AIS Transactions on Human-Computer Interaction

Volume 13 | Issue 3 Article 1

9-30-2021

Should Gamification be Personalized? A Self-deterministic Approach

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Recommended Citation

Passalacqua, M., Senecal, Ph.D., S., Fredette, M., Nacke, L. E., Pellerin, R., & Leger, P. (2021). Should Gamification be Personalized? A Self-deterministic Approach. *AIS Transactions on Human-Computer Interaction, 13*(3), 265-286. https://doi.org/10.17705/1thci.00150
DOI: 10.17705/1thci.00150

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Transactions on Human-Computer Interaction

Volume 13 Issue 3

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Passalacqua, M., Sénécal, S, Frédette, M, Nacke, L.E., Pellerin, Robert, & Léger, P.M. (2021). Should Gamification be Personalized? A Self-deterministic Approach. *AIS Transactions on Human-Computer Interaction*, *13*(3), pp. 265-286.

DOI: 10.17705/1thci.00150

Available at http://aisel.aisnet.org/thci/vol13/iss3/1

Transactions on Human-Computer Interaction

Research Paper DOI: 10.17705/1thci.00150 ISSN: 1944-3900

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Abstract:

Information system (IS) gamification has been successful in many contexts. Yet, research has shown gamification's success to vary between individuals. In this paper, we compare personalized versus non-personalized gamification in a warehouse management setting. We devised a 26-participant within-subject experiment in which we programmed goal setting and feedback gamification elements into a wearable warehouse management system to evaluate the effectiveness of personalized gamification in terms of user performance. We examined the extent to which personalized gamification succeeded by categorizing participants into one of six user types through the HEXAD scale and then evaluating their performance time and errors across user types and conditions. We found that personalized gamification is more effective than non-personalized gamification. We present and discuss the motivational mechanisms through which personalized gamification can be more effective.

Keywords: Gamification, Personalization, Motivation, Self-determination Theory, Goal-setting Theory.

Chee-Wee Tan was the accepting senior editor for this paper.

1 Introduction

In the past 15 years, gamification has emerged as a successful method to engage and motivate users in various contexts. Human-computer interaction (HCI) research has defined gamification as using gaming elements in a non-gaming context. In essence, gamification focuses on transposing video games' intrinsically motivating nature into a more serious context. Since gamification often revolves around motivating users to reach a goal, researchers have unsurprisingly used motivational theories in the psychological literature to uncover users' underlying cognition. None have been more present in gamification literature than self-determination theory (SDT) (Deci, Olafsen, & Ryan, 2017; Nacke & Deterding, 2017). In short, this influential theory states that people need to satisfy three universal psychological needs (competence, connection, and autonomy) to achieve intrinsic motivation—a catalyst for long-term user performance, meaningful user engagement, and other positive outcomes related to gamification. SDT categorizes motivation as intrinsic, which comes from within, or extrinsic, which comes from an external source. The motivational literature has established that individuals display significant variability in terms of internalizing motivators. For gamification, that variability means that users will be intrinsically/autonomously motivated to different degrees in response to different gamification elements. Certain game elements will elicit a more intrinsic motivation from users with particular personality traits. For example, gamification elements that involve helping others will intrinsically motivate a person with philanthropic traits. Thus, by personalizing a gamified system, one can achieve better outcomes.

Personalizing a system does not represent a novel idea in HCI. Personalization, which refers to tailoring content or a system to a user's characteristics, has seen success in user interface (UI) design and game design (Adomavicius & Tuzhilin, 2005). In personalizing gamification, one uses user typologies to classify users in order to understand how different user types interact with and are motivated by gamified systems. Results have shown that personalized gamification can be more effective in terms of user performance than non-personalized gamification (Tondello, 2019). However, researchers have implemented and empirically evaluated personalized gamification primarily in educational contexts (Rodrigues, Toda, Palomino, Oliveira, & Isotani, 2020). Unlike educational settings, where students' learning can be ever changing and progressive in nature, industrial settings are characterized by monotonous and largely uniform work throughout the day. Work environments with these particular characteristics have rarely been explored in gamification literature and have never been addressed in personalized gamification literature despite gamification's growing presence in warehouses (e.g., Amazon's warehouse employee gamification program) (Anderson, 2021; Bensiger, 2019; Small, 2017) and despite their well-documented negative effect on employee engagement/motivation (Harter, Schmidt, Agrawal, Plowman, & Blue, 2016; Mann & Harter, 2016). Given that industrial settings such as warehouse management typically feature monotonous work and low employee engagement/motivation, they represent an ideal empirical context to further explore and break down the effects of personalized gamification.

Indeed, monotonous or repetitive tasks that directly negatively affect some of gamification's success criteria (i.e., engagement, motivation, enjoyment, and performance) represent an ideal topic to examine in order to further explain personalized gamification. In addition to considering unexplored work characteristics, we need research with strong theoretical roots in the well-established motivation literature to understand the motivational underpinnings through which personalization positively affects autonomous motivation and performance (Tyack & Mekler, 2020). Research that addresses these gaps will further ameliorate gamification's positive outcomes by identifying how one can meaningfully motivate different user types, which can lead to better performance with a gamified system. In short, we address the following research question (RQ):

RQ: Does personalized gamification lead to better user performance in a monotonous work context compared to non-personalized gamification?

