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The effects of player type on performance: A gamification case study

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ABSTRACT

The objective of this work was to explore the effects that an individual's Hexad player type has on their performance in gamified applications. Previous studies sought to explore the relationship between player types of individuals and their preference of game elements. However, these studies have been theoretical in nature, never exposing participants to actual gamified applications or analyzing their real-time performance. Consequently, the biases inherent in humans may impact the validity of these studies since humans are rarely mindful of their behavior and preferences before they are faced with the stimuli (e.g., game elements). Moreover, the effects of game elements on an individual's motivation and performance may differ when implemented in an application. With existing theory-based studies on player types, a designer may spend valuable resources tailoring an application according to an individual's player type and his/her perceived preferences and yet, not see any positive effects on performance. In light of these gaps, a case study with a randomized controlled experiment is presented in which individuals' player type, their perception of game elements, and their performance, are assessed. The results indicate that player type correlates with individuals' perception of game elements and performance in the gamified application. These findings support the importance of exploring the relationship between player type and individuals' performance in gamified applications. Moreover, only after controlling for player type, the results reveal that participants who interacted with the gamified application performed better than those who interacted with the non-gamified application. These results highlight the importance of considering individuals' player type and the need for tailoring applications. Given these findings, this work provides guidelines to help tailor gamified applications, based on an individual's player type.

1. Introduction

In the last decade, the research community has gained increased interest in gamification (Nacke & Deterding, 2017; O'Donnell et al., 2017; Seaborn & Fels, 2015), particularly in the fields of education, health and wellness, and business (Ferreira, Araújo, Fernandes, & Miguel, 2017; Looyestyn et al., 2017; Slomski, 2017; Warmelink, Koivisto, Mayer, Vesa, & Hamari, 2018). Gamification aims to implement game elements (e.g., Points, Badges, Leaderboards) to improve individuals' motivation to perform a task or set of tasks, with the goal of meeting a certain objective. The objective can vary based on the intentions of the designers and the context of the application. For example, in an educational context, the objective of a gamified application might be to improve students' knowledge by increasing their motivation to participate in forums and review class material (Barata, Gama, Jorge, & Gonçalves, 2017; O'Donovan, Gain, & Marais, 2013). Likewise, in the health and wellness context, the objective of a gamified application might be to improve individuals' physical fitness or health awareness by motivating them to perform physical tasks (e.g., Physically-interactive gamified application, Exergames) (Brauner, Calero Valdez, Schroeder, & Ziefle, 2013; Patel et al., 2017; Slomski, 2017).

Most of the current gamified applications are designed with a "*one-size-fits-all*" approach, which assumes that individuals are a homogenous group that reacts similarly to game elements (Jia, Xu, Karanam, & Voida, 2016; Klock, Gasparini, Pimenta, & de Oliveira, 2015). However, studies have shown that individuals perceive and respond to gamified applications in different ways (Hamari & Tuunanen, 2014; Nicholson, 2012). Consequently, in some studies, the effects of gamification vary significantly among participants (Barata et al., 2017; Fitz-Walter, Johnson, Wyeth, Tjondronegoro, & Scott-Parker, 2017; Thom, Millen, DiMicco, & Street, 2012). Moreover, several studies indicate that a game element that positively impacts the performance of one individual might not improve or could even worsen the performance and motivation of another individual (Codish & Ravid, 2014; Orji, Vassileva, & Mandryk, 2014; Witt, Scheiner, & Robra-Bissantz, 2011). Decades of motivational game research indicate that treating

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individuals as a homogenous group is not an optimal design approach since preferences and perceptions vary at an individual level (Bartle, 1996; Tondello et al., 2016; Yee, 2006). Researchers argue that this is one of the reasons why several studies that implement gamified applications designed with a "*one-size-fits-all*" approach tend to present mixed results on its effectiveness (e.g., either positive and neutral, or negative and positive effects) (Hamari, Koivisto, & Sarsa, 2014; Nacke & Deterding, 2017; Seaborn & Fels, 2015). Thus, as stated by Nacke and Deterding (2017) "*one size does not fit all*" (p. 3).

Due to the limitations of the existing "*one-size-fits-all*" design approach, researchers are starting to explore how player type models can be implemented to assess the preferences of an individual and tailor gamified applications (Böckle, Micheel, & Bick, 2018; Ferro, Walz, & Greuter, 2013; Tondello, Orji, & Nacke, 2017). Player type models aim to capture the differences between individuals' behavior and attitudes in relation to game elements and game applications (Busch et al., 2016). However, most of the current studies that explore player type models focus on analyzing the relationship between the player type of individuals, and their self-reported game element preferences. This analysis is done without exposing individuals to the elements in an application nor analyzing their performance on an application that implements those game elements in which they reported on (Orji, Mandryk, & Vassileva, 2017; Orji, Nacke, & DiMarco, 2017; Orji, Tondello, & Nacke, 2018).

Unfortunately, individual biases might play a significant role when asking participants to rate their preferences for game elements without being exposed to them since humans are rarely mindful about their true behavior and preferences before they are faced with the stimulus itself (e.g., game element) (Codish & Ravid, 2014; Laffan, Greaney, Barton, & Kaye, 2016; Orji, Nacke, et al., 2017). Moreover, the effects of game elements on an individual's motivation and performance may differ when implemented in an application (Orji et al., 2014; Tondello, Mora, & Nacke, 2017). Hence, the relationships between individuals' player type, their performance on gamified applications, and their preferences for game elements after interacting with them in an application, need to be explored. A better understanding of these relationships can potentially help designers advance gamification and improve individuals' performance. As a result of the current knowledge gap, the authors of this work present an empirical study on the effects that individuals' player type has on their preferences of game elements and task performance in gamified applications. A case study with a randomized controlled experiment involving a gamified and a non-gamified application is presented.

2. Literature review

Researchers agree that gamification has the potential to improve individuals' performance and motivation (Mekler, Brühlmann, Tuch, & Opwis, 2017; Nacke & Deterding, 2017). However, studies indicate that implementing game elements in non-game contexts may not lead to increased motivation or behavioral changes in every condition (Hamari et al., 2014; Seaborn & Fels, 2015). For example, the results of Hanus and Fox (2015) indicate that students who interacted with a gamified course had less satisfaction, motivation, and empowerment over time, compared to those in the non-gamified course. Similarly, the results of Fitz-Walter et al. (2017) show that even though their gamified application was perceived as motivating and enjoyable by participants, it did not have any significant effects on individuals' behavior, compared to the non-gamified application. Moreover, their results reveal that individuals enjoyed different elements of the application. Multiple studies have indicated that perception of game elements differ at an individual level (Barata, Gama, Jorge, & Gonçalves, 2016; Kim, Rothrock, & Freivalds, 2018; Tondello, Mora, et al., 2017). According to the Self-Determination Theory (SDT), one of the most recognized motivational theories within the gamification community (Deterding, 2015; Mekler et al., 2017), individuals will be motivated if their innate psychological needs for *autonomy*, *competence* and *relatedness* are satisfied. Nonetheless, the fulfillment of these psychological needs rely on individuals' perception and not on objective judgment (Ryan & Deci, 2000). Likewise, the Cognitive Evaluation Theory, a sub-theory of SDT, indicates that the influence of external stimuli (e.g., game elements) on individuals' motivation is mediated by their perception of how these stimuli are controlling or informational (Deci, Ryan, & Koestner, 1999; Ryan & Deci, 2000; Vansteenkiste, Niemiec, & Soenens, 2010).

