamification study found that participants valued certain basic psychological needs more than others and suggested that more research is needed to better understand how this weighting process takes place in gamification [28]. Moreover, a study exploring the counterproductive effects of gamification found that individuals had different gamification beliefs, and these beliefs were correlated to their perception of the application as useful [29]. Along with the motivational theories, these studies support the need to consider individuals' unique characteristics when designing gamified applications.

### 2.1 Player Type Models

In light of the heterogeneity across individuals, researchers are exploring the use of player type models to improve gamified applications [18–20,30,31]. The "Gamification User Types Hexad Framework" was introduced by Marczewski [32] to evaluate individuals' preference for game elements in gamified applications. Subsequently, Tondello et al. [33] proposed a 24-item questionnaire to assess individuals' Hexad player type. Recent studies support the validity and reliability of this Hexad player type questionnaire [34,35]. Because of this, several gamification studies have used the Hexad player type questionnaire as a basis to explore individuals' game element preferences and perceptions [7,10,12,14,20]. In the field of gamification, the Hexad player type model is the most frequently used model [3,13]. Moreover, a recent study that compared several personalities and player types models concluded that the "*Hexad is the most relevant typology to identify user preferences for game elements*" [15]. The Hexad player type model introduces six-player type dimensions: (i) Philanthropists, (ii) Disruptors, (iii) Socialisers, (iv) Free Spirits, (v) Achievers, and (vi) Players. Table 1 shows a summary of the Hexad player types from the literature.

**Table 1.** Summary of Hexad player types

| Hexad player type dimension | Description |
|---|---|
| Philanthropists | These players are motivated by purpose and meaning. They show altruistic behavior and are willing to give without expecting a reward. |
| Disruptors | These players are motivated by change. They tend to disrupt and challenge the system. They often test the limitations of the system and try to push it further. |
| Socialisers | These players are motivated by relatedness. These players want to interact with other players and create social connections. |
| Free Spirits | These players are motivated by autonomy and self-expression. They like to have meaning, freedom, act without external control, and explore within a system. |
| Achievers | These players are motivated by competence and mastery. They seek to progress within a system by completing tasks or prove themselves by tackling difficult challenges. |
| Players | These players are motivated by extrinsic rewards. They will do what is needed to earn a reward within a system, independently of the type of activity. |

*Note*: This summary was adapted from Tondello et al. (2016) and Marczewski's Gamified UK website [https://www.gamified.uk/user-types]

Researchers have used storyboards to explore the correlation between individuals' Hexad player type and their game element preferences and perceptions [10,12,20,33]. In the context of physical-interactive applications, the Hexad player type model was used to explore the relationship between individuals' player type, their perception of game elements, and their performance on a gamified and a non-gamified application [14]. The results of this study indicate that individuals' Hexad player type correlates with their perception of game elements and performance in the applications used. Moreover, this study supports the need to consider partial membership between the Hexad player types. That is, an individual's dominant Hexad player type does not have enough discriminative power to differentiate individuals according to their game element preferences, similar to other studies [15].

While the previous studies indicate that individuals with different player types perceived game elements differently, it is still not clear if implementing different game elements in an application based on individuals' player type will motivate them to perform differently. That is, it is still unclear if a designer can negatively or positively impact the performance of an individual by implementing specific game elements based on the individual's player type. This is because none of these studies have tested the impact of adaptive gamification. Therefore, while studies and motivational theories suggest that individuals can be motivated by game elements differently, there is still a need to better comprehend how player type models can be used to advance the field of gamification and improve individuals' performance [3,22,36].

### 2.2 Adaptive Gamified Applications

Several studies have started exploring different methods for adapting gamified applications based on individuals' Hexad player types. For example, [30] proposes an adaptive framework for educational gamified applications. Similarly, a recommender system framework to adapt gamified applications based on individuals' player type and their game element preferences was proposed in [19]. Lastly, a machine learning model to tailor the content of gamified applications based on individuals' player type was proposed in [21]. Unfortunately, these studies only provide conceptual frameworks and no empirical evidence of their implementation nor the effectiveness of their framework for improving individuals' performance.