2 Related Work and Hypothesis Development

2.1 Gamification

Researchers have applied gamification, which refers to using game elements in a non-gaming setting (Deterding, Dixon, Khaled, & Nacke, 2011), to multiple domains such as public engagement (Palacin-Silva et al., 2018), fitness (Zhao, Arya, Whitehead, Chan, & Etemad, 2017), education (Denny, McDonald, Empson, Kelly, & Petersen, 2018), health (Tabor, Bateman, Scheme, Flatla, & Gerling, 2017), and marketing (Cechanowicz, Gutwin, Brownell, & Goodfellow, 2013). However, researchers have rarely rigorously and experimentally evaluated gamification in a warehouse setting (Warmelink, Koivisto, Mayer, Vesa, & Hamari, 2020). Nevertheless, in the last decade, the human-computer interaction literature has established gamification as a design approach that can lead to success with regards to both instrumental and experiential outcomes (e.g., performance, satisfaction, engagement, enjoyment) (Koivisto & Hamari, 2017; Tondello & Nacke, 2020; Warmelink, Koivisto, Mayer, Vesa, & Hamari, 2018). Some commonly used gamification elements in the gamification literature include goals, feedback, progress bars, badges, narratives/storylines, leaderboards, and points. Because gamification originates from games, it has a goal-oriented nature (Deterding et al., 2011; Tondello, Premsukh, & Nacke, 2018). In reviewing the literature, Tondello et al. (2018) found that many gamification elements such as badges, leaderboards, progress bars, feedback, challenges, and levels often revolve around goal setting. Nevertheless, gamification research has usually used well-established motivational theories (SDT and goal-setting theory) that explain what motivates people to reach goals in a superficial manner (Tondello et al., 2018; Tyack & Mekler, 2020). Indeed, many researchers have expressed concern about the fact that the gamification literature lacks theory-driven experiments (Nacke & Deterding, 2017; Seaborn & Fels, 2015; Warmelink et al., 2018, 2020).

2.2 Self-determination Theory

Researchers have refined SDT, a psychological theory of human motivation, over four decades and used it in various contexts. SDT has become the leading theory that researchers use to explain games' motivational effect (Deci & Ryan, 1980; Ryan, Rigby, & Przybylski, 2006). At its core, SDT explains and predicts how situations, contexts, or events affect a person's motivation (Deci et al., 2017; Tyack & Mekler, 2020). In particular, it may prove useful in providing actionable insight to mitigate the ill effects that monotony and boredom have on workers' motivation and performance in a warehouse management context (Small, 2017). This theory posits that satisfying three innate psychological needs leads to intrinsic motivation, which refers to performing an activity for its inherent satisfaction (Ryan & Deci, 2000). Autonomy refers to the feeling that behavior or actions come from within as opposed to external factors, competence to the feeling that one has an effect on one's environment, and relatedness to the feeling that one has meaningful interactions with others (Ryan & Deci, 2000). According to SDT, motivation lies along a continuum from amotivation to extrinsic motivation to intrinsic motivation.

The continuum ranges from not self-determined motivation types on one end to self-determined types on the other end. In other words, the continuum ranges from controlled forms of motivation (externally regulated) to more autonomous forms (intrinsically regulated). Amotivation describes a complete lack of motivation. SDT divides extrinsic motivation into four different categories that differ in their control/autonomy. External regulation, the first category, refers to behaviors that individuals do to satisfy external rewards or avoid punishment. Introjected regulation, the second category, refers to behaviors that individuals do to avoid internal rewards/punishment and to protect their ego or self-esteem. Identified regulation, the third category, refers to a more autonomous form of extrinsic motivation. An identified form of regulation occurs when individuals attribute a personal importance to a behavior and, thus, regulate it more internally. Integrated regulation, the final and most autonomous type of extrinsic motivation, occurs when individuals fully internalize an identified regulation (attributing personal importance). In other words, they incorporate the reasons for a behaviour or action into their self (Ryan & Deci, 2000). On the opposite end of amotivation lies intrinsic motivation, which individuals regulate intrinsically. Intrinsic regulation means that individuals perform an action/behaviour for the enjoyment and satisfaction associated with it. Although similar, intrinsic regulation and integrated regulation differ. Intrinsic regulation implies that individuals perform an action/behaviour simply to do it, whereas integrated regulation implies that individuals perform an action/behaviour for an instrumental outcome (Ryan & Deci, 2000). In summary, each stage along the continuum represents a different level of internalization as to why individuals do an action or a behavior.

Just as individuals internalize behaviors or actions to varying degrees, so too do they internalize their reasons for pursuing goals, which produces different types of motivation along the self-determination continuum. A large body of research has shown that goals that individuals internalize to a greater extent yield greater goal success (Koestner & Hope, 2014). In other words, when the motivation underlying goal pursuit is further towards the intrinsic type, goals are more often reached because individuals expend more effort and encounter less conflict. Since satisfying the three basic psychological needs (autonomy, competence, and relatedness) fosters internalization and more autonomous motivation, SDT posits that these needs must be considered when setting goals, which implies that autonomy, competence, and relatedness play a central role in whether individuals successfully set and reach their goals.

2.3 Goal-setting Theory

As opposed to SDT, which focuses on the underlying reasons for which individuals pursue goals, goal-setting theory mainly focuses on how to best set goals. Goal-setting theory, which has emerged from hundreds of empirical findings, states that goal setting is linked to performance (Locke & Latham, 1990). As research has progressed, it has seemingly come to a consensus about the kinds of goal characteristics that lead to the best performance: specific goals, measurable goals, goals that one can attain through one's own effort, realistic goals, and time-bound goals (or SMART for short). Goal-setting theory also distinguishes between self-set and assigned goals. Results have shown that self-set goals seem to be more effective in terms of goal attainment (Erez & Arad, 1986; Harkins & Lowe, 2000; Locke & Latham, 2002). In addition, goals and feedback are more effective together than separate (Locke & Latham, 2013) because feedback allows users to monitor their progress towards a goal and adjust their effort accordingly (Tondello et al., 2018). We refer interested readers to Locke and Latham (2013) who more deeply examine goal-setting theory. In summary, goal-setting theory provides three insights for goal setting that maximizes user motivation and performance in gamified systems: SMART goals lead to the best performance, self-set goals differ from assigned goals, and individuals require feedback about their effort toward achieving a goal. We applied these goal-setting principles in our study. Specifically, in designing our gamified system, we created SMART goals, used both self-set and assigned goals, and included feedback when the system assigned a goal.