In recent years, researchers have started studying how gamification affects different groups of individuals with common attributes (e.g., personality traits, learning style, and player type). Studies have shown the moderating effects of individuals' personality traits and player type on their propensity of being motivated to perform a task (Judge & Ilies, 2002; Nunes & Hu, 2012; Orji et al., 2014). Both personality traits and player type models aim to capture the differences between individuals, which can help explain differences in their behavior and attitudes. Both share significant similarities that have been empirically studied (Tondello, Mora, et al., 2017; Zeigler-Hill & Monica, 2015). However, personality trait models can be understood as a high-level conceptualization of individual differences not focused on any specific domain or behavior. In contrast, player type models are considered to be more specific and focused on the differences of individuals' behavior and attitudes in relation to game elements and game applications (Busch et al., 2016).

Researchers are exploring the potential of employing player type models to improve and personalize gamified applications (Böckle et al., 2018; Monterrat, Desmarais, Lavou, & George, 2015; Tondello, Orji, et al., 2017). One of the first player type models was presented by Bartle (1996). Bartle's player typology is based on the self-reported game preference data of Multi-User Dungeon players (Bartle, 1996). However, as presented by Aldemir, Celik, and Kaplan (2018), Bartle's player typology reliability and validity could be improved when it comes to classifying individuals based on their playing habits. Moreover, Bartle's player typology assumes that each player type is mutually independent. Thus, it does not take into account possible interaction or partial membership between player types. To overcome this limitation, Yee (2006) proposed a new player typology for Massively Multiplayer Online Role-Playing games based on a factor analysis of Bartle's questionnaire. Nonetheless, both Bartle's and Yee's player typologies focus on one specific game type, which limits their applicability to the context of gamification (Tondello, Mora, et al., 2017).

Recently, Nacke, Bateman, and Mandryk (2014) presented the BrainHex player typology, which is founded on the Demographic Game Design models (Bateman, Lowenhaupt, & Nacke, 2011). The BrainHex synthesizes important elements from previous neurobiological player satisfaction and game emotion research, as well as previous player typologies (Bateman & Nacke, 2010). With the use of the BrainHex, Orji et al. (2014) explore the relationship between individuals' player type and their preferences for game elements. They summarize their findings and provide guidelines for the "*best*" and "*worst*" strategies of game elements for each of the BrainHex player types. Their results indicate that some game elements could be perceived as positive by a group of individuals, while at the same time perceived as negative by other groups. Nonetheless, these findings were based on the self-reported perception of individuals who were not exposed to the game elements in an application. As highlighted by the authors, the actual effects of game elements may differ if implemented in a specific application and not on a storyboard, as in their study (Orji et al., 2014). Moreover, this method may have compromised the external validity of the results since the actual effects of the game elements on individuals' performance was not explored (Laffan et al., 2016). Finally, even though the BrainHex has been used by researchers due to its diverse range of player types, an empirical study of its psychometric properties has shown low reliability, indicating that the model could be improved (Busch et al., 2016).

The previous player type models provide valuable insights when exploring individuals' differences. However, they were intended for

Table 1
Summary of Hexad player types.

Hexad Player type	Description
(i) Philanthropists	These players are motivated by purpose and meaning. They show altruistic behavior and are willing to give without expecting a reward.
(ii) Disruptors	These players are motivated by change. They have a tendency to disrupt and challenge the system. They often test the limitations of the system and try to push it further.
(iii) Socialisers	These players are motivated by relatedness. These players want to interact with other players and create social connections.
(iv) Free Spirits	These players are motivated by autonomy and self-expression. They like to have a meaning, freedom, act without external control, and explore within a system.
(v) 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.
(vi) 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 the activity.

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

non-gamified applications (Tondello, Mora, et al., 2017). As a result, Marczewski (2015) proposed the "*Gamification User Types Hexad Framework*" to evaluate individuals' preferences for game elements in gamified applications. The framework introduces six player types: (i) *Philanthropists*, (ii) *Disruptors*, (iii) *Socialisers*, (iv) *Free Spirits*, (v) *Achievers*, and (vi) *Players*. Tondello et al. (2016) introduced a standard 24-item questionnaire to assess individuals' preferences for game elements, based on the Hexad framework. Table 1 shows a summary of Hexad player types from the literature. Orji et al. (2018) use the Hexad framework to study how individuals perceived different persuasive strategies with the use of storyboards. Similarly, analyze the perceived enjoyment of commonly used game elements on individuals with different Hexad player types. Nonetheless, in these studies, participants reported their perception of game elements without experiencing the game elements in an application. While these studies provide insights into the relationship of individuals' Hexad player type and their perception of game elements, researchers indicate that future studies should focus on exploring the correlation between individuals' behavior in gamified applications and their Hexad player type (Tondello, Mora, et al., 2017).

Table 2 summarizes existing studies that have analyzed the relationship between player type and individuals' perception and preference of game elements. While these studies are first steps towards a better understanding of individuals' preferences in relation to player types, they still have several limitations. The majority of the studies have focused on exploring the relationship between player types and individuals' perception of game elements, without exposing individuals to the elements in an application or analyzing their performance. Consequently, individual biases could impact the validity of these studies since humans are rarely mindful of their true behavior and preferences before they are faced with the stimuli (e.g., game elements) (Codish & Ravid, 2014; Laffan et al., 2016; Orji, Nacke, et al., 2017). Furthermore, the effects of a game element on an individual's motivation and performance may differ if implemented in an application. Researchers indicate that there is still a need for more empirical studies to better comprehend these player type models and how they can be used to advance the field of gamification (Böckle & Bick, 2017). As stated by Nacke and Deterding (2017) "*We know extremely little about the actual effect of 'player types,' and the effectiveness of designing with player types in mind, let alone individual differences beyond them*" (p.4). Hence, a designer might spend valuable resources tailoring an application according to an individual's player type and not see any positive effects on his/her performance. In light of these gaps, this work presents a case study that explores how gamification impacts the performance of individuals with different player types by implementing the Hexad player type model. A better understanding of these relationships could potentially guide designers and save valuable resources during the development of gamified applications.

3. Hypotheses

This work explores the effects that player type has on the effectiveness of gamification. The relationship between player type and individuals' performance is analyzed. Moreover, the relationship between player type and individuals' perception of game elements implemented in an application is explored. Fig. 1 illustrates the relationships between the variables analyzed in this work. As shown in Fig. 1, this work aims to test the three hypotheses presented below. Testing these hypotheses will provide a better understanding of the relationships between player types, performance, and perception of game elements, as it focuses on a real-world gamification application, unlike previous studies.

Based on previous studies that have explored the relationship between player type and individuals' perception of game elements, the authors hypothesized that (h_1) individuals' performance in gamified applications is dependent on their Hexad player type. Similarly, the authors hypothesized that (h_2) individuals' perception of the game elements as useful, fun, motivating, preferable, or frustrating is dependent on their Hexad player type. That is, the performance of individuals and their perception of game elements vary based on their Hexad player type. In this work, individuals' perception of game

Table 2
Summary of studies that explore the relationship between individuals' player type and the effects of gamification.

Study	*Independent Variables*	*Dependent variables*		
	Player Type	Reported perception without exposure*	Reported perception with exposure ǂ	Performance
Orji et al. (2014)	BrainHex	Perceived persuasiveness of game elements		
Orji, Mandryk, et al. (2017)	BrainHex	Perceived change in attitude, self-efficacy, and intention		
Tondello et al. (2016)	Hexad	Preferences of game elements		
Tondello, Mora, et al. (2017)	Hexad	Perceived enjoyment of game elements		
Orji et al. (2018)	Hexad	Preference of persuasive strategy		
This work	Hexad		Perceived usefulness, preference, fun, motivation, and frustration of game elements	X

Notes:*Participants provide their self-reported perception of game elements without being exposed to the elements in an application. ǂParticipants provide their self-reported perception of game elements after being exposed to the elements in an application (i.e., after interacting with the game elements in an application).