Some studies have shown promising results by adapting educational gamified applications based on students' player type. For example, [37] implement four different educational gamified applications in which the game element of Rewards was adapted based on students' Hexad player type. That is, the specific rules about who gets the rewards and how the scoring was achieved differed between the applications. Their results did not show any statistically significant difference between the intervention group (adapted reward application) and the control group (non-adapted reward application). However, their descriptive statistics suggest that adaptation works better than generic approaches when it comes to improving the behavioral and emotional engagement of the students. Similarly, [18] propose a design framework to adapt gamified applications based on individuals' Hexad player types. In their study, they implement their framework to adapt the feedback provided in a gamified online platform for physicians. Their results indicate that by gamifying and adapting the application, user acceptance and system usage increased. Moreover, [38] implement a matrix factorization approach to select what game elements students would interact with, in an educational gamified application. In their matrix factorization approach, they used "experts" to match individuals' player type to five different game elements. Their results indicate that students that interacted with the non-adapted application have a higher level of amotivation (i.e., not motivated). However, their adapted application only had a positive effect on the most engaged students (i.e., students who used the environment the longest).

**Table 2.** Summary of current literature of adaptive gamification

| *Study* | *Empirical Evidence*[†] | *Non-adapted Group* | *Non-gamified Group* | *Counter-adapted Group* | *Measure Performance* |
|---|---|---|---|---|---|
| [19,21,30] | No | No | No | No | No |
| [37] | Yes* | Yes | No | No | No |
| [18] | Yes** | No | Yes | No | No |
| [38] | Yes*** | No | Yes | Yes | No |
| *This work* | Yes | Yes | Yes | Yes | Yes |

*[†]If the study presents evidence of the implementation of a tailored gamified application; if not, only a method is presented.* * [37] *did not find any statistically significant results* **[18] *used a within-subject experimental design, so the control group was the same as the intervention group. The group interacted with the non-gamified version of the application first.* ***[38] *results indicate that the adapted application only had a positive effect on the students who used the environment the longest.*

Table 2 summarizes current studies that have explored the use of individuals' player type to adapt gamified applications. While these studies are a first step towards understanding the value of adaptive gamified applications using individuals' player types, several limitations still exist. First, some of these studies only provide conceptual frameworks or little empirical evidence of the effects that adaptive gamification has on individuals [19,21,30]. Secondly, some studies only compare the effects of their adapted application against a non-gamified application. Hence, it cannot be concluded if the positive effects shown are due to the adaptation or the gamification aspect of the application [18]. Similarly, while [38] did compare the results of an adapted gamified application against a non-gamified application, and a counter-adapted gamified application, it is not clear if there would be any incremental improvement by moving from a non-adapted gamified application to an adapted one. Moreover, their results only show that students that interacted with the counter-adapted and the non-gamified applications have a higher level of amotivation and that the adapted application only had a positive effect on the most engaged students. Likewise, while [37] compared an adapted gamified application vs. a non-adapted gamified application, they did not find any statistically significant results. More importantly, in their adapted application, all participants interacted with the same game elements of Reward. The rules about who gets the rewards and how the scoring was achieved, was the only aspect tailored. Lastly, all these studies only measured the effects of adapted applications on individuals' emotional engagement or usage of the applications, and not on the individuals' performance. All these studies have focused on educational applications, which makes it difficult to demonstrate the impact of adaptive gamification on individuals' performance [38]. Hence, it is still not clear if designers should spend valuable resources adapting a gamified application according to individuals' player type to improve their performance on a task.

In light of current knowledge gaps, this work presents a randomized between-subject experiment to measure the effects that (i) an adapted gamified application, (ii) a non-adapted gamified application, (iii) a non-gamified application, and (iv) a counter-adapted gamified application have on individuals' performance. In this work, a matrix factorization approach is used to adapt and counter-adapt the gamified applications, similar to [38]. However, in this work, the relationship between individuals' player type dimensions and game element preferences were drawn from previous empirical studies and not from the input of "experts" (see Table 4).