2.4 Personalization

The degree to which goal pursuit is internalized varies across individuals. Certain individuals better internalize certain types of motivators (e.g., money), while some individuals better internalize other types of motivators (e.g., social connection). Thus, no one-size-fits-all motivator can best lead to autonomous motivation and, for gamification, no one game element or set of elements can best lead all user types to autonomous motivation. The gamification literature shows a clear need to research personalized gamified systems (Tondello et al., 2016). Researchers have created most user/player classification models specifically for game design (Bartle, 1996; Bateman & Boon, 2005; Nacke, Bateman, & Mandryk, 2014; Xu et al., 2012; Yee, Ducheneaut, & Nelson**,** 2012), and one cannot generalize them to gamified systems (Tondello, 2019). To fill the need, Tondello et al. (2016) created the HEXAD scale based on Marczewski's (2015) work. To date, this user typology constitutes the only one that researchers have designed specifically for gamified systems (Rodrigues et al., 2020). We chose the HEXAD scale for this study because it has strong theoretical underpinnings (SDT) that address our current outcome variable (performance), because researchers have validated its use in gamified systems, and because the gamification literature has used it more than any other typology since its creation. This six user-type model has foundations in SDT: intrinsic and extrinsic factors in a gamified system motivate each user type differently. In other words, each user type differently internalizes motivators (or gamification elements). Based on findings from motivation and gamification literature, we expect that user type will moderate the goal-performance relationship. To our knowledge, other than Tondello et al. (2016), only Lopez and Tucker (2019) have examined the relationship between user type and user performance using the HEXAD scale. They found no significant differences between user types for performance. However, they used a video game rather than a gamified work application, which greatly limits its generalizability to the current study as Tondello et al. (2016) designed the HEXAD scale for gamified applications.

Next, we describe the six user types based on Tondello et al.'s (2016) original work and Krath and von Korflesch's (2021) further validation. We also present hypotheses related to each user type based on the motivation and gamification literatures. Achievers, the first user type, are more autonomously motivated by game elements related to SDT's need for competence. They feel the need to perform to the best of their abilities. Some recommended game elements for achievers include levels, boss battles, and challenges. In other words, achievers, compared to other user types, better internalize goals, which leads to a more intrinsic goal attainment motivation and, thus, better performance (Krath & von Korflesch, 2021; Tondello et al., 2016). Thus, in the warehouse management context we consider in this study, participants classified as achievers should more quickly and accurately pick items from the warehouse shelves compared to the other user types.

> **H1a:** Achievers perform faster in all conditions (no gamification, self-set goals, assigned goals) compared to the other user types.

H1b: Achievers make fewer errors in all conditions (no gamification, self-set goals, assigned goals) compared to the other user types.

Free spirits, the second user type, are more autonomously motivated by game elements related to SDT's need for autonomy. They like to explore and do not like to be controlled by external forces. Some recommended game elements for free spirits include creativity tools, self-set goals, and exploratory tasks. In other words, free spirits will be most intrinsically motivated when they perceive that they have a choice (Krath & von Korflesch, 2021; Tondello et al., 2016). Thus, in the warehouse management context we consider in this study, free spirits should more quickly and accurately pick items from the warehouse shelves when they can select their own goals as opposed to having no goals or having a goal assigned to them.

H2a: Free spirits perform faster when they set their own goals (second condition) compared to the other conditions (no gamification, assigned goals).

H2b: Free spirits make fewer errors when they set their own goals (second condition) compared to the other conditions (no gamification, assigned goals).

Socializers, the third user type, are more autonomously motivated by game elements associated with SDT's need for relatedness. They like to interact with others and like gamified systems' social aspect. Some recommended game elements for socializers include teams, social network, and social competition (Krath & von Korflesch, 2021; Tondello et al., 2016). Philanthropists, the fourth user type, are also more autonomously motivated by game elements associated with SDT's need for relatedness. They are altruistic and like to feel a certain sense of purpose. Some recommended game elements include gifting, narrative, trading, and knowledge sharing (Krath & von Korflesch, 2021; Tondello et al., 2016). Thus, in the warehouse management context we consider in this study, no game elements relate to socialization or a sense of purpose. As such, socializers and philanthropists should have low goal internalization and low intrinsic motivation, which will lead to their exhibiting slower and less accurate item picking from the warehouse shelves when compared to the other user types.

H3a: Socializers and philanthropists perform the slowest in all conditions (no gamification, self-set goals, assigned goals) compared to the other user types

H3b: Socializers and philanthropists make the most errors in all conditions (no gamification, self-set goals, assigned goals) compared to the other user types

Players, the fifth user type, are more autonomously motivated by extrinsic reward. They like to earn rewards in gamified systems. Some recommended game elements include points, badges, and achievements. In other words, players better internalize goals that lead to external rewards (e.g., praise, points). Thus, they will be more motivated and perform better when an external source (e.g., a company or experimenter) assigns a goal to them (Krath & von Korflesch, 2021; Tondello et al., 2016). Thus, in the warehouse management context we consider in this study, players should more quickly and accurately pick items from the warehouse shelves when an external source assigns them a goal as opposed to having no goal or selecting their own goal.

H4a: Players perform faster when an external source assigns a goal to them (third condition) compared to the other conditions (no gamification, self-set goals).

H4b: Players make fewer errors when an external source assigns a goal to them (third condition) compared to the other conditions (no gamification, self-set goals).