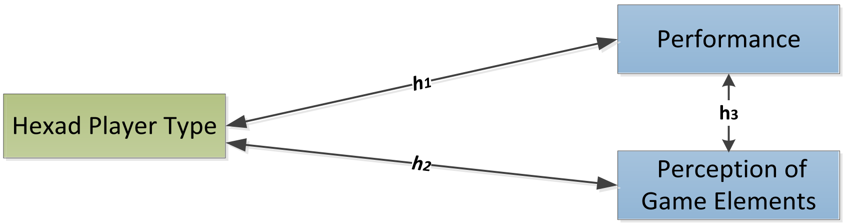

Fig. 1. Hypotheses.

elements is assessed after they interact with the elements in a gamification application. These hypotheses can be mathematically expressed as follow:

(h_1) H_0: $\bar{P}_{|n} = \bar{P}_{|m}$ vs H_a: $\bar{P}_{|n} \neq \bar{P}_{|m}$

(h_2) H_0: $\overline{GP}_{j|n} = \overline{GP}_{j|m}$ vs H_a: $\overline{GP}_{j|n} \neq \overline{GP}_{j|m}$

For,

n and m ε set of Hexad player type, and $n \neq m$.
j ε set of perception responses {useful, fun, motivating, preferable, frustrating}

Where,

- $\bar{P}_{|n}$ is the average performance, given the n^{th} Hexad player type.
- $\overline{GP}_{j|n}$ is the average perception j of game elements given the n^{th} Hexad player type.

Moreover, according to the Self-Determination Theory, individuals will be motivated if their innate psychological needs are satisfied. Nonetheless, the fulfillment of these psychological needs rely on individuals' perception and not on objective judgment. Therefore, the authors hypothesized that (h_3) individuals' performance in a gamification application is correlated with their perception of the game elements implemented in the application. That is, individuals will perform better in gamified applications that implement the game elements they perceive as useful, fun, motivating, or preferable. This hypothesis can be expressed as follows:

(h_3) H_0: $\rho_{P,\, GPj} = 0$ vs H_a: $\rho_{P,\, GPj} \neq 0$

Where,

$\rho_{P,\, GPj}$: is the correlation between an individual's task performance and perception j of game elements.

4. Case study

To test the hypotheses, a case study with a randomized controlled experiment was conducted. The experimental group interacted with a gamified physically-interactive application, while the control group interacted with a non-gamified version of the same application (i.e., without game elements). The applications required the participants to use full body motions (e.g., bend, extend an arm, jump) in order to complete a series of physical tasks, similar to the applications used by Lopez and Tucker (2017). The tasks consisted of passing through a series of obstacles without touching them (i.e., obstacle avoidance), like the show "*Hole in the Wall*™" (Ludia, 2011). Each participant was allowed to interact with the application for two levels. The applications contained the same set of 14 tasks in each level. For this study, the Microsoft Kinect tracking sensor (Microsoft Research, 2011) was implemented, which allowed participants to interact with the applications via a projected virtual environment (see Fig. 2). Due to the characteristics of performing physical tasks with the use of a tracking sensor, the applications used in this work could fall within the umbrella of Exergames (Brauner et al., 2013; Hamari & Koivisto, 2013). Nonetheless, during the initial experiment debriefing, participants were 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. The experimental protocol used in this work was reviewed and approved by the Institutional Review Board of the Pennsylvania State University to ensure any potential risks to participants were mitigated.

4.1. Applications

Fig. 2 shows the experimental setup, in which the Microsoft Kinect sensor was positioned between the projected display of the applications and the participants. The projection allowed participants to visualize the physically-interactive applications in the virtual environment. Moreover, Fig. 2 shows the virtual environment display for the A) gamified application (i.e., experimental group) and B) non-gamified application (i.e., control group). The gamified application only differed from the non-gamified application by the game elements implemented. The set of game elements implemented were selected based on their presence in *"successful"* applications (see Bharathi, Singh, Tucker, & Nembhard, 2016). Table 3 shows a brief description of the game elements and how they were implemented in the gamification application.

By looking at the persuasive strategies that relate to each of the game elements implemented, both the *Points* and *Content Unlocking* game elements can be mapped to a *Reward* strategy, while the *Avatar* game element can be mapped to a *Customization* strategy (see Orji et al., 2014; Tondello, Mora, et al., 2017). Hence, the gamification application can be understood as a *Reward-Customization* strategy application. Based on previous studies that have explored the relationship between Hexad player type and individuals' perception of game elements, the game elements shown in Table 3 are more suited and should motivate individuals with the Hexad player types shown in Table 4. This table shows a summary of the findings of previous studies that relate the game elements implemented in the gamified application to a particular Hexad player type. From Table 4, it is clear that while these studies show some agreement on their findings (i.e., *Player* will be motivated by *Reward-Customization* strategy applications), other results are not as consistent (e.g., *Free Spirit* and *Socialiser*). Testing the hypotheses presented in this work will help understand which Hexad player types will perform better in applications that implement a *Reward-Customization* strategy.

4.2. Sample

In this case study, a total of 30 participants (17% females) were part of the experiment. All participants were students from the Pennsylvania State University, with age ranging from 18 to 31 years old (M = 22.13, SD = 2.65 years of age). Fifty percent (50%) of the participants identified themselves as *Asian/Pacific Islanders,* and twenty-seven percent (27%) as *Caucasian*. While only seventeen percent (17%) as *Latino/Hispanic* and seven percent (7%) as *African American*. Moreover, participants reported playing games an average of 3.93 days per week (SD = 2.34 days) and spent an average of 2.2 hrs (SD = 1.6 hrs) playing games during those days. Table 5 shows detailed information about the demographics and playing habits of participants. All of the participants were randomly assigned to either the experimental group (i.e.,

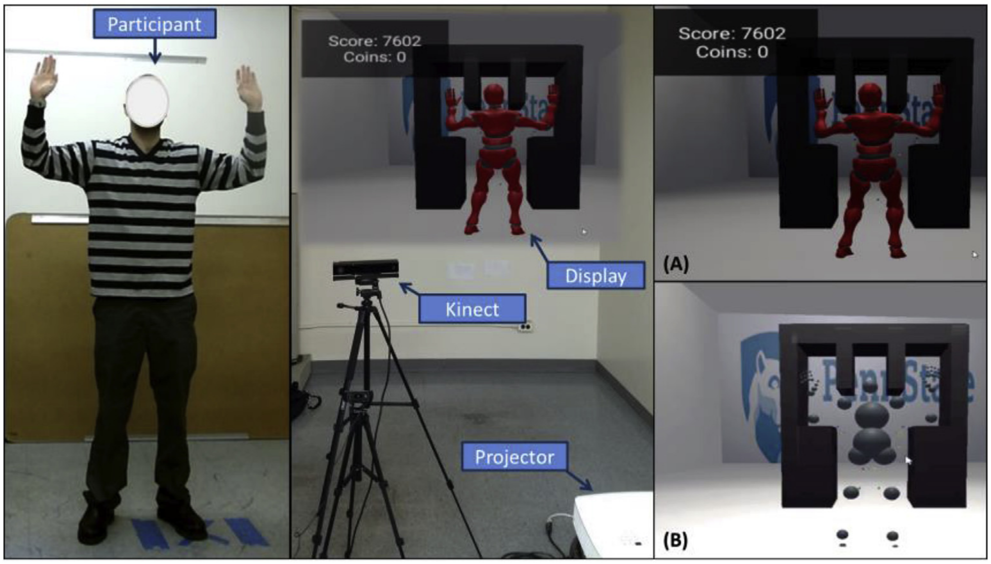

Fig. 2. Experimental setup and applications.

application A) or the control group (i.e., application B). Before the experiment, participants were introduced to the informed consent documents and debriefed on the experimental protocol. Once participants provided their consent, they (i) completed a pre-experiment questionnaire, (ii) interacted with their assigned application, and (ii) completed a post-experiment questionnaire. In the questionnaires, their Hexad player type and perception of game elements were assessed. Details regarding the questionnaires implemented are provided next.

