Gamify: Towards Tailored Gamification Informed by Users' Personality, Emotional State, and Demographics

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Abstract: Recently, gamification has gained world-wide interest in several domains, especially educational ones, to increase user engagement and learning effectiveness. Using gamification, there are several mechanics that designers leverage to motivate users to engage with the game (e.g. streaks, progress, time limit, .. etc). However, it remains unclear which gamification mechanic would be most effective for individuals with different personality traits and emotional states, age, gender, and field-of-study. To this end, we introduce "Gamify", a user-profile empirical study ($N = 65$) that sheds light on how gamification mechanics, namely rewarding and penalizing, along with user profile (made up of (1) personality (represented by Big-Five Model), (2) emotional state, (3) age group, (4) field-of-study, and (5) gender) affect users' experience. To achieve this, we have designed a trivia-based game, where users have riddles that they should answer using 4 provided choices. Within our user-study, we had 4 different levels (reward only, penalty only, reward and penalty, no gamification mechanic). Our results show that the preference of specific gamification mechanic differed according to user profiles. For instance, users below 18 preferred being exposed to both the rewarding and penalizing mechanic. Using Gamify, game developers can create a tailored gaming experience that engages users having different user profiles.

1 INTRODUCTION

Gamification is a key strategy for enhancing user engagement and experience when interacting with digital content, as it boosts users motivation by tracking their progress and achievements (Khodabandelou et al., 2023; Suartama et al., 2023; Weber et al., 2023; Huang et al., 2023; Hallifax et al., 2020). Despite its positive impact, gamification can be counterproductive and ineffective (Khaleghi et al., 2021; Tan et al., 2023). Using inopportune gamification mechanic can lead people to (1) take a task lightheartedly, or (2) being distracted from the primary goal which the game address (Toda et al., 2018). Therefore, a need for tailoring gamification mechanics to different user profiles arose. Several studies have been conducted to address this (e.g. (Rodrigues et al., 2022; Hallifax et al., 2019)) by constructing user profile based on player typology, personality traits, or learning style (Pessoa et al., 2023) which are not exhaustive or mutually exclusive (Carneiro et al., 2022). To address this gap, we introduce Gamify, an empirical study that aims to understand how different gamification mechanics (rewarding and penalizing) along with user profile affect user's experience. Within Gamify, we constructed more granular user profiles that are based on user demographics (age group, field-of-study, and gender) along with personality traits and emotional state (valence, and arousal) which is unprecedented (see literature review (Klock et al., 2020)). Afterwards, we (1) developed FlexiLearner, a trivia-based game that is independent of any topic and context, (2) implemented two different gamification mechanics, rewards (score) and penalties (health points) within FlexiLearner, and (3) conducted a mixed-study ($N = 65$) to see how users with different profiles are affected by different gamification mechanics. At the beginning, we aspired to assess the effect of 4 gamification mechanics, but having 4 different gamification mechanics would require

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exposing participants to 16 configurations of FlexiLearner. To reduce the complexity of our study and minimize confounds, we opted for reducing the number of gamification mechanics to two of the most basic gamification mechanics (rewards and penalty), as these mechanics would help us draw helpful insights about management strategy to adopt for different user profiles. Our results have shown user experience is impacted by both user profile and gamification mechanic adopted. For example, users with low neuroticism perceive a less effective gaming experience when they are penalized for their incorrect choices, meanwhile male users perceive a less effective gaming experience when they are being rewarded for their correct ones. Through Gamify, game developers can construct engaging gaming experience tailored to specific user profile.