Disruptors, the sixth user type, like to test a system's boundaries to initiate positive/negative change. Tondello et al. (2016) state that this user type does not relate to SDT but that they derived it from empirical observation data. Some recommended game elements for disruptors include development tools and anonymity.

Thus, we can see a theoretical fit between user type and gamification element in the sense that specific gamification elements autonomously motivate user types to varying degrees. In other words, alignment between user type and gamification elements leads to better performance. A deviation from this fit/alignment can hinder user performance (Venkatraman, 1989). Not many studies have evaluated the alignment between game elements and user type in relation to performance or, in other words, how different user types have a certain fit with specific game elements.

3 Methodology

3.1 Experimental Design

We manipulated two experimental factors (goals and feedback) in a within-subject design, which resulted in three conditions: 1) no gamification, 2) self-set goals and feedback, and 3) assigned goals and feedback. Participants ranged from 19 to 26 years old (mean: 24.4, SD: 2.1; median = 24). In total, 26 participants took part in the experiment (11 males and 15 females). The 20 to 24 age range constitutes the second most common age range for stock and material movers (also known as order pickers) (United States Bureau of Labor, 2018). The 16 to 19 age range constitutes the most common. Thus, the 20 to 24 age range constitutes the most common adult age range for stock and material movers, which made our sample selection adequate. Our institutional review board approved our study. Finally, we gave subjects a CA$40 gift card at the end of the experiment for their participation.

3.2 Experimental Setup, Stimuli, and Task

Warehouse order picking, which accounts for about 55 percent of total warehouse expenditure, involves retrieving an item from a particular location in order to fill a specific order (Bartholdi & Hackman, 2019; Chackelson, Errasti, & Tanco, 2012). Order pickers typically use a management information system (MIS) to aid them. A warehouse MIS is a “complex software package that helps manage inventory, storage locations, and the workforce, to ensure that customer orders are picked quickly, packed, and shipped” (Bartholdi & Hackman, 2019, p. 33). While advancements have led to automated warehouses, about 80 percent of warehouses use humans for order picking due to their flexibility and ability to accommodate high product diversity and constantly changing product catalogues (Grosse, Glock, & Neumann, 2017). Research in operations management seems to focus on optimizing the order-picking task through storage assignment, routing, and batching (Grosse et al., 2017). However, researchers have rarely explored ways to optimize the people behind the tasks (Passalacqua et al., 2020; Small, 2017). Organizations can gamify IS, which has seen success in terms of employee motivation and performance, to improve order picker efficiency. In addition, it would be relatively easy to integrate gamification into order picking since it involves repetitive objectives and tracking data through an MIS (Small, 2017). Thus, warehouse order picking represents an appropriate context to run the current experiment (Klevers, Sailer, & Günthner, 2016).

Participants in the current experiment executed an order-picking task for each condition. The experiment had three conditions and, therefore, three picking tasks. In each task, participants had to pick varying amounts of 12 items from a specific location (e.g., in one pick, to pick seven blue paper clips from location A01004). To ensure all three conditions involved the same pick complexity, we used a picking complexity matrix based on Errasti’s (2011) and Chackelson et al.’s (2012) work. In short, each pick had a complexity score based on the number of items participants had to pick and various characteristics (e.g., type, color, size). Participants obtained instructions from the wearable device that we show in Figure 1. We minimized the learning effect related to an item’s location by making sure each pick had a different location.

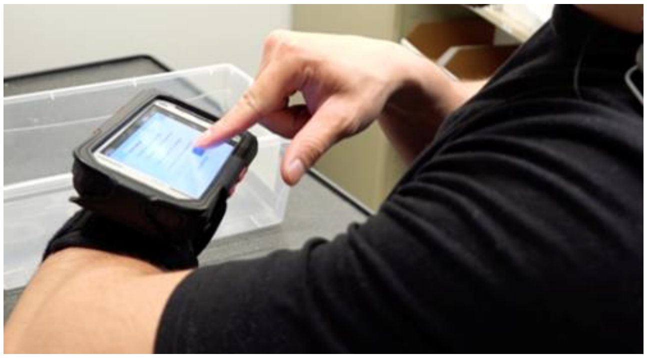

Figure 1. Wearable Management Information System

With this study, we take a step forward in exploring these gaps by integrating goal setting and feedback gamification elements into a wearable management information system (MIS) to then evaluate user performance across the HEXAD user types. Specifically, we integrated self-set goals, assigned goals, and feedback into a MIS to test users’ performance while performing a warehouse order-picking task. In short, results show that user type affects the relationship between goals/game elements and performance. Results indicate that personalized gamification more effective than non-personalized gamification.

We built a mock 3.4 by 5.2-meter warehouse in our laboratory. It contained five tall racks that each had 20 labeled bins. Each bin represented a location (e.g., A01004). All participants' took the same path through the warehouse.

3.3 Procedure

We (either an author or a research assistant) told all participants that the experiment involved testing a warehouse management prototype. We gave them basic information about the tasks (taking a specific quantity of items from bins on racks in various locations). At this point, subjects completed pre-experiment questionnaires (demographics and the HEXAD scale). After they completed both questionnaires, a research assistant attached the wearable device to them. We then gave them more specific task instructions followed by a non-gamified training task with six picks. We made sure that subjects comprehended the task procedure. The training task also minimized the learning effect. Once we were sure that the participants understood the task, we began the first condition.

The first condition (no gamification (NG)) did not have any game elements. Figure 2 shows the picking screen for this condition. One can see that an upwards counting timer appeared the top right corner of the screen. This figure illustrates that a participant was executing the fourth pick. When participants took items from the rack and placed in the bin on the trolley, they needed to use the wearable device's touchscreen to click on "item number", which copied the item number (PRD34201) into the field. Participants needed to manually enter item quantity then click continue to proceed to the next pick. After the first condition, they completed the second and third conditions in a randomized and counterbalanced order.