4.3. Questionnaires and metrics

To assess participants' Hexad player type, the 24-point questionnaire introduced by Tondello et al. (2016) was implemented. This questionnaire evaluates participants' player type in six dimensions: (i) *Philanthropists*, (ii) *Disruptors*, (iii) *Socialisers*, (iv) *Free Spirits*, (v) *Achievers*, and (vi) *Players* (see Table 1). The questionnaire asks participants to rate, on a 7-point Likert scale, how well a set of 24 statements describe them (i.e., 4 statements per dimension) (see Tondello et al., 2016, p. 14). Each of these statements was presented in random order to reduce any possible order-effects, as suggested by Tondello et al. (2016). In the post-experiment questionnaire, participants in the experimental group were asked to rank the game elements of the gamified application (see Table 3), based on the degree to which they perceived the elements as (i) fun, (ii) useful, (iii) preferable, (iv) motivating, and (v) frustrating. These questions were also presented in random order to reduce any possible order-effects. In addition, participants were asked at the end of the experiment to provide feedback about their interaction with the application via an open-ended question.

The Microsoft Kinect sensor used in the case study also allowed the applications to measure participants' performance in real-time. The participants' performance on the physical tasks of the applications (i.e., obstacle avoidance) was a function of the deviation between their joint location while passing through the obstacles and the target body position required for passing through the obstacles without touching them. In other words, the performance score given to the participants for each obstacle (i.e., task) was negatively correlated to the area of the obstacle they touched while trying to pass through it. This performance metric allowed the authors to convey to the participants how to succeed in the applications (i.e., pass the obstacles with minimal contact). In this work, the participants' final score after interacting with the application for two levels (*P*), and the difference between their score on the levels (*PD*) was used as performance metrics.

Table 4
Summary of existing studies for Reward-Customization elements.

Study	Appropriate for Hexad Player Type:
Tondello et al. (2016)	Free Spirit, Achiever, Player.
Tondello et al. (2017)	Achiever, Player, Disruptor, Philanthropists
Orji et al. (2018)	Player, Disruptor, Socialiser

Before testing the hypotheses, the authors analyzed the reliability and validity of the Hexad questionnaire. The (i) reliability of items, (ii) composite reliability, (iii) average variance extracted (AVE), and (iv) the loadings of a factor analysis were assessed to evaluate the convergent and discriminant validity of the questionnaire (see Tables A1 and A2, Appendix). The results indicate that the square root of the AVE was greater than the inter-construct correlation of the questionnaire's items, supporting the discriminant validity of the questionnaire. However, the items of *Philanthropist, Free Spirit, Achiever,* and *Disruptor* show AVE values less than the recommended value of 0.5 (Feng, Jonathan Ye, Yu, Yang, & Cui, 2018). While only the item of *Free Spirit* shows a Cronbach's alpha of less than 0.5. Table A1 (see Appendix) also indicates that there were moderate correlations between the Hexad player type dimensions (Cohen, 1988). Several of these correlations are supported by the theoretical background and empirical findings of previous studies (e.g., *Philanthropist* with *Socialiser*, *Philanthropist* with

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.

Table 5
Participants' summary statistics.

	Application				Total	
	A		B			
Age	Count	%	Count	%	Count	%
18-22	11	73%	10	67%	21	70%
23-27	4	27%	4	27%	8	27%
28-31	0	0%	1	7%	1	3%
Gender	Count	%	Count	%	Count	%
Male	13	87%	12	80%	25	83%
Female	2	13%	3	20%	5	17%
Ethnicity	Count	%	Count	%	Count	%
African American	1	7%	1	7%	2	7%
Caucasian	2	13%	6	40%	8	27%
Latino/Hispanic	3	20%	2	13%	5	17%
Asian/Pacific Islanders	9	60%	6	40%	15	50%
How many times have you played physically-interactive applications (e.g., Wii-Sports, Kinect Sports)?	Count	%	Count	%	Count	%
Never	4	27%	2	13%	6	20%
Once	1	7%	0	0%	1	3%
Two to five times	4	27%	2	13%	6	20%
More than five times	6	40%	11	73%	17	57%
How many days per week do you spend playing games?	M	SD	M	SD	M	SD
	3.53	2.34	4.33	2.29	3.93	2.34
How many hours do you spend playing games on those days?	M	SD	M	SD	M	SD
	2.2	1.6	2.2	1.27	2.2	1.6
Participants	15		15		30	

Table 6
Summary of Hexad Scale questionnaire.

Hexad player type dimensions	Application						Total		
	A			B					
	μ	σ	Count	μ	σ	Count	μ	σ	Count
Philanthropists	24.9	2.2	5	23.1	4.2	4	24.0	3.4	9
Socialisers	22.3	4.5	2	21.1	4.2	0	21.7	4.3	2
Free Spirits	24.4	2.3	4	24.0	2.6	5	24.2	2.5	9
Achievers	23.5	2.6	1	24.2	3.0	2	23.8	2.8	3
Disruptors	17.4	2.6	0	16.3	5.0	1	16.9	4.0	1
Players	22.2	3.9	3	22.4	3.3	3	22.3	3.6	6

Note: Hexad questioner uses a 7-point Likert-scale with 4 questions per dimension.

Player, *Achiever* with *Player*, *Achiever* with *Free Spirit*) (Tondello, Mora, et al., 2017). Finally, the factor analysis results indicate that the six factors explained 59% of the variance in the response data. The results of Table A2 (see Appendix) reveal that overall the factors corresponded to the Hexad player type dimensions, showing the best structure for the item of *Socialiser* according to the guidelines of Osborne and Costello (2005). Even though the results also indicate that there were some important cross-loadings between several items, these are in line with the correlation found between the different player type dimensions in Table A1 and previous studies (Tondello, Mora, et al., 2017). While the validity of the Hexad player type questionnaire was previously confirmed (Tondello et al., 2016) and the results of this work support its discriminant validity, they also indicate that the convergent validity for some of its items could be improved. The difference in the ratio of participants to items between this work and previous studies (i.e., 5:1 vs. 22:1 from Tondello, Mora, et al., 2017) might help explain some of the differences between the validity results (Osborne & Costello, 2005). Table 6 shows a summary of the participants' Hexad player type dimensions, which presents the mean and standard deviation values for the dimensions of the Hexad player type. Additionally, it shows the number of participants (i.e., count) who reported the highest values in each of the dimensions.

