Predicting Consumer Acceptance of Gamification Strategies: A Machine Learning Approach

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Abstract. Gamification is currently a powerful marketing strategy that contributes to higher consumer engagement and brand loyalty. However, this strategy comes with significant implementation costs and potential high failure rates, so a careful market assessment should be carried out before investment. This work addresses a critical gap that currently exists by developing a machine learning-based predictive model to identify consumers that are most likely to adopt gamification. Grounded on the theory of consumption values and innovation adoption literature, three classification algorithms (Random Forests, Support Vector Machines, and MARS) were tested on data collected from consumers. Results demonstrate that Random Forests achieve 84% prediction accuracy (AUC: 0.91) using just three key variables: functional value, emotional value, and consumer innovativeness. These results provide managers with a simple and practical tool for market segmentation and targeted gamification deployment, contributing to the maximization of return on investment while minimizing risk, since it will prevent the adoption of a strategy that will not have the desired impact among consumers. The decision tree model that was built allows for a clear interpretation of decision rules. Practitioners will be able to quickly assess whether gamification aligns with specific customer segments and why.

Keywords: gamification · machine learning · consumer adoption · market segmentation · classification algorithms

1 Introduction

Gamification can be defined as the application of game design elements in non-game contexts. It has transformed significantly digital marketing strategies over the past decade and it continues to influence and impact current practices [1]. Some reasons that justify the growing popularity of gamification can be identified: the impressive increase of digital platforms, the proliferation of mobile technologies, and significant changes in consumer behavior, especially in the post-pandemic period [2]. The global gamification market, valued at approximately $36 billion in 2026, is projected to reach $112

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billion by 2031, reflecting its huge growth across e-commerce and digital platforms [3]. The mechanisms that make gamification appealing are already well-documented: by incorporating points, badges, leaderboards, challenges, and narrative elements, for instance, organizations successfully increase consumer engagement (emotional, cognitive, and behavioral), improve brand loyalty, increase purchase intentions, and increase the likelihood of positive word-of-mouth [4–6].

Although it has been demonstrated that gamification clearly brings benefits, it is also important to acknowledge that its implementation can bring significant challenges. Firstly, it requires substantial investment in financial, human, and technological resources. Effective implementation of gamification involves high associated costs, similar to other marketing actions [7], such as developing websites or mobile applications [8], as well as development time, effort, expertise, continuous maintenance and some adjustments to match the brand's identity [7, 9]. Secondly, empirical evidence has shown that gamification effectiveness is far from being guaranteed: 36% of consumers report that gamification does not influence purchasing decisions, and only 17% indicate that gamification captures their attention and increases purchase likelihood [10]. Thirdly, consumer responses to gamification vary significantly across demographic and psychological segments, with individual characteristics such as age, digital profile, personal motivations, and consumption habits significantly influencing engagement levels [11, 12].

These findings identify a strategic dilemma for organizations with limited budgets: how can managers evaluate feasibility and potential adoption of gamification strategies before assigning resources to these strategies? Recent literature emphasizes that market segmentation and targeted positioning of gamified strategies are essential to ensure effectiveness [13]. However, to the best of the authors' knowledge, prior work has not provided practical tools that support rapid, accurate market assessment during the pre-implementation phase in this context.

This study fills this gap by developing and validating a machine learning-based classification model that predicts individual consumer willingness to adopt gamification. Our research addresses three managerial questions: (1) What consumer characteristics determine gamification acceptance? (2) How can companies segment clients to target gamification to high-probability adopters? (3) Can a minimal set of questions enable rapid assessment of new clients' gamification receptivity?

Using data from consumers and comparing three classification algorithms, we demonstrate that Random Forests achieve 84% prediction accuracy using only three predictor variables grounded in consumption value theory and innovation adoption literature: functional value, emotional value, and consumer innovativeness.

2 Theoretical Framework

Gamification's effectiveness stems from its capacity to activate intrinsic motivations - autonomy, competence, and relatedness - through game mechanics [14]. Incorporating these elements into otherwise only practical experiences allows organizations to create emotional appeal and promote continued consumer engagement. Marketing research has shown that gamification has the potential to improve brand attitude, brand equity, and long-term customer lifetime value [15]. However, these benefits are strongly dependent on a correct alignment between game mechanics and target audience preferences.