# 3 Case Study

Before the randomized controlled experiment, participants were introduced to the informed consent documents, informed about the concept of gamification, and that they were going to interact with a physically-interactive application intended to promote and motivate them to perform several physical tasks. Once participants provided their consent, they (i) completed a pre-experiment questionnaire, and (ii) interacted with their respective applications. The pre-experiment questionnaire captured participant's Hexad player type, their demographics, and background information.

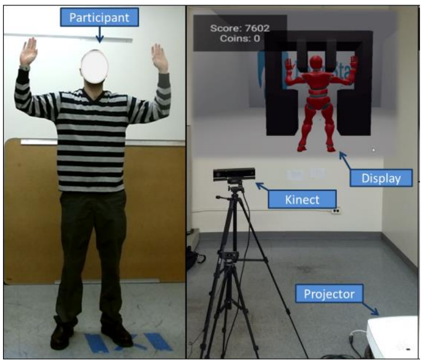


**Fig. 1.** Experimental setup

## 3.1 Applications

The applications required the participants to use full-body motions (e.g., bend, extend an arm, jump) to complete a series of physical tasks, similar to the applications introduced by [14]. Each participant interacted with the application twice. The applications contained the same set of 14 tasks. Figure 1 shows the experimental setup used in this work, where the Microsoft Kinect sensor was positioned between the projected display and the participants. The same set of game elements used in the non-adapted gamified application introduced in [14] were implemented in this study (see Table 3). However, in this work, the game elements that each participant interacted with in the adapted or counter-adapted application were selected based on a recommender system.

**Table 3.** Game elements implemented

| Game element | Description |
|---|---|
| Points | The score measurement of an individual was shown in the top left corner of the projected display. |
| Content Unlocking | Coins were placed throughout the application in different locations. If more than 21 coins were collected, the individual was allowed to change the gaming environment background. |
| Avatar | The individuals were given the option to change the color of the avatar that would represent them in the virtual environment. |

One of the advantages of the matrix factorization approach used in the recommender system is that it uses individuals' Hexad player type dimensions. Hence, it does not discretize individuals into single-player type categories; rather, it considers partial membership between player types. This overcomes some of the limitations of previous studies, helping designers adapt applications at a more individualized level [9,15]. In this study, the matrices used are obtained by implementing the Hexed player type questionnaire [33] and constructed based on the results of previous studies that have explored the relationship between individuals' game element preferences and their Hexad player type (see Table 4). In this study, participants in the adapted group were only shown the elements that were recommended, while participants in the counter-adapted group were shown the elements that were not recommended.

**Table 4.** The matrix that matches individuals' player type  dimensions to the game elements

| | Hexad scale dimensions | | | | | |
|---|---|---|---|---|---|---|
| Game element | Free Spirit | Philanthropist | Achiever | Player | Socialiser | Disruptor |
| Avatar | $0.130^{\circ}$ | - | $-0.570^{‡}$ | $-0.680^{‡}$ | $0.170^{\circ}$ | $-0.150^{\circ}$ |
| Content Unlocking | - | - | - | $0.351^{*}$ | $-0.535^{‡}$ | $0.024^{‡}$ |
| Points | $0.563^{‡}$ | $-0.027^{‡}$ | $0.591^{‡}$ | $0.247^{*}$ | $0.619^{‡}$ | $0.183^{*}$ |

*Correlations from [10]. °Correlations from [12]. ‡ Correlations from [14], - no significant correlations found (p-value>0.05).