5. Results

The authors hypothesized that an individual's performance (h_1) and perception of game elements (h_2) are dependent on his/her Hexad player type. Fig. 3 shows multiple boxplots of participants' final score performance (*P*) and performance difference (*PD*), condition by their Hexad player type and application used. The plots indicate that participants with the Hexad player type of *Disruptor* tended to perform worse and did not improve as much from level 1 to level 2 compared to other participants. In contrast, participants with the Hexad player type of *Achiever* tended to improve more than other participants. Moreover, Fig. 3 indicates that participants with the Hexad player type of *Player* tended to perform worse on the gamified application (i.e., A) than on the non-gamified application (i.e., B). When considering Hexad player type as categorical variable, the ANOVA results does not show any statistically significant difference in the final performance (P) or performance difference (PD) between participants with different Hexad player types (P: $F_{(5,29)} = 0.782$, *p-value* = 0.574, PD: $F_{(5,29)} = 1.035$, *p-value* = 0.424), or between application used (P: $F_{(1,29)} = 0.008$, *p-value* = 0.93, PD: $F_{(1,29)} = 0.001$, *p-value* = 0.99). However, partial membership between player types exists since an individual can report high score in more than one dimension of the Hexad Scale (see Table A1). In this work, partial membership between the different Hexad player types was considered. Not recognizing partial membership between player types is one of the limitations reported by previous studies (Orji et al., 2014). Hence, in this work, a series of linear regression analyses were performed in which the Hexad player type dimensions of participants were considered to be on a continuous scale. The ANOVA results indicate that when considering the final score performance (P) as the dependent variable, the model that contained the main and interaction terms of the Hexad player type dimensions and the application used as independent variables, provided an explanatory power significantly greater than the model without the interaction term ($F_{(16,22)} = 3.89$, *p-value* = 0.002). The Shapiro-Wilk test (*p-value* = 0.605) and Bartlett's test (*p-value* = 0.085) indicate that the assumptions of normality and homogeneity of variance were not violated in this ANOVA test.

Table 7 shows the summary statistics of the linear regression model fitted for the metric of final score performance (P). A significant equation was found ($F_{(13,16)} = 2.626$, *p-value* = 0.035), with a R^2 of 0.681. Moreover, the Shapiro-Wilk test reveals that the residuals of the model were normally distributed (*p-value* = 0.245). The results of the linear regression analysis indicate that when controlling for the Hexad player type dimensions, the participants who interacted with the non-gamified application performed worse than the participants who interacted with the gamified application. The results also reveal that a model that controls for the Hexad player type dimensions provided significantly greater explanatory power than a model that did not control for these factors ($F_{(16,28)} = 2.814$, *p-value*: 0.027, $\Delta R^2 = 0.466$). Moreover, the results indicate that participants who scored high in the dimensions of *Philanthropist* and *Free Spirit* performed significantly better than average. Furthermore, there was a statistically significant interaction between the dimension of *Free Spirit* and application used. This reveals that participants who scored high on the dimension of *Free Spirit*, performed worse in the gamified application than in the non-gamified application. While there is not enough evidence to indicate a statistically significant interaction between the other player type dimensions and the application used, the results provide evidence that indicates a tendency that participants who scored high in the dimension of *Philanthropist*, *Socialiser*, or *Player*, tended to perform worse in the gamified application. Finally, an *a posteriori* power analysis of the regression model indicates that with a sample size of n = 30, a significant alpha level of 0.05, and an R^2 of 0.681, the predicted power of the

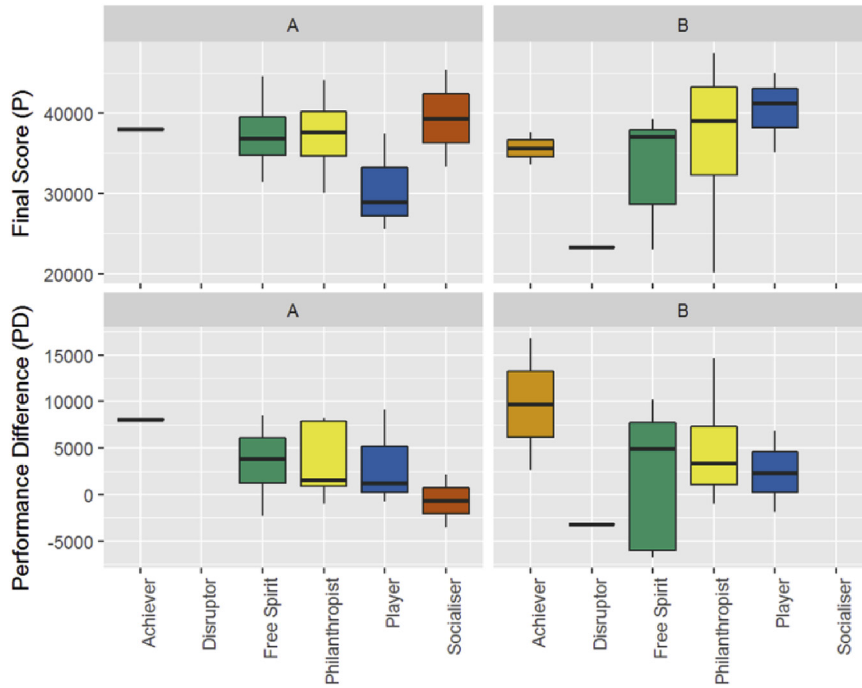

Fig. 3. Boxplots of final score performance and performance difference.

Table 7
Summary of linear regression model fitted for the final score performance (P).

Variable	Standardized β	Std. Error	t-value	p-value
Intercept	−13.111	4.007	−3.272	0.005**
App A	14.892	5.453	2.731	0.015*
Philanthropists	0.184	0.083	2.220	0.041*
Socialisers	0.050	0.070	0.715	0.485
Free Spirits	0.345	0.100	3.443	0.003**
Achievers	−0.051	0.091	−0.556	0.586
Disruptors	0.023	0.060	0.390	0.702
Players	0.013	0.110	0.114	0.911
App A*Philanthropists	−0.027	0.144	−0.186	0.855
App A*Socialisers	−0.014	0.093	−0.153	0.880
App A*Free Spirits	−0.555	0.155	−3.586	0.002**
App A*Achievers	0.129	0.149	0.868	0.398
App A*Disruptors	0.024	0.109	0.215	0.832
App A*Players	−0.191	0.127	−1.502	0.153

Note: Significance level codes (*p-values*): < 0.01**, < 0.05*, < 0.1′.

analysis is 0.913 (Cohen, 1988).

When considering the performance difference (PD) as the dependent variable, the ANOVA results indicate that the model that contained the main and interaction terms of the Hexad player type dimensions and the application used as independent variables, did not provide an explanatory power significantly greater than the model without the interaction term ($F_{(16,22)} = 0.982$, *p-value* = 0.469). Similarly, the Shapiro-Wilk test (*p-value* = 0.789) and Bartlett's test (*p-value* = 0.404) indicate the assumption of normality and homogeneity of variance were not violated in this ANOVA test. Table 8 shows the summary statistics of the linear regression model fitted for the metric of performance difference (PD). While the Shapiro-Wilk test reveals that the residuals of the model were normally distributed (*p-value* = 0.883), the regression equation was not significant ($F_{(13,16)} = 0.32$, *p-value* = 0.109) with an R^2 of 0.324. Moreover, an *a posteriori* power analysis of the regression model indicates that the predicted power of the analysis is only 0.659. Nonetheless, the results provide evidence that indicates that there was a difference between the performance of participants who interacted with the gamified application, and the participants who interacted with the non-gamified application. The results also reveal that participants who

Table 8
Summary of linear regression model fitted for the performance difference (PD).

Variable	Standardized β	Std. Error	t-value	p-value
Intercept	−2.338	3.148	−0.743	0.466
App A	0.099	0.398	0.248	0.806
Philanthropists	−0.026	0.080	−0.320	0.752
Socialisers	0.015	0.050	0.296	0.770
Free Spirits	−0.164	0.084	−1.960	0.063
Achievers	0.230	0.083	2.784	0.011*
Disruptors	0.083	0.056	1.476	0.154
Players	−0.015	0.061	−0.244	0.809

Note: Significance level codes (*p-values*): < 0.01**, < 0.05*, < 0.1′.

scored high in the dimension of *Achiever* tended to improve more than other participants. These results are in line with the results shown in Fig. 3, indicating that participants' that scored high in the dimension of *Achiever* improved their performance from level 1 to level 2, more than other participants.