2 BACKGROUND AND RELATED WORK

2.1 Character-Computing: Aspects of Human Character

From the perspective of the founder of Character Computing, character is a holistic construct that spans all aspects that differentiate individuals from one another (El Bolock, 2020). These aspects include user's personality, affect, history, beliefs, morals, appearance, preference, and background (El Bolock, 2020). The main benefit of Character-Computing systems is to design interfaces and experiences that dynamically respond to individual needs (Bolock et al., 2020). Relying on the Character-Behavior-Situation (CBS) triad, computing systems can (1) learn human character by inspecting their behavior in a given situation, (2) predict human behavior in a given situation in light of their detected character, or (3) create artificial situations that are plausible and believable given a well-established behavior and definition of an individual's character (El Bolock, 2020). Although adapting computing systems based on character has enormous benefits, developers should consider when making character-based adaptation is necessary (e.g. adaptation for navigation apps is not necessary because their functionality is basic) (El Bolock, 2020). In order to capture aspects related to character, researchers often rely on the Five-Factor Model (FFM) of personality, also known as OCEAN or the Big Five (John et al., 1999; McAdams and Pals, 2006) and the Self Assessment Manikin (SAM) to assess the emotional states of users (Bradley and Lang, 1994). The Big Five Model categorizes personality into five broad traits: openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism and has been wide;y used to predict empirical findings in terms of individual's stable personality traits (Mount and Barrick, 1998). The SAM model relies on two dimensions to capture emotional state: (1) Valence (the feeling is pleasant or not) and (2) Arousal (the user is calm or not) (Bradley and Lang, 1994). Users' emotional state is a key indicator of engagement and interaction within a given experience (Bolock et al., 2020). In our work, we capture user's personality traits using the big five model and their emotional state using the SAM model to construct user character. Moreover, we construct our user profile by capturing user's character and demographics in terms of gender, age group, and their field-of-study in line with Elbolock's definition of character (El Bolock, 2020).

2.2 Personalized Gamification

Gamification refers to using games in non-entertainment context (e.g. education) (Schöbel et al., 2021). Meanwhile personalized gamification refers to tailoring game mechanics toward individual user needs (e.g. gamer typology, gender, age) (Rodrigues et al., 2022). There are several gamer typologies, but the hexad and brain hex are two of the most adopted ones. The hexad typology categorize players based on their motivation for gamification into six categories: achievers, disruptors, free spirits, philanthropists, players, and socializers, while brainhex maps each player type to the human body neurobiological responses and categorizes players into seven types: achievers, conquerors, daredevils, masterminds, seekers, survivors, and socializers (Klock et al., 2020). Also, some researchers tailor their gaming experience based on domain specific parameters, such as learning style and learning activity type (Rodrigues et al., 2022). When comparing personalized gamification to one-size-fits all gamification within education domain, (Xiao and Hew, 2024) concluded that personalized gamification boosted students positive emotions and motivation toward learning. Moreover, (Fischer and Fischer, 2024) classified users into player types (relying on Hexad Scale) and constructed a decision tree that assigns various game elements (e.g. badges, points) according to the player type assigned to a given user. Similarly, (Shabadurai et al., 2024) analyzed users' input during gameplay to infer their player type and adapt the game mechanics accordingly. Along with designing adaptive games based on player type, (Lopez and Tucker, 2021) compared user performance in adaptive and non-adaptive gamified application along with non-gamified and counter-adaptive ones, and concluded that users performed best in the adaptive gamified application condition. (Hallifax et al., 2020) investigated the impact of user profile (motivation and player type) and gamification mechanics on learner motivation and engagement and concluded that tailoring games using both player type and motivation boosted user's motivation. Following the same pattern, (Rodrigues et al., 2021) used user profile (gender, experience in gamification research, education, preferred gaming genre) to tailor gamified systems and also compared user's experience within tailored gamified systems to that in one-size-fits-all one. They conclude that users perceived their experience as motivating and need-supporting when using tailored gamified systems. (Hallifax et al., 2019) conducted an empirical study to identify how different user profiles (in terms of personality traits, hexad, and brainhex) link to specific game mechanic by constructing storyboards of each game mechanic and then making participants assess which game mechanic should be considered while tailoring the gamified experience.

2.3 Research Gap

So far, related work relied upon character computing systems to construct (1) recommender systems (e.g. (Bolock et al., 2020)), (2) identify how user profiles are linked to specific game mechanic (e.g. (Hallifax et al., 2019)). There is also a major research interest in comparing personalized gamified systems to one-size-fits-all-ones (Xiao and Hew, 2024) and non-gamified systems (Lopez and Tucker, 2021). Researchers have also used user-profiles to tailor gamfication mechanics, but often relied on (1) single dimension profile consisting of player type (e.g. (Fischer and Fischer, 2024)) or (2) dual-user profiles (e.g. (Rodrigues et al., 2021; Hallifax et al., 2019)). However, it remains unclear to developers which gamification mechanic to enable for certain user profile. Moreover, little is known regarding how user profile (e.g. gender) affect users performance in tailored gamification (Klock et al., 2020). Therefore, **Gamify aims to identify how rewards in terms of scores and penalties in terms of health points link to each factor within a granular multidimensional user profile** that considers users' stable aspects of character like personality and demographics along with variable ones like emotional states.