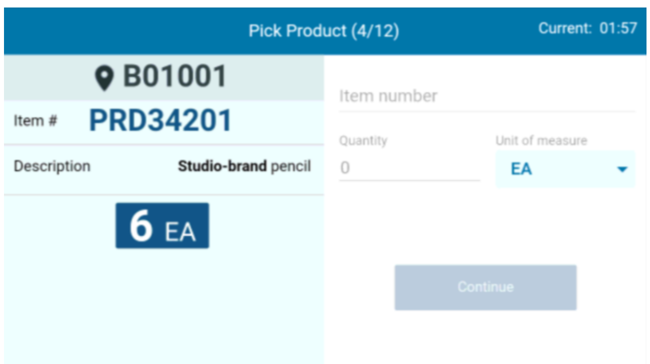

Figure 2. Condition 1 (NG) Picking Screen

In the second condition (self-set goals (SSG)), participants chose one of three goal times as Figure 3 shows. The middle goal choice (6:38) corresponded to the average time to complete the task in an identical pilot study with nine participants. The first goal (5:38) was the most difficult goal, while the last goal (7:38) was the easiest. An area right under the upwards counting timer in this condition always showed the selected goal time as Figure 4 shows. When participants completed the task, the wearable device informed them about whether they had achieved their chosen goal.

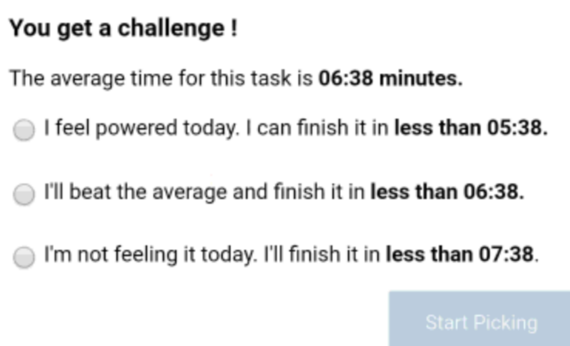

Figure 3. Condition 2 (SSG) Goal Selection Screen

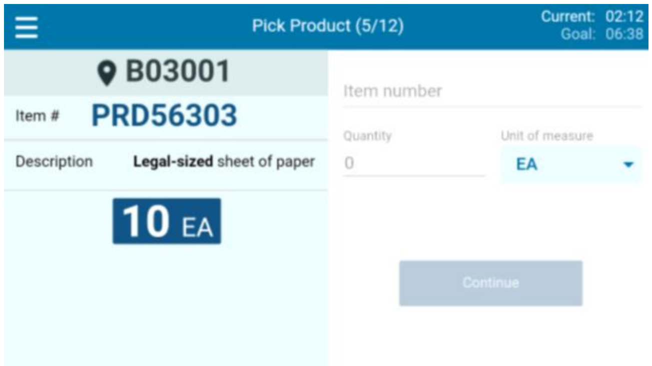

Figure 4. Condition 2 (SSG) and Condition 3 (AG) Picking Screen

In the third condition (assigned goals (AG)), we gave subjects a goal that always corresponded to the middle choice (average time) in the second condition (6:38). The wearable device's screen matched the screen in the second condition (see Figure 4). When participants completed the task, the wearable device informed them about whether they had achieved their chosen goal.

The goal-setting literature agrees that, when presented with a task without a goal after a task with a goal, participants will perform less well in the task without a goal (Locke & Latham, 2006). For this reason, we presented the first condition (NG) first for all participants. We then counterbalanced the second and third conditions to avoid sequencing effects. Additionally, we randomly assigned sequences. Figure 5 demonstrates the experiment's procedure.

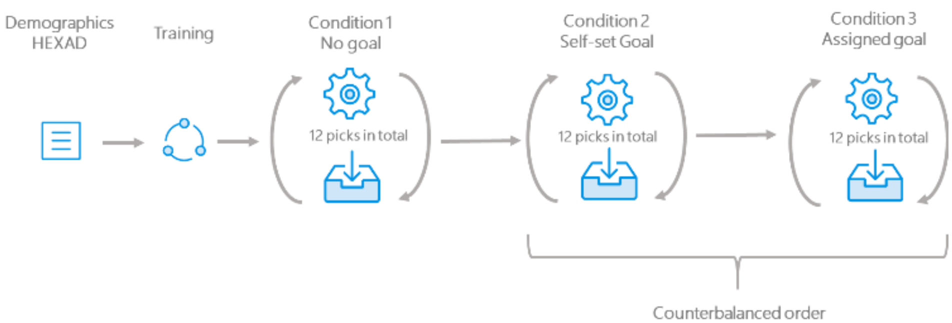

Figure 5. Experimental Procedure

3.4 Research Variable Operationalization

3.4.1 Performance

We operationalized performance based on the two most used warehousing key performance indicators for order picking: 1) number of errors 2) time taken to complete the task (Bartholdi & Hackman, 2019). We chose these two performance indicators because they contribute to this study's ecological validity since organizations in the real world use them more than any other indicators to measure order picker performance. When comparing SSG and AG conditions in terms of time taken to complete the task, we deducted the goal time from the time it took participants to complete the task, which led to a more precise comparison since it considered the chosen/assigned goal. We conceptualized the number of errors using the percentage of correctness/accuracy. Errors in more complex tasks, as per the picking complexity matrix, led to a smaller deduction in terms of correctness percentage. We weighted both error types (quantity and type of item) equally.