To analyze the relationship between participants' perception of game elements and their Hexad player type (h_2), a non-parametric Kruskal-Wallis ANOVA test (see Table A3, Appendix) was conducted since Bartlett's test rejected the null-hypothesis for homogeneity of variance (*p-value* < 0.05). The test results indicate a statistically significant difference between the response of individuals with different player type on the question regarding their perception of the game element of *Points* as frustrating ($\chi^2_{(4)} = 9.489$, *p-value* = 0.049). Fig. 4 shows a series of boxplots of participants' responses regarding their perception of the game element of *Points* as frustrating, provided after interacting with the gamified application. Fig. 4 indicates that participants with the Hexad player type of *Achiever* and *Player* reported the game element of *Points* as the least frustrating (i.e., least frustrating = -1). In contrast, participants with the Hexad player type of *Philanthropist* reported the *Points* element as the most frustrating (i.e., most frustrating = 1). The independent Mann-Whitney U tests reveal that the responses of participants with the Hexad player type of *Philanthropist* were statistically significantly different than the responses of participants with the Hexad player type of *Player* (U = 0.5, *p-value*: 0.036) (see Table A4, Appendix). These results provide evidence to reject the

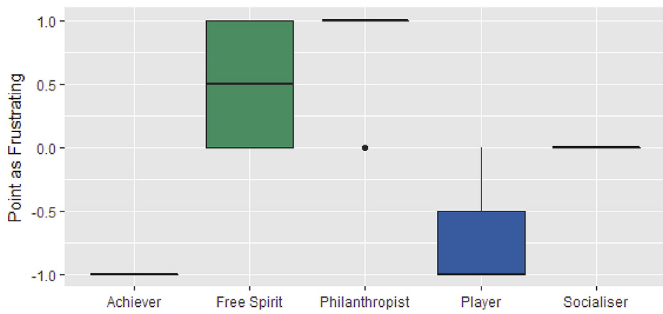

Fig. 4. Boxplot of participants' perception of Points as frustrating.

Table 9
Significant correlations between Hexad dimensions and participants' perception of game elements.

	Hexad dimensions			
	Socialisers	Free Spirits	Achievers	Players
Content Unlocking Usefulness	−0.548 (0.035)			
Content Unlocking Preferable	−0.535 (0.040)			
Point Frustrating	−0.619 (0.014)	−0.563 (0.029)	−0.591 (0.020)	
Avatar Frustrating			0.577 (0.024)	0.68 (0.005)

Notes: ρ (p-value).

null hypothesis number two (h_2).

Similarly, when analyzing the participants' perception of game elements and considering the Hexad player type dimensions to be on a continuous scale, more insights on the relationship between these variables are obtained. Table 9 shows the statistically significant correlation estimates (i.e., *p-value* < 0.05) between the Hexad player type dimensions and participants' perception of game elements. These results indicate that the Hexad dimensions were correlated, not only to participants' perception of the game element of *Point* as frustrating, but also with their perception of the game element of *Content Unlocking* as useful and preferable, as well as the perception of the game element of *Avatar* as frustrating.

Finally, the authors hypothesized that individuals' performance is correlated with their perception of the game elements implemented in the application (h_3). Table A5 (see Appendix) shows the results from the Pearson correlation tests between participants' perception of game elements and their final score performance (P), as well as their score performance difference (PD). They reveal that participants who reported the game element of *Points* as the most fun and preferable on average performed better. In contrast, participants who reported the game element of *Avatar* as the most frustrating on average performed worse. In addition, participants who reported the game element of *Content Unlocking* as the most fun on average improved less than other participants. Nonetheless, the results only indicate a statistically significant correlation, at an alpha level of 0.05, between the participants' final score and their perception of the *Avatar* game element as frustrating (ρ = −0.676, *p-value* = 0.006).

5.1. Summary of results

The results regarding the relationships between individuals Hexad player type with their performance on the gamified application are summarized in Table 10. The findings of previous studies and their similarity with the results of this work, measured using the Manhattan distance metric (i.e., dissimilarity metric), are also presented. The similarity index indicates that the results from previous works do not correlate to the performance achieved in by individuals with the Hexad player types of *Philanthropist*, *Free Spirit,* and *Player*. That is, the findings of this work indicate a negative relationship while previous studies have estimated a positive or no relationship between the gamified application and the performance of individuals with these player types (see Table 4). The results are consistent with regards to the performance of individuals with Hexad player types of *Socialisers* and *Achievers*.

Table 10
Player type relationship with performance on Reward-Customization strategy applications.

Hexad Player Type	Tondello et al. (2016)*	Tondello, Mora, et al. (2017)*	Orji et al. (2018)*	This work‡	Similarity Index◊
Philanthropists	∘	+	∘	–	4
Disruptors	∘	+	+	∘	2
Socialisers	∘	∘	+	∘	1
Free Spirits	+	∘	∘	–	4
Achievers	+	+	∘	+	1
Players	+	+	+	–	6

Notes: + positive relationship, - negative relationship, ∘ no relationship. * inferred relationship based on the perception of game element. ‡ relationship based on the measured performance. ◊ Similarity Index measured with the Manhattan distance metric, smaller numbers mean more similar.

Similarly, the results regarding the relationships between Hexad player type with individuals' perception of game elements, after interacting with them in a gamified application, are summarized in Table 11. The findings of previous studies and their similarity with the results of this work are also shown. The similarity index indicates that for the Hexad player types of *Socialiser, Achiever*, and *Player,* the results from previous works do not correlate to their perception of game elements reported in this work. That is, while previous studies indicate that the game elements of *Points*, *Content Unlocking*, and *Avatar* should have been perceived as positive by individuals with Hexad player type of *Socialiser, Achiever*, and *Player,* the findings of this work indicates that after interacting with the elements in an application they were perceived as negative.

In summary, the new findings of this work indicate that:

- When controlling for Hexad player type dimensions, participants who interacted with the gamified application (i.e., experimental group) performed better than those who interacted with the non-gamified application (i.e., control group).
- Participants who scored high in the Hexad player type dimension of *Achiever* improved their performance more than other participants.
- Participants who scored high in the Hexad player type dimension of *Philanthropist* or *Free Spirit* performed better than other participants.
- Participants who scored high in the Hexad dimension of *Free Spirit, Philanthropist,* or *Player,* performed worse in the gamified application than in the non-gamified one.
- The Hexad player type dimensions of participants were correlated to their perception of the game elements of *Point* and *Avatar* as frustrating, and the game element of *Content Unlocking* as useful and preferable.

6. Discussion

Studies indicate that a gamified application that motives an individual might not have the same effect on another individual (Codish & Ravid, 2014; Orji et al., 2014; Witt et al., 2011). Researchers argue that this is one of the reasons why several studies that implement gamified applications designed with a "*one-size-fits-all*" approach tend to present mixed results on its effectiveness (e.g., either positive and neutral, or negative and positive effects) (Hamari et al., 2014; Nacke & Deterding, 2017; Seaborn & Fels, 2015). While the participants in this work were presented with the same set of applications, the results

Table 11
Player type relationship with the perception of game elements.