3 GAMIFY: STUDY DESIGN

To properly link each dimension within user profiles to specific gamification mechanic, we have conducted a mixed-subject study with 11 independent variables: (1) age group, (2) gender, (3) field-of-study, (4) extroversion, (5) agreeableness, (6) conscientiousness, (7) neuroticism, (8) openness, (9) valence, (10) arousal, and (11) gamification mechanic. Each independent variable represents a dimension within the user profile we constructed and are between-subject variables except for gamification mechanic one. Gamification mechanic is a within-subject variable consisting of four levels: (A) No gamification mechanic, (B) Reward only (score), (C) Penalty only (health point), (D) Reward and Penalty (score + health point). The aim of the study is to determine which gamification mechanic is best suited to a certain factor within a user profile by measuring user's experience while playing the game in each of the four levels. Since it was not possible to have each participant answer 26-item questionnaires after each round of the 4 rounds, we used short version of user experience questionnaire (UEQ) (Hinderks et al., 2018). Figure 1 shows our experiment procedure and FlexiLearner in each of the four configurations. To properly prepare for the main experiment, we have (1) developed a trivia-based game with 4 question rounds, where each round is followed by in-game usability questionnaire (More details in Section 3.1) and (2) made a pilot study with different game rounds and mechanics details, e.g., like 4 hearts for longer rounds containing 7 questions (More information in Section 3.2).

3.1 Gamify: Apparatus and Implementation

To draw insights from Gamify, we have developed a trivia-based game that enables its players to solve riddles through answering a 4-choice multiple choice question. When users enter the correct answer their choice becomes green colored. On the other hand, when users made an incorrect choice, their choice becomes red and the correct choice is highlighted in green. To make user's experience flow more smooth, we have incorporated user experience questionnaire to be in game. After each game-round, users are shown a window that contains short version of user experience questionnaire (UEQ). Within the game, we have implemented two different gamification mechanic: (1) Points, represented as a score that increments by 5 whenever the user answers a question correctly, and (2) Health Points, represented as hearts that their number decrease whenever the user

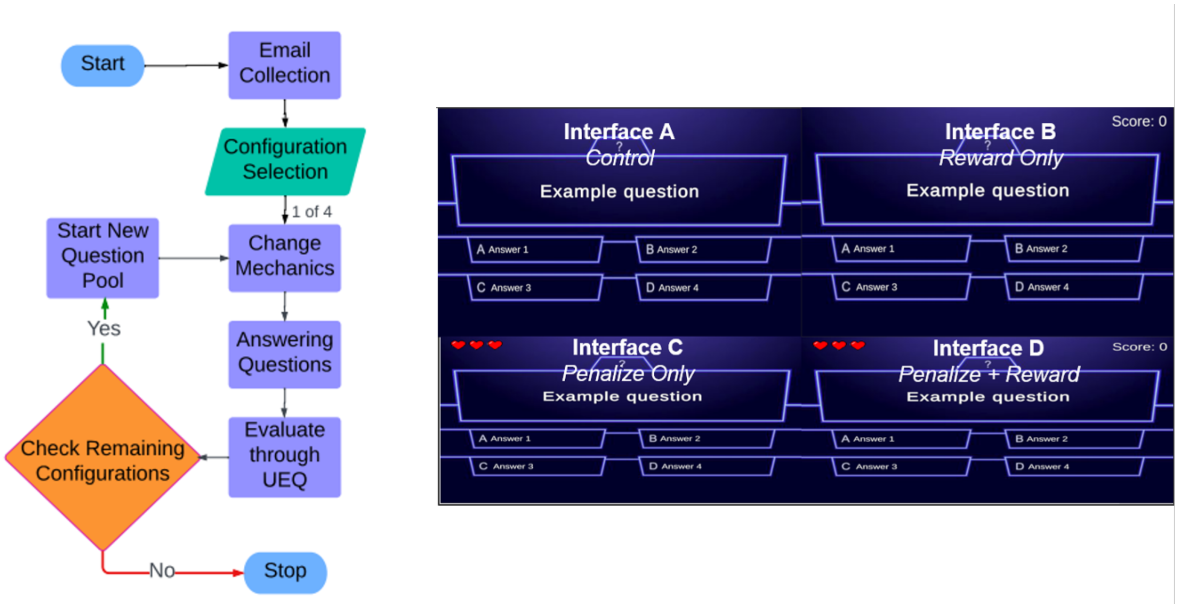

Figure 1: The figure on the left show a flowchart of our experiment procedure. The figure on the right shows FlexiLearner's interface in each of the configuration (levels) within the gamification mechanic factor.