3.4.2 HEXAD

To determine participant user typology, we employed the HEXAD scale. The HEXAD has 24 items with scores that use a seven-point Likert scale. We randomized the order of the 24 items as Tondello et al. (2016) recommend. Each user type has four items associated with it. The scale asks participants to rate how well each item describes them. One sums the scores on items associated with each user type, which gives a score for each user type. The category with the highest score indicates the participant's user type (Tondello et al., 2016).

3.5 Apparatus

We placed four webcams (Logitech, Newark, USA) around the simulated warehouse to record the participants. We presented the MIS through the Panasonic FZ-N1 (Osaka, Japan), a wearable Android device. JDA (Waukesha, USA) created the MIS using Axure RP 8 (San Diego, USA). We recorded video using Media Recorder (Noldus, Wageningen, Netherlands). We recorded the MIS's screen using Teamviewer (Göppingen, Germany).

3.6 Statistical Analysis

We used Wilcoxon rank-sum tests to analyze data related to goal difficulty, performance time, and performance errors. We used non-parametric tests because the data lacked a normal distribution and because they prove more robust when using small to medium-sized sample sizes (Cohen, 1992; Wilcoxon, 1992). We used SAS 9.4 (Cary, USA) for our statistical analyses.

4 Results

We found no significant differences related to demographic variables (age, gender, income, education, or occupation). Mixed Poisson and mixed linear regression models showed that task order had no effect on the results. We classified no participants as disruptors. We found no significant differences between philanthropists and socializers for any variable. Therefore, we grouped together for simplicity. We provide the descriptive statistics in Appendices A and B.

The distribution of user types was follows: five achievers, six free spirits, four philanthropists, five socializers, and five players. The HEXAD scale classified one participant as equally both a free spirit and socializer. We excluded this participant because we could not assign a user type to them.

4.1 Performance Time and Performance Errors

4.1.1 Achievers

Results showed that achievers performed faster in all three conditions than free spirits ($d = -1.21$, $p < 0.05$) and socializers and philanthropists ($d = -1.04$, $p < 0.05$). However, we found no significant differences when comparing achievers to players ($p = 0.29$). Figure 6 shows performance time between user types. Thus, we found partial support for H1a.

Results showed that achievers made fewer errors in all three conditions than free spirits ($d = -0.79$, $p < 0.05$) and socializers and philanthropists ($d = -1.06$, $p < 0.05$). However, we found no significant differences when comparing achievers to players ($p = 0.26$). Figure 7 shows performance errors between user types. Thus, we found partial support for H1b. Results also showed that, in the second condition (SSG), achievers selected a more difficult goal than socializers and philanthropists ($d = 1.19$, $p < 0.05$), free spirits ($d = 0.99$, $p < 0.05$), and players ($d = 1.30$, $p < 0.05$).

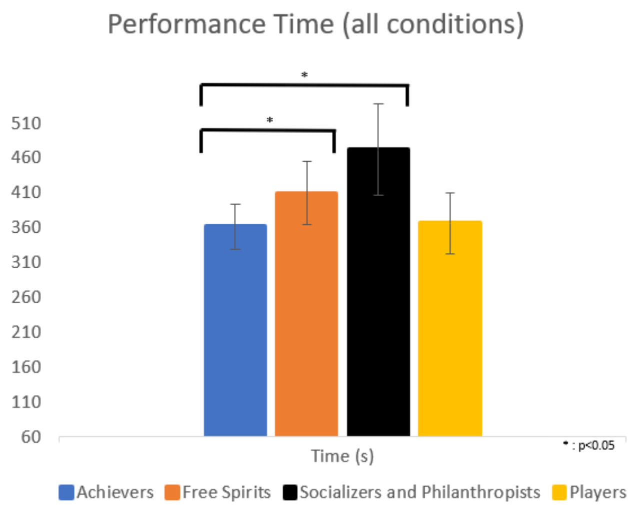

Figure 6. Performance Time across User Types

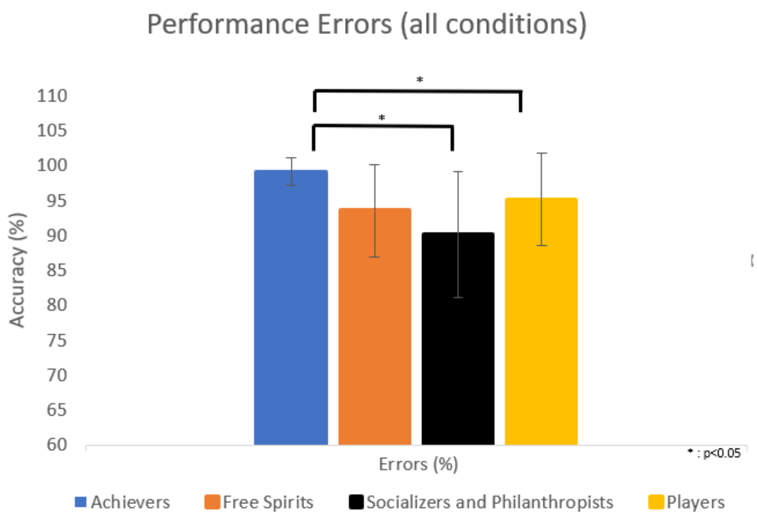

Figure 7. Performance Errors across User Types

4.1.2 Free Spirits

Results showed that free spirits performed faster in the second condition than in the first ($d = -0.64$, $p < 0.05$) and third conditions ($d = -0.63$, $p < 0.05$). Thus, we found support for H2a. Results showed that free spirits made fewer errors in the second condition than in the first condition ($d = 0.88$, $p < 0.05$). However, we found no significant differences when comparing the second and third conditions ($p = 0.13$). Figure 8 shows free spirit performance time and errors between conditions. The three columns on the left side represent performance time for each condition. The three shorter columns on the right side represent performance errors (accuracy percent) for each condition. Thus, we found partial support for H2b.