Hexad Player Type	Tondello et al. (2016)*	Tondello, Mora, et al. (2017)*	Orji et al. (2018)*	This workǂ	Similarity Index◊
Philanthropists				P^{-}	3
Disruptors		CU^{+}/P^{+}	A^{+}		3
Socialisers			$A^{+}/CU^{+}/P^{+}$	CU^{-}/P^{+}	7
Free Spirits	A^{+}/CU^{+}			P^{+}	5
Achievers		CU^{+}/P^{+}		P^{+}/A^{-}	6
Players	CU^{+}/P^{+}	CU^{+}/P^{+}	CU^{+}/P^{+}	P^{+}/A^{-}	6

Notes: A = *Avatar*, CU = *Content Unlocking*, P = *Points*, + perceived as positive, - perceived as negative. * self-reported perception without being exposed to the elements in an application. ǂ self-reported perception after being exposed to the elements in an application. ◊ Similarity Index measured with the Manhattan distance metric, smaller numbers mean more similar.

reveal that a model that controlled for the Hexad player type dimensions of participants provided significantly greater explanatory power than a model that did not control for these factors. After controlling for their player type dimensions, the results indicate that participants who interacted with the gamified application (i.e., experimental group) performed better than those who interacted with the non-gamified application (i.e., control group). These results indicate that gamification had a positive effect on individuals' performance. If player type were not controlled for, the results would have indicated no effects on the value of gamification on improving participants' performance. Thus, these findings highlight the importance of considering player types and exploring the relationship between player types with individuals' performance in gamified applications.

In addition, researchers are starting to explore the potential of employing player type models to personalized gamified applications in order to improve individuals motivation and performance (Böckle et al., 2018; Monterrat et al., 2015; Tondello, Orji, et al., 2017). However, these methods are based on studies that explore the relationship between player types and individuals' self-reported game element preference without exposing individuals to the elements in an application or analyzing their performance. The results of this work could help designers tailor their gamified applications based on individuals' Hexad player type with the objective to improve individuals' performance. The results reveal that the participants who scored high in the Hexad dimension of *Achiever* improved more compared to other participants. This reveals that *Reward-Customization* strategy gamified applications are suited for *Achievers*. These results are supported by Hexad player type model that indicates that *Achievers* will prefer gamified applications with reward game elements and be motivated to master a task. In contrast, the findings that participants who scored high in the Hexad dimension of *Philanthropist* or *Free-Spirit,* on average performed better than other participants were not entirely supported by previous studies. These results could be linked to the objective and type of applications used in this work. The objective of the applications was to promote physical activity by motivating individuals to perform a series of physical tasks using full body motions. Participants who scored high in the dimension of *Free Spirit* may have been motivated by the freedom the non-wearable Kinect sensor provided (see Table 1). Similarly, participants who scored high in the dimension of *Philanthropist* may have been motivated by the purpose and meaning of the applications (see Table 1). These arguments are supported by the open-ended feedback given by participants. For example, when asked to provide feedback about the applications, ID-33 said: "*Amazing application, gives physical boost*," while ID-19 said: "*I enjoyed the experiment, love its purpose, and would participate again or encourage others to do so*." Both participants had a *Philanthropist* player type and provided positive feedback about the application and its purpose to promote physical activity. Similarly, ID-17 said: "*It was interesting. I've never done something with the Kinect thing before so that was a good first experience,*" while ID-24: "*Felt good as its kind of fun to see my actions captured on the screen.*" Both participants had a *Free Spirit* player type and provided positive feedback about the application and the sensor used to capture their motion.

Moreover, based on previous research, participants who scored high in the Hexad dimension of *Player* should have performed better in the gamified application than in the non-gamified application. In addition, participants who scored high in the dimension of *Free Spirit* or *Philanthropist* should not have performed worse in the gamified application compared to the non-gamified one. However, the results indicate that the participants who scored high in the dimensions of *Free Spirit, Philanthropist,* or *Player* tended to perform worse in the gamified application than in the non-gamified application. Studies that have explored the effects of extrinsic rewards on individuals' motivation may help explain these findings. The Cognitive Evaluation theory indicates that the effect of extrinsic rewards (e.g., *Points*, *Content Unlocking*) on an individual's motivation are mediated by their perception of these elements as controlling or informational (Deci et al., 1999; Ryan & Deci, 2000; Vansteenkiste et al., 2010). This theory indicates that when perceived as informational, reward game elements may promote individuals' motivation; hence, improve their performance. In contrast, if the reward game elements are perceived as controlling, they may hinder individuals' motivation (Mekler et al., 2017). The results presented in Fig. 4 reveal that the participants with the player type of *Free Spirit* on average reported perceiving the *Points* element as the most frustrating one. This indicates that the interaction effect between the dimension of *Free Spirit* and application used may be explained by the participants' perception of this game element as controlling or constraining their autonomy. In the non-gamified application, where the *Points* game element was not implemented, participants' that scored high in the dimension of *Free Spirit* may have perceived themselves to have more freedom and autonomy. Similarly, individuals with the player type of *Philanthropist* on average reported perceiving the *Points* element as the most frustrating. Furthermore, the results indicate that by taking into consideration partial membership between the Hexad player types, a better understanding of individuals' perception of game elements was obtained. For example, individuals that scored high in the dimension of *Socialiser* did not prefer the *Content Unlocking* element or find it useful.

Finally, according to the Self-Determination Theory (SDT), individuals will be motivated if their innate psychological needs are satisfied. Nonetheless, the fulfillment of these psychological needs rely on individuals' perception and not on objective judgment (Ryan & Deci, 2000). Hence, the authors hypothesized that individuals will perform better in gamified applications that implement the game elements they perceive as useful, fun, motivating, or preferable. The results of this work support the hypothesis that individuals' performance is correlated with their perception of the game elements implemented in the application. The findings show that there were several correlations between participants' performance and their perception of game elements. For example, participants who reported to perceive the game element of *Points* as the most fun tended to perform better in the gamified application. In contrast, participants who reported to perceive the game elements of *Content Unlocking* and *Avatar* as the most frustrating tended to perform worse. Insights as to why participants who reported the *Avatar* game element as the most frustrating performed worse can be obtained by analyzing the feedback given by participants in the open-ended question. For example, participant ID-11 and ID-15 reported having difficulties with the *Avatar* element: ID 15-"*Couldn't see the obstacles with the avatar in front of it*," ID 11-"*It didn't, at times, accurately capture my movements, thus affecting game-play*." This feedback indicates that there are still some improvements to be done in the design of the applications used. Moreover, it reveals that the characteristics of an application can have a significant impact on the motivation and performance of individuals. More importantly, these findings provide evidence on the relationship between individuals' performance and their perception of the game elements implement in a gamification application, which was missing from the literature.

In summary, the findings of this work indicate that designers should tailor gamified applications and game elements based on individuals' Hexad player type. Moreover, based on its empirical findings, this work provides new insights on how to tailor the game elements of applications in order to improve individuals' performance, which previous studies have not provided. For example, for *Philanthropists* player type, more emphasis should be given to the objective and purpose of the application and not so much on implementing *Reward* strategy game elements. For *Achievers,* more progression and mastery should be included in the application, while more *Reward* strategy game elements should be emphasized instead of *Customization* elements. Finally, implementing *Rewards* strategy game elements does not ensure that participants who scored high in the Hexad dimensions of *Player* or *Free Spirit* will perform well, as indicated by previous studies. Instead, designers should take into consideration how the game elements of their applications are implemented and perceived by individuals.

7. Conclusion and future works

Most of the existing gamified applications are designed on the assumption that individuals are a homogenous group that will react and perceive game elements in a similar manner. However, studies indicate that individuals respond and perceive gamification differently according to individual attributes. Thus, a gamified application that motives one individual might not have the same effect on another individual. Due to the limitations of the existing applications, researchers are starting to explore how individuals with different player types perceive and interact with gamified applications. However, researchers advise that there is a need for more empirical studies since there is a limited understanding of player type models and their value in advancing gamification. Most of the existing studies have focused on exploring the relationship between player type and individuals' perception of game elements without exposing them to the elements in an application or analyzing their performance on an application that implements those game elements in which they reported on. This can impact the validity of the results since humans are rarely mindful of their behavior and preferences before they are faced with the stimulus itself. Hence, a designer might spend valuable resources tailoring an application according to an individual's player type and yet, not see any positive effects on his/her performance.