answers a question incorrectly. Flexilearner was implemented using Unity and all its functionalities have been scripted using C#. During a single game round, number of questions answered correctly, and the average question response time along with UEQ scores are logged to a json file.

3.2 Gamify: Study Preparation

A pilot testing of a simplified version of FlexiLearner was conducted on 15 participants to determine the optimal number of questions per game round for the main experiment. Our pilot test had three configurations: 3 Questions with 2 hearts, 5 Questions with 3 hearts, and 7 Questions with 4 hearts. We considered several factors like (1) whether gamification mechanics were noticed by participants without experimenter intervention, (2) were their function apparent, and (3) whether participants were willing to play a full-length version, i.e. 4 game rounds for each gamification mechanic level. The pilot game builds were developed using Unity WebGL and hosted on itch.io. Participants were randomly selected and asked a series of questions via voice call to gather feedback. The results showed that participants noticed hearts and points, and were willing to play a game four times. Feedback from participants included comments on the UI, and recommendations for: adding sound effects, increasing difficulty, and having fewer lives. We refrained from adding sound effects to adequately measure the impact of our incorporated mechanic and minimize confounds. We have also opted out of increasing difficulty or decreasing lives (hearts) to avoid inducing unnecessary mental load on users.

3.3 Gamify: Procedure

Participants were screened for English communication and given 15 minutes to complete the experiment. Afterwards, they complete a Self-Assessment Manikin (SAM) test to assess their emotional state, take a BFI-10 test to assess their personality traits, and provide their age group, gender, and field-of-study. Then, the experimenter selects a game order configuration based on the Balanced Latin Square method. Participants answered each set of five questions while being exposed to 4 different levels within gamification mechanic factor. After each game round, participants fill out User Experience Questionnaire (UEQ), which assesses the pragmatic and hedonic quality of the game experience.

3.4 Gamify: Participants and Recruitment

65 participants (38 male, 37 female) were recruited by word of mouth and approached arbitrarily by the experimenters on university campuses or in public areas. We had 39 participants from Engineering field, 3 from graphic design, 5 from Business Informatics, 3 from Business, 1 from Architecture, 12 from Pharmacy, 1 from Literature, and 1 from Medicine field. All participants could speak English fairly well and could solve riddles in English. Their ages varied from

under 18 to between 35-44 years with 3 participants below 18, 46 participants within 18-24 age group, 12 participants within 25-34 age group, and 3 participants within 35-44 age group.

3.5 Limitations

Using Gamify, we were able to draw useful insights regarding which gamification mechanic, reward or penalty, would affect the experience of different user profiles. Due to the sample size, we have restricted our analysis to only assessing the effect of each factor within the user profile along with its interaction with gamification mechanics affect user experience. For future work, a larger user study is needed (N = 10K-20K) to fully link each individual user profile (11-dimensional user profile we constructed) to a certain gamification mechanic based on user experience. Also, we acknowledge that our sample has an age bias, where the majority were young adults, but this limitation is an opportunity to draw insights about young adults behavior, as these age groups are the most productive one in the work sector (Shanahan et al., 2002). We have targeted users with varying field of study, but also, most of our sample is from the STEM field, which is not a limitation but rather an opportunity to assess the effectiveness of gamification mechanics within STEM domain, especially that gamification is proven to be an effective learning tool in STEM fields (Ortiz-Rojas et al., 2025), i.e., would be frequently used.

4 GAMIFY: ANALYSIS AND RESULTS

In order to link each dimension within our constructed user profile toward a gamification mechanice, we relied on Generalized Linear Mixed Models (GLMM), where we fitted a Cumulative Link Mixed Model (CLMM) with Laplace Approximation to analyze user experience results. When we fitted the models, our primary focus was to identify the fixed effects of our 11 factors and how the interaction between gamification mechanic and each individual factor (10 independent factors of user profile) affected user experience, in terms of overall experience and hedonic and pragmatic quality.