Figure 2 shows the application used in this study with only one game element enabled at a time. For example, if all game elements are enabled, the application would look like the application shown in Fig. 1. Based on participants' Hexad player type and the recommender system, of the group that interacted with the adapted gamified application, 50% (10 participants) were exposed to the Points and Content Unlocking elements, while the remaining 50% were exposed only to the Points game element. In the group that interacted with the counter-adapted gamified application, 40% (8 participants) were exposed to the Avatar and Content Unlocking elements, while the remaining 60% were exposed to just the Avatar game element. Finally, in this study, the participants' final score after interacting with the application twice (performance score: P), and the difference between their scores from each interaction (performance difference: PD) are used as dependent variables.


**Fig. 2.** Illustration of the application with only one element enabled at a time

### 3.2 Participants

A total of 40 participants were part of this study. The age of participants ranged from 18 to 30 years old (M=21.45, SD=3.39 years of age). Forty-eight percent (48%) of the participants identified themselves as Caucasian, and thirty-three percent (33%) as Asian/Pacific Islanders. Only eighteen percent (18%) of the participants identified themselves as Latino/Hispanic and three percent (3%) as African American. Moreover, participants reported playing games an average of 3.78 days per week (SD=2.34) and spent an average of 2.00 hours (SD=1.69) playing games during those days.

## 4 Results and Discussions

In this work, the experiment was conducted in the same location, with the same equipment, and following the same experimental protocol as the experiment presented in [14]. This allows comparisons to be drawn between the performance of participants from this work that interacted with (i) an adapted gamified application and (ii) a counter-adapted gamified application, against the performance of participants from [14] that interacted with (iii) a non-adapted gamified application and (iv) a non-gamified application. The results of a series of t-tests and $\chi$-square tests indicate that from a demographic, playing habits, and Hexad player type point of view, there is no significant difference between the distribution of participants in the four groups. Table 5 show the summary statistics of participants' performance score and performance difference.

**Table 5.** Summary of participants performance

| Application | Number of Participants | Performance Score | | Performance Difference | |
|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD |
| Adapted | 20 | 37,632.45 | 6,939.01 | 3,292.00 | 4,147.97 |
| Non-Adapted | 15 | 33,814.72 | 6,292.55 | 3,711.70 | 4,862.22 |
| Non-Gamified | 15 | 33,182.80 | 8,116.41 | 3,732.70 | 6,691.41 |
| Counter Adapted | 20 | 22,778.95 | 8,389.93 | 1,535.00 | 7,583.88 |

Out of the participants that interacted with the adapted gamified application, 40% achieved a performance score greater than the maximum score achieved by any participant in the counter-adapted group, and 10% achieved a performance score greater than the maximum score obtained by any participant in the non-adapted or non-gamified groups. Similarly, out of the participants that interacted with the counter-adapted gamified application, 50% achieved a performance score lower than the minimum score obtained by any participant in the adapted or non-adapted groups, and 30% achieved a performance score lower than the minimum score achieved by any participant in the non-gamified group. Figure 4 shows a bar plot with the average performance score of participants who interacted with the adapted gamified application (A-G), non-adapted gamified application (G), the non-gamified application (N-G), and the counter-adapted gamified application (C-A-G).

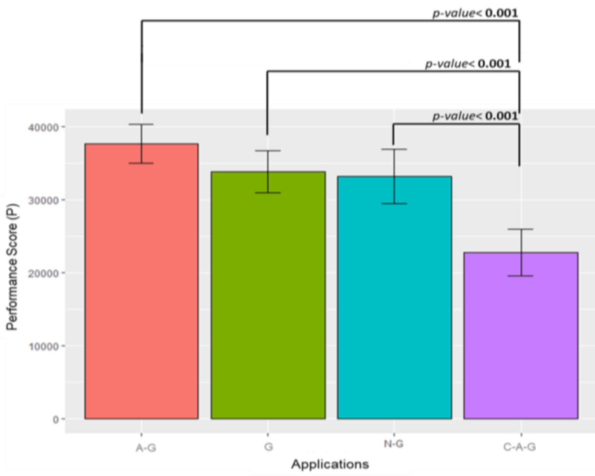


**Fig. 3.** Summary of participants' performance conditioned on the application used

The one-way between-subjects ANOVA results indicate a significant effect of application type on participants' performance for the four conditions ($F_{(3,66)}$ = 15.13, p-value<0.0001). Moreover, a pairwise comparison with a Bonferroni correction shows that individuals' performance on the counter-adaptive application was statistically significantly lowered than the performance of any other group. While not statistically significant after a Bonferroni correction, the results also show that the performance of individuals who interacted with the adapted gamified application was, on average, greater than any other group.