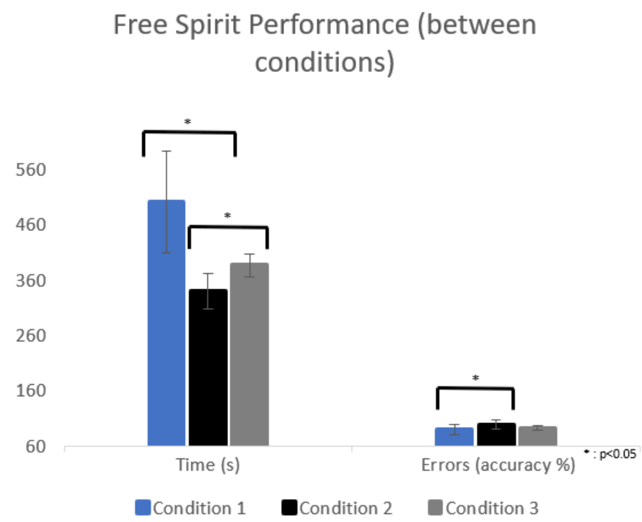

Figure 8. Free Spirit Performance between Conditions

4.1.3 Socializers and Philanthropists

Results showed that socializers and philanthropists performed more slowly than free spirits ($d = -1.04$, $p < 0.05$), players ($d = 1.05$, $p < 0.05$), and achievers ($d = 0.94$, $p < 0.05$). Thus, we found support for H3a. Results showed that socializers and philanthropists made more errors in all three conditions than free spirits ($d = 0.80$, $p < 0.05$), players ($d = 0.91$, $p < 0.05$), and achievers ($d = 1.07$, $p < 0.05$). Thus, we found support for H3b.

4.1.4 Players

Results showed that players performed more quickly in the third condition than in the first ($d = -0.57$, $p < 0.05$) and second conditions ($d = -0.57$, $p < 0.05$). Thus, we found support for H4a. Results showed that players made fewer errors in the third than first condition ($d = 0.75$, $p < 0.05$). However, we found no significant differences when comparing the third and second conditions ($p = 0.19$). Figure 9 shows player performance time and errors between conditions. The three columns on the left side represent performance time for each condition. The three shorter columns on the right side represent performance errors (accuracy percent) for each condition. Thus, we found partial support for H4b.

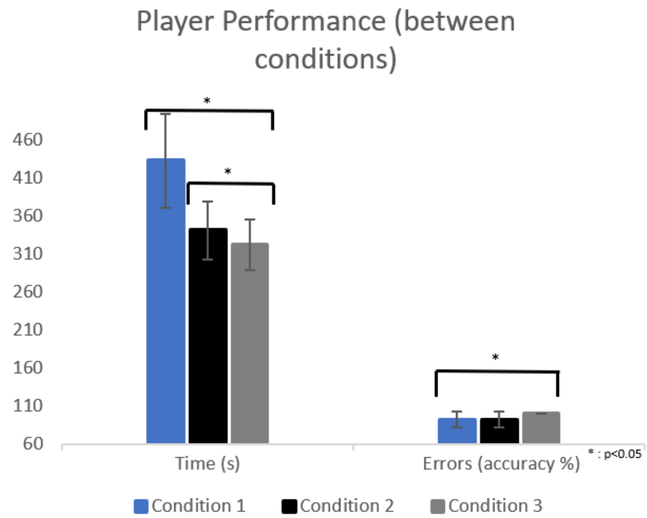

Figure 9. Player Performance between Conditions

4.1.5 User Type (Moderation)

We conducted logistic regressions to determine whether user type moderated the relationship between gamification (three conditions) and task performance (time, errors). Results show that user type moderated the relationship between gamification and performance time when we compared the first and second conditions ($d = -0.65$, $p < 0.05$), when comparing the first and third conditions ($d = -0.58$, $p < 0.05$), and when comparing the second and third conditions ($d = 0.42$, $p < 0.05$). However, user type did not moderate the relationship between gamification and performance errors.

5 Discussion

We generally found support for the effectiveness of and, thus, the need for personalized gamification. We found a certain fit or alignment between user type and gamification elements. Deviation from this fit leads to worse performance (e.g., free spirits performed less well in the assigned goal condition). In Sections 5.1 to 5.4, we break down the results for each HEXAD user type.

5.1 Achievers

Achievers performed better than free spirits, philanthropists, and socializers, which seems intuitive since they feel the need to perform to the best of their abilities. Game elements related to goals help achievers feel competent and, therefore, lead this user type to a more autonomous motivation type via internalizing the goal pursuit. Achievers take goals seriously and strive to reach them. We also found that achievers selected more difficult goals than all the other types, which further supplements the fact that competence concurs with their internal values and helps them internalize goals. Congruence with internal values indicates a more self-determined regulation type (identified or integrated), which is synonymous with more autonomous motivation.

However, achievers did not perform better than players possibly due to the fact that players themselves feel more motivated and performant when external sources assign goals to them (third condition). Yet, when breaking down performance between achievers vs. players by task, we found no significant difference in the first (NG), second (SSG), and third conditions (AG). Achievers and players performed equally well in each condition.

5.2 Free Spirits

We found that free spirits performed better when they selected their own goal (second condition). Self-set goals lead to an increased sense of autonomy, one of SDT's three needs. As the motivation literature describes, self-set goals facilitate goal internalization, which leads to more autonomous motivation and better performance. The first condition (NG) did not foster autonomy, relatedness, or competence. For free spirits, this condition did not lead to autonomous motivation. In the third condition (AG), an extrinsic motivator constituted the assigned goal. Free spirits do not internalize this type of motivator as well as the player user type, for example. Therefore, the first and third conditions did not enhance free spirits' autonomous motivation, which affected their task performance.