4.1 Gamify: Overall User Experience

The model converged ($loglikelihood = -784.48, AIC = 1798.95$) with a significant fixed effect of study field, personality trait, and emotional state, where users majoring in Business Informatics ($\beta = 4.94, SE = 2.02, z = 2.44, p = 0.014$), Engineering ($\beta = 3.62, SE = 1.76, z = 2.05, p = 0.040$), Graphic Design ($\beta = 7.24, SE = 2.96, z = 2.45, p = 0.014$), Medicine ($\beta = 10.38, SE = 3.49, z = 2.97, p < 0.001$), and Pharmacy ($\beta = 4.05, SE = 1.84, z = 2.197, p = 0.03$) showed positive overall experience values. Also, users with low oppenness ($\beta = 1.71, SE = 0.73, z = 2.34, p = 0.019$), and low arousal ($\beta = 1.45, SE = 0.73, z = 1.99, p = 0.045$) experienced a positive overall experience, meanwhile those with low valence ($\beta = -1.81, SE = 0.70, z = -2.58, p = 0.010$) experienced a negative overall experience. There was a significant gamification mechanic × age group interaction, where users (1) aging 35-44 showed negative overall experience when playing the game using gamification mechanic B ($\beta = -4.49, SE = 2.10, z = -2.14, p = 0.032$) and (2) those aging 25-34 experience a negative overall experience when playing the game using gamification mechanic C ($\beta = -2.25, SE = 1.03, z = -2.20, p = 0.029$). However, users aging below 18 showed a positive overall experience when playing the game using mechanic D ($\beta = 4.14, SE = 1.96, z = 2.11, p = 0.035$).

4.2 Gamify: Hedonic Quality

The model converged ($loglikelihood = -645.43, AIC = 1442.86$) with a significant fixed effect of study field, where users majoring in Architecture ($\beta = 3.79, SE = 1.87, z = 2.03, p = 0.043$), Business Informatics ($\beta = 2.52, SE = 1.18, z = 2.15, p = 0.032$), Engineering ($\beta = 2.53, SE = 1.05, z = 2.40, p = 0.016$), Graphic Design ($\beta = 3.50, SE = 1.76, z = 1.99, p = 0.046$), Literature ($\beta = 4.14, SE = 1.96, z = 2.11, p = 0.032$), Medicine ($\beta = 7.54, SE = 2.05, z = 3.68, p < 0.001$), Pharmacy ($\beta = 3.29, SE = 1.10, z = 2.99, p = 0.003$) showed a positive hedonic quality when playing the game, irrespective of the gamification mechanic they were exposed to. There was a significant gamification mechanic × age group interaction, where users aging 35-44 showed a negative hedonic quality while playing the game using gamification mechanic B ($\beta = -5.24, SE = 1.65, z = -3.18, p = 0.001$), and C ($\beta = -3.45, SE = 1.48, z = -2.33, p = 0.020$).

4.3 Gamify: Pragmatic Quality

The model converged ($loglikelihood = -630.12, AIC = 1414.23$) with a significant fixed effect of study field, emotional state, and personality trait. Users majoring in Business ($\beta = 3.83, SE = 1.78, z = 2.15, p = 0.031$), Business Informatics ($\beta = 4.81, SE = 1.64, z = 2.94, p = 0.003$), Engineering ($\beta = 3.11, SE = 1.45, z = 2.15, p = 0.032$), Graphic Design ($\beta = 6.35, SE = 2.45, z = 2.63, p = 0.009$), Medicine ($\beta = 10.81, SE = 2.90, z = 3.73, p < 0.001$), Pharmacy ($\beta = 4.66, SE = 1.51, z = 3.08, p = 0.002$) showed a positive pragmatic quality. Similarily, users with low openness ($\beta = 1.74, SE = 0.71, z = 2.44, p = 0.014$) experienced a positive pragmatic quality. However, users with low valence ($\beta = -2.12, SE = 0.68, z = -3.11, p = 0.002$) experienced negative pragmatic quality while playing the game, regardless of gamification mechanic shown. We have also observed a significant gamification mechanics $\times$ age group, gamification mechanics $\times$ gender, and gamification mechanics $\times$ personality traits interaction. Male users ($\beta = -1.51, SE = 0.75, z = -2.01, p = 0.045$) showed negative pragmatic quality while playing the game using gamification mechanic B, and those with low neuroticism ($\beta = -1.44, SE = 0.71, z = -2.04, p = 0.041$) showed negative pragmatic quality when they played the game using gamification mechanic C. However, users aging below 18 showed positive pragmatic quality when playing the game using gamification mechanic D.