When controlling for participants' Hexad player type dimensions, the results of a linear regression analysis indicate that participants who interacted with (i) the non-adapted gamified application, (ii) the non-gamified application, and (iii) the counter-adapted application, had a lower performance score than the participants who interacted with the adapted gamified application. Table 6 shows the summary statistics of the linear regression model fitted. A significant equation was found ($F_{(9,60)}$= 5.707, p-value< 0.001), with a $R^2$ of 0.461. Moreover, the Shapiro-Wilk test reveals that the residuals of the model were normally distributed (p-value=0.651), and an a posteriori power analysis of the regression model indicates that with a sample size of n=70, a significant alpha level of 0.05, and an $R^2$ of 0.461, the predicted power of the analysis is 0.98 [39].

**Table 6.** Summary of linear regression model fitted for the final score performance (P)

| Variable | Standardized β | Std. Error | t-value | p-value |
|---|---|---|---|---|
| Intercept | 0.419 | 1.075 | 0.389 | 0.698 |
| Non-adapted | -0.601 | 0.294 | -2.043 | 0.045 |
| Non-gamified | -0.677 | 0.285 | -2.379 | 0.021 |
| Counter-adapted | -1.627 | 0.252 | -6.464 | <0.01 |
| Free Spirits | 0.011 | 0.038 | 0.288 | 0.774 |
| Philanthropist | 0.019 | 0.032 | 0.571 | 0.570 |
| Achiever | 0.057 | 0.039 | 1.480 | 0.144 |
| Player | -0.063 | 0.034 | -1.862 | 0.068 |
| Socialiser | 0.012 | 0.025 | 0.47 | 0.637 |
| Disruptor | -0.029 | 0.026 | -1.135 | 0.261 |

These results indicate that participants performed better in the gamified application that implemented the game elements which were selected based on their Hexad player type (i.e., adapted gamified application) than participants who interacted with the application in which the game elements were not selected based on their player type (i.e., non-adapted gamified application). Moreover, the results indicate that individuals performed worse in gamified applications that are counter-adapted compared to individuals who interacted with gamified applications that adapted, non-adapted, and even the application that did not implement any game elements (i.e., non-gamified).

Looking at the performance difference (PD), the t-test results indicate that it was statistically significantly greater than zero for the participants who interacted with the adapted gamified application ($t_{19}$= 3.449, p-value=0.001), the non-adapted gamified application ($t_{14}$= 2.965, p-value=0.005), and the non-gamified application ($t_{14}$= 2.161, p-value=0.024). However, there was not enough evidence to indicate that participants who interacted with the counter-adapted gamified application had a performance difference significantly greater than zero ($t_{19}$= 0.905, p-value=0.188). The t-test results also reveal that there was not enough evidence to indicate that the performance difference of participants was statistically significantly different between groups, even after controlling for participants' Hexad player type dimensions. Moreover, Table 7 shows the number and proportion of participants that performed better or worse the second time they interacted with the application given each group. While Table 7 shows a clear trend, the $\chi$-square test results indicate that there was not a statistically significant difference between the groups.

**Table 7.** Distribution of performance difference

| Group | Performed better the 2nd time *[Number of participants/percentages]* | Performed worse the 2nd time *[Number of participants/percentages]* |
|---|---|---|
| Adapted application | 17 / 85% | 3 / 15% |
| Non-adapted application | 12 / 80% | 3 / 20% |
| Non-gamified application | 11 / 73% | 4 / 27% |
| Counter-adapted application | 14 / 70% | 6 / 30% |

The results of the performance difference reveal that participants who interacted with the counter-adapted application did not improve as they interacted with the application for a second time. In contrast, participants who interacted with the other applications improved their performance. This performance improvement can be attributed to a possible learning effect. However, the lack of performance improvement by participants who interacted with the counter-adapted gamified application could be attributed to a lack of engagement and motivation.