5.3 Socializers and Philanthropists

Socializers and philanthropists resonate with social game elements, which means that they better internalize motivators associated with relatedness. Socializers are more autonomously motivated from game elements such as guilds, clans, and social competition. Whereas philanthropists are more autonomously motivated from game elements such as gifting, knowledge sharing, and trading. We did not use any social game elements. Thus, it makes sense that philanthropists and socializers performed less well than the other user types.

5.4 Players

Players constitute a unique user group in the sense that extrinsic rewards such as external praise, monetary rewards, or points motivate them. They have the capacity to more autonomously regulate extrinsic motivators when compared to the other user types. As expected, players performed better when an external source assigned goals to them (third condition). They internalize this extrinsic motivator and exhibit self-determined regulation and autonomous motivation without the need for any of SDT's three needs.

These results suggest that personalized gamification has the potential to lead to better outcomes when compared to non-personalized gamification. While non-personalized gamification has seen success, some implementations have not succeeded or showed mixed results (e.g., Allen, 2011; De-Marcos, Domínguez, Saenz-de-Navarrete, & Pagés, 2014; Domínguez et al., 2013). These gamification implementations may have been successful had they used personalized gamification rather than a one-size-fits-all gamification implementation. Additionally, these results provide evidence that one can use the HEXAD model to assess user preference and then personalize gamification in a work context that involves very repetitive actions. Researchers have shown jobs with this characteristic (e.g., warehouse order pickers) to be particularly harmful to employee motivation and engagement (Harter et al., 2016; Mann & Harter, 2016) and have never used the HEXAD user typology or personalized gamification to empirically examine them. Thus, with this study, we build on Tondello et al.'s (2016) work by providing much-needed theory-driven experimental evidence that shows the effectiveness of personalized gamification in a particularly demotivating context.

Organizations that want to implement gamified systems should first evaluate employees' user type and adapt game element selection accordingly. More specifically, organizations should implement a personalized gamified system for each user type among their employees. For example, organizations should present free spirit employees with gamified systems that contain components that make them feel a sense of freedom to choose. One possible component could simply be self-set goals as we evaluated in this study. Another possible component could be customization tools, which allow people to enable and disable particular gamification elements. Gamification adapted to user type will lead to more autonomous employee motivation, which will lead to better performance in the long term. In addition, the literature has established that autonomously motivated employees have better wellbeing compared to less autonomously motivated employees. Companies also benefit from autonomously motivated employee through lower absenteeism, fewer safety incidents, less turnover, and better employee performance (Rigby & Ryan, 2018).

As with any study, ours has several limitations. First of all, we measured user performance in the short term rather than the long term. Therefore, we could not determine if the effects of personalized gamification endured over time. While research related to self-determination theory has found that autonomously motivated goal pursuit does lead to long-term performance, we need to test it in a gamification context. Second, we did not measure need satisfaction, goal internalization, and autonomous motivation directly. Thus, we cannot verify their role in the goal-performance relationship in this particular context even though the motivational literature has empirically validated it. Third, we assessed user type via self-reported measures (HEXAD). As such, we could not control the distribution of user types across the sample. In our sample, we classified no participant as a disrupter. However, as HEXAD's creators mentioned (Tondello et al., 2016), disruptors should represent about one percent of the sample. As such, the fact that our sample lacked disrupters did not constitute an abnormality. Finally, since we used a within-subject design, the ordering effect could introduce confounds. To clarify, half of the participants completed the first condition (NG) followed by the second (SSG) then third one (AG). While the other half completed the first condition followed by the third then second one. We did, however, control for the ordering effect in two ways: by randomly assigning and counterbalancing the order in which we presented the conditions and by using statistical tests to verify whether the condition order affected the results.

6 Conclusion

Overall, the results show that the game elements we used in our study affected each user type differently. According to well-established motivational literature, the way in which individuals internalize different motivators varies greatly depending on their user types/personality. Internalization leads to more self-determined goal regulation, which implies autonomous motivation. As the gamification and motivation literatures show, autonomous motivation plays a key role in whether gamified systems succeed in the long term. In other words, successful gamification requires autonomous motivation. As such, one needs to consider personalized gamification when gamifying systems.

Future research needs to integrate more game elements to see if each user type responds as expected to the measured outcomes in various contexts. Future research should also directly measure need satisfaction (autonomy, competence, and relatedness), internalization, and autonomous motivation in a gamification to quantify their impact on the goal-performance relationship.

Acknowledgments

This work was funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) under grant IRCPJ 514835-16 and by Mitacs under grant IT10115.

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Appendix A

Table A1. Means and Standard Deviations for Performance Time (seconds)

User types	First condition (no goals)		Second condition (self-set goals)		Third condition (assigned goals)	
	Mean	SD	Mean	SD	Mean	SD
Achievers	446.75	62.925	318.5	22.782	317.5	21.517
Free spirits	500.8	91.906	356	31.914	386.6	20.768
Socializers	614.25	77.856	429.25	39.076	387.667	60.501
Philanthropists	600.286	133.773	411.429	54.824	384	29.755
Players	433.25	62.243	341.75	38.37	322.75	33.52

Appendix B

Table B1. Means and Standard Deviations for Performance Errors (% of Correctness)

User types	First condition (no goals)		Second condition (self-set goals)		Third condition (assigned goals)	
	Mean	SD	Mean	SD	Mean	SD
Achievers	100	0	97.06	5.88	100	0
Free spirits	89.808	8.8743	98.432	7.7662	92.16	3.5062
Socializers	84.31	10.78	88.813	12.4477	86.61	10.78
Philanthropists	82.64	8.5755	82.08	8.941	84.04	10.9379
Players	92.65	10.1687	92.65	10.1687	100	0

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Transactions on Human – Computer Interaction