5 DISCUSSION

5.1 Study Field, Emotional State, and Personality Traits Impact on Experience

Our analysis shows that user profile elements like emotional state, personality traits, and study field affected user experience irrespective of the gamification mechanic adopted. In general, we observed that users' study field significantly affected their user experience, although generic trivia questions were added in our game. Gamify identified a positive association between users majoring in STEM fields like Engineering, Medicine, and Pharmacy and (1) hedonic, (2) pragmatic, and (3) overall user experience. Also, users majoring graphic design and business informatics showed the same behavior. For users from artistic background like literature and architecture fields, they reported positive hedonic (i.e. experience is pleasant) experience. Users studying business reported positive pragmatic (i.e. task-oriented nature of experience) quality. **We foresee this finding as an indicator for how gamification can make learning experience more entertaining in several fields of study, especially STEM related ones.** For personality traits, we only observed significance for Openness, where users who have low openness rates showed positive pragmatic and overall experience, but openness showed no significant impact on hedonic quality. **Therefore, trivia gaming would be nice for conventional individuals who prefer routine**, which is in accord with findings from tailored gamification literature (Klock et al., 2020). Similarly, individuals who are calm (low arousal) showed positive overall experience, which means FlexiLearner provided a pleasant experience for them. Lastly individuals with low valence rates (low pleasantness rate) show negative overall experience and pragmatic one.

5.2 User Profile and Gamification Mechanic's Impact on Experience

Our analysis shows a significant interaction between age and gamification mechanic with respect to overall experience and hedonic (related to pleasantness) aspect of the experience. **Individuals from older age groups (35-44, 25-34) showed negative overall experience when exposed to a single gamification mechanic**, e.g., people aging 35-44 showed negative overall experience when playing the game with the reward or score shown to them. For age group 25-34, users experienced a negative overall experience when playing the game with the penalty shown to them. Moreover, age group 35-44, found the experience to be less pleasant (negative hedonic quality) when an individual gamification mechanic was shown. However, users below 18 showed positive overall experience, thought the experience was pleasant (positive hedonic quality), and enjoyed the task performed (positive pragmatic quality) when both penalties and rewards were shown within the game. We have also seen an interaction between gender and gamification mechanic, where **male users enjoyed the task less when they played the game with reward or score shown to them.** This finding is an addition to tailored gamification literature, as little is known regarding how gamification mechanic affect men and masculinity (Klock et al., 2020). Lastly, only Neuroticism, from personality traits affected pragmatic quality of experience, where users with low neuroticism showed a negative pragmatic quality when playing the game with penalty being shown. **This implies that stable, emotionally resilient people do not enjoy the task when being penalized (e.g. lose one health point)**, which is in accord with findings from tailored gamification literature (Klock et al., 2020).

6 CONCLUSION

Recently, gamification has gained widespread attention across various fields, particularly in education, as a means to boost user engagement and enhance learning outcomes. Designers employ a variety of gamification mechanics, such as streaks, progress points, and time limits, to motivate users to interact with the game. However, the effectiveness of these mechanics for individuals with different personality traits and emotional states remains uncertain. To address this gap, we introduce Gamify, an empirical study with 65 participants that explores how different gamification mechanics—specifically rewarding and penalizing—interact with user profiles, including personality (based on the Big Five model), emotional state, age group, field of study, and gender, influence user experience. For this study, we developed a trivia game where users solve riddles by choosing from four possible answers. Our findings reveal that user experience with specific gamification mechanics vary based on their profiles. For example, participants under 18 showed enjoyed the experience when both rewarding and penalizing mechanics were used. Older age groups 25-34 and 35-44 showed negative overall experience when being exposed to a single gamification mechanic, meanwhile male users enjoyed the task performed in-game less when being penalized for their incorrect choices. Using Gamify, we extended tailored gamification literature by drawing findings on the negative effects of gamification mechanics along with positive ones (see literature review (Klock et al., 2020)). Insights drawn from Gamify can help game developers create personalized experiences that engage users with different needs and characteristics more effectively.

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