In light of this gap, this work explored the relationship between individuals' player type and their performance in gamified applications. Furthermore, the relationship between individuals' player type and their perception of game elements, after interacting with them in an application, was analyzed. A case study with a randomized controlled experiment involving a gamified and a non-gamified application is presented. In this experiment, individuals' Hexad player type, their performance in a set of applications, and their perception of the game elements were assessed. The results indicate that player type correlates with individuals' perception of game elements and performance in the applications. The findings of previous studies, which only explored the relationship between player type and individuals' preference of game elements, did not completely explain the effects that the gamified application had on the performance of participants. These findings support the importance of exploring the relationship between player type and individuals' performance in gamified applications, and not just their preference of game elements. Moreover, only after controlling for individuals' Hexad player type dimensions, the results indicate that participants who interacted with the gamified application (i.e., experimental group) performed better than those who interacted with the non-gamified application (i.e., control group). These results show the value of gamification while highlighting the importance of considering player types and the need to move away from the "*one-size-fits-all*" design approach. Finally, based on the findings of this work, guidelines to help personalized gamified applications with the objective to improve individual's performance were presented.

While the results of this work provide a better understanding of the relationship between individuals' player type, their performance in gamified applications, and their perception of game elements, several limitations still exist. First, while the validity of the Hexad player type questionnaire was previously confirmed (Tondello et al., 2016) and the results of this work support its discriminant validity, they also indicate that the convergent validity for some of its items could be improved. Second, the sample of participants in the case study was not homogeneously distributed between the different Hexad player types due to the randomized controlled experiment implemented and the underlying population distribution of participants. Essentially 80% of participants were composed of individuals classified as *Philanthropists, Free Spirits,* and *Players* (see Table 5). Future works should focus on exploring the effects of player types on individuals' performance using other types of gamified applications. The findings of this work might not generalize to other applications due to the characteristics of the physically-interactive applications used. Similarly, future work should explore how the perceptions of game elements as controlling or informational affect individuals' performance. Finally, future work should explore possible interaction effects between individuals' player type and other attributes (e.g., physical fitness). Nevertheless, this work provides initial groundwork for the study of the effects that player type have on individuals' performance in gamified applications. Based on this findings, guidelines to help tailor gamified applications were provided. This could potentially help designers develop personalized gamified applications that improve individuals' motivation and performance.

Acknowledgements

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APPENDIX

Table A1
Summary statistics for the Hexad scale convergent validity analysis.

	Means	SD	CA	CR	AVE	Philanthropist	Socialiser	Free Spirit	Achiever	Disruptor	Player
Philanthropist	23.89	3.53	0.76	0.77	0.48	0.69					

(*continued on next page*)

Table A1 (*continued*)

	Means	SD	CA	CR	AVE	Philanthropist	Socialiser	Free Spirit	Achiever	Disruptor	Player
Socialiser	22.00	4.33	0.85	0.86	0.60	0.56	0.78				
Free Spirit	24.39	2.39	0.49	0.51	0.21	−0.11	0.03	0.45			
Achiever	23.89	2.73	0.62	0.62	0.28	0.28	0.36	0.33	0.53		
Disruptor	17.14	3.72	0.63	0.64	0.33	−0.55	−0.40	0.00	−0.33	0.58	
Player	22.32	3.55	0.75	0.80	0.50	0.45	0.32	0.19	0.41	−0.22	0.70

Notes: Diagonal elements are the square root of the average variance extracted.
SD: Standard deviation; CA: Cronbach's alpha; CR: Composite reliability, AVE: Average variance extracted.

Table A2
Summary statistics for the Hexad scale factor analysis.

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6
PH1			0.62			
PH2	0.38	0.46				−0.54
PH3					−0.66	−0.26
PH4			0.49		−0.37	
SO1	0.79					
SO2	0.98					
SO3	0.64			0.43		
SO4	0.65			−0.27		
FS1			−0.28	0.20		
FS2	−0.23	0.36	−0.34			0.27
FS3	0.48					0.63
FS4	−0.24					
AC1	0.30	0.43	−0.33		−0.21	
AC2		0.28		0.36		
AC3				0.88		
AC4				0.23	−0.43	0.60
DI1		−0.29			0.71	
DI2				0.55	0.39	
DI3			−0.40		0.26	
DI4		0.31			0.78	
PL1	0.44	0.62			−0.20	
PL2		0.83				
PL3			0.55			
PL4		0.79	0.32			0.21
Eigenvalue	3.68	2.84	1.67	1.75	2.67	1.45
% of Variance	0.15	0.12	0.07	0.07	0.11	0.06
Cumulative Var	0.15	0.27	0.34	0.41	0.53	0.59

Notes: Extraction method: Principal Component Analysis. Rotation method: Oblimin with Kaiser normalization as per (Tondello et al., 2016). Rotated factor loads of < 0.20 are not shown to help visualize the results.

Table A3
Summary statistic for Kruskal-Wallis ANOVA tests.

Variables	$\chi^2_{(4)}$	p-value
Point Usefulness	4.534	0.3385
Content Unlocking Usefulness	3.629	0.4585
Avatar Usefulness	1.175	0.8821
Point Preferable	3.947	0.4132
Content Unlocking Preferable	3.526	0.4739
Avatar Preferable	3.352	0.5007

(*continued on next page*)

Table A3 (*continued*)

Variables	$\chi^2_{(4)}$	p-value
Point Motivational	3.609	0.4615
Content Unlocking Motivational	2.637	0.6203
Avatar Motivational	4.190	0.3809
Point Fun	2.608	0.6255
Content Unlocking Fun	2.431	0.6571
Avatar Fun	3.023	0.554
Point Frustrating	9.489	0.049*
Content Unlocking Frustrating	2.190	0.7008
Avatar Frustrating	6.344	0.1749

Note: Significance level codes (*p-values*): < 0.01**, < 0.05*, < 0.1′.

Table A4
Summary statistic for Mann-Whitney U tests.

Pairwise comparisons	U	p-value
Free Spirit-Achiever	4	0.264
Philanthropist-Achiever	5	0.166
Player-Achiever	2	1.000
Socialiser-Achiever	2	0.479
Philanthropist-Free Spirit	13	0.456
Player-Free Spirit	1	0.092’
Socialiser-Free Spirit	2	0.402
Player-Philanthropist	0.5	0.036*
Socialiser-Philanthropist	1	0.118
Socialiser-Player	5	0.317

Note: Significance level codes (*p-values*): < 0.01**, < 0.05*, < 0.1’.

Table A5
Correlation analysis between participants' performance and perception of game elements.

	ρ	
	P	PD
Point Usefulness	0.290	−0.02
Content Unlocking Usefulness	−0.034	−0.161
Avatar Usefulness	−0.262	0.126
Point Preferable	0.433	−0.083
Content Unlocking Preferable	−0.382	−0.346
Avatar Preferable	−0.202	0.356
Point Motivational	0.302	0.027
Content Unlocking Motivational	−0.369	−0.174
Avatar Motivational	0.121	0.189
Point Fun	0.454′	0.149
Content Unlocking Fun	−0.370	−0.469’
Avatar Fun	−0.119	0.195
Point Frustrating	0.333	−0.198
Content Unlocking Frustrating	0.452	0.075
Avatar Frustrating	−0.676**	0.102

Note: Estimated Pearson correlation. Significance level codes (*p-values*): < 0.01**, < 0.05*, < 0.1’.

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