Most of the studies to date only explore user modeling to help adapt applications without measuring the impact of adapted gamification on individuals' performance. This work provides empirical evidence that validates the value of using individuals' Head player type when designing gamified applications. The findings show that designers can improve individuals' performance by using the Hexad player type model to select the game elements individuals interact with. Moreover, this work shows that designers need to be cautious when implementing one-size-fits-all applications (i.e., applications that do not consider individuals' player type) since some individuals might perform worse in gamified applications that implement game elements that are not aligned with their Hexad player type dimensions, than in applications that are not gamified (i.e., do not implement any game elements), as shown by the results of the counter-adapted group. These findings could help explain why some studies that have used gamified applications designed without considering individuals' player type (i.e., a one-size-fits-all approach) have shown mixed results [36,40,41].

## 5 Limitations and Future Works

While the results of this work provide quantitative evidence of the effects of adapted and counter-adapted gamified applications on individuals' performance, several limitations still exist. First, in this study, only three game elements were implemented. This limited the number of different game element combinations individuals were exposed to. Moreover, this could have also generated some possible confounding effects. For example, the results show that participants performed better in the adapted gamified application than in the counter-adapted gamified application. Nonetheless, this performance difference might be confounded by a possible interaction effect related to the exposure of the Point and Avatar game elements. This is because based on the recommender system the participants who interacted with the adapted application were exposed to the Points element and not to the Avatar element, while the participants who interacted with the counter-adapted gamified application were exposed to the Avatar element and not to the Points element. However, participants in the non-adapted group performed better than the participants in the counter-adapted group; even though they interacted with both the Point and Avatar game elements. Similarly, participants in the non-gamified group performed better than the participants in the counter-adapted group; even though they did not interact with the Point or Avatar game elements.

Finally, a limitation that this work shares with many other gamification studies is the potential issue of generalizability. For example, the recommender system, which guided the adaptation process, might not generalize to other applications. Moreover, the tasks that participants performed in the applications were physical in nature. Hence, future work must focus on measuring the effects of adapted gamified applications based on individuals' player types in other contexts or with non-physical tasks. Nevertheless, this study provides valuable evidence of the effects of adapted gamified applications and the value of using the Hexad player type model for adapting applications.

## 6 Conclusion

Motivational theories reveal that treating individuals as a homogenous group is not an optimal design approach since what motivates one individual might demotivate another. Moreover, studies have shown that individuals' perception of game elements differ based on individual characteristics. Because of this, researchers have started exploring how player type models can be used to adapt gamification. Unfortunately, most of the existing studies only provide conceptual frameworks or little empirical evidence of their implementation and effectiveness in improving individuals' performance. In light of this, a randomized experiment was conducted to test the effects that adapting gamified applications, based on individuals' player type, have on their performance.

The results of this work revealed that individuals who interacted with the adapted gamified application performed better than participants that interacted with a non-adapted gamified application, a non-gamified application, and a counter-adapted gamified application. In contrast, participants who interacted with the counter-adapted gamified application performed worse than any other group and did not show any performance improvement after interacting with the application for a second time. The results of this work provide empirical evidence of the value of adapting gamified applications based on individuals' Hexad player type. These findings support the need to consider individuals' player type when designing gamified applications. This is because adapted gamified applications could potentially produce better results than non-adapted applications. Furthermore, a non-adapted gamified application could potentially produce worse results than a non-gamified application if the users' player type is not considered when selecting the game elements to implement. Thus, this works highlights the need to consider individuals' player type when designing gamification applications and the potential latent detrimental effects of not doing so.

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