The theory of consumption values provides a robust framework for understanding different consumer responses to marketing innovations including gamification [16]. Consumption value theory states that individuals choose alternatives based on multiple value dimensions [17, 18]:

- **Functional Value** captures the perceived utility that comes from practical and utilitarian attributes, including quality, efficiency, reliability, ease of use, price, and accessibility. In the context of gamification, it reflects whether consumers understand these attributes as being advantageous to them, such as easy point accumulation, transparent reward structures, and efficient engagement mechanisms.
- **Emotional Value** represents the perception of feelings or affective states evoked by an alternative - pleasure, enjoyment, fun, entertainment, and playfulness [14]. Gamification's core promise is emotional value creation; thus, consumers with high emotional value orientation toward gaming elements should demonstrate greater adoption propensity.
- **Social Value** is related with the image that individuals want to project among their social groups through their choice behavior [19]. It represents a consumer's belief that the use of gamified systems will increase his/her social status, acceptance, or approval through mechanisms such as leaderboards, social comparison, or public achievements [20].
- **Epistemic Value** refers to the perceived utility derived from novelty, curiosity, and opportunities for learning or exploration offered by gamification [21]. Epistemic value is generated when game elements introduce new experiences, challenges, narratives, or interactive features that stimulate curiosity and provide users with opportunities to acquire new knowledge or skills.
- **Conditional Value** represents the situational utility of an alternative given specific contexts or circumstances. In gamification contexts, the value of game elements may vary depending on temporal, task-related, or environmental conditions.

In this study, multiple value dimensions are examined in order to identify the primary drivers that enable the prediction of whether a customer will engage in a gamification experience.

3 Research Methodology

3.1 Data Collection and Sample

The empirical analysis focuses on current and potential users of a company that provides services specifically designed for students, whose primary market segment is university students. The questionnaire was therefore administered to individuals enrolled in higher education, reflecting the firm's actual and prospective customer base. This sampling frame ensures that the resulting predictive model is aligned with the decisions faced by managers operating in a student-services environment, where digital literacy is high and gamification is a plausible strategic option [22].

A total of 1,450 printed questionnaires were distributed to students. The full questionnaire is presented in Appendix 1. The participants were instructed to fill in the questionnaires and deposit them in ballot boxes so they could be totally reassured the

answers would be anonymous. Of the 1,450 questionnaires distributed, 605 were collected. Questionnaires containing missing data were discarded being the final sample composed of 347 questionnaires that were used in the analysis. As for the respondents, 54.5% were women and 45.5% men, the average age being 23 years, and 65.4% of whom were full time students. Initially, the questionnaire invited respondents to read a gamification scenario and then answer to all questions made considering that gaming experience described. The scenario was created based on characteristic elements of gamification systems widely used on digital platforms, to ensure the plausibility and representativeness of the described experience. The variables hypothesized to influence willingness to engage in gamification were measured using previously developed and validated measurement scales, adapted to this context, namely: Trust [23], Positive and Negative Affect Schedule (PANAS) [24], consumption values [25, 26], technology readiness [27], impulsive personality trait [28], big five [29], experience with games [30] and intention to enter [31]. A five-point Likert scale was used, ranging from 1 "strongly disagree" to 5 "strongly agree".

The dataset was reduced to a subset of relevant attributes, focusing on key demographic and behavioral variables, including gender, age, income, and purchase frequency. These are categorical variables. To reduce dimensionality while preserving the key dimensions of the study, several composite variables were created by averaging the multiple questionnaire items used to evaluate each dimension. This approach generated summary measures for trust, functionality, emotional engagement, social interaction, epistemic curiosity, conditions, optimism, innovation, technology, insecurity, discomfort, gaming, neuroticism, extraversion, openness, empathy, conscientiousness, and impulsivity, capturing the underlying information of multiple correlated items in a single score. All numeric variables were standardized using z-score normalization. This ensured that each variable had a mean of zero and a standard deviation of one. The target variable was transformed into a binary target variable (classification problem) by coding as 1 if the corresponding response score was greater than 3, indicating acceptance and 0 otherwise. The sample exhibited initial class imbalance: 191 records with target = 1 (engaging) and 156 with target = 0 (non-engaging).

3.2 Experimental Design and Cross-Validation Protocol

To reduce bias caused by class imbalance and ensure robust estimation across multiple random samples, the following procedure was applied: (1) **Balanced Dataset Generation**: We generated datasets with all the 156 non-engaging (negative) cases and then randomly sampled 156 cases with positive outcomes from the pool of 191, creating balanced datasets with 312 observations each (156 per class). (2) **Iterative Replication**: This balancing procedure was repeated 100 times using different random samples to ensure that the results were not influenced by any single sampling instance. (3) **Leave-One-Out Cross-Validation**: For each balanced dataset iteration, we employed leave-one-out cross-validation (LOOCV): each observation was excluded one at a time, models trained on the remaining 311 observations, and predictions generated for the held-out case. This procedure prevents overfitting and contributes to a more accurate assessment of generalization performance.

3.3 Classification Algorithms and Performance Metrics

We compared three state-of-the-art machine learning algorithms. All computational experiments were conducted using the R programming environment. Libraries used were: *rpart, earth, randomForest, pROC, caret, e1071.*

- **Random Forests** (RF) construct multiple decision trees through bootstrap sampling and random feature selection, aggregating predictions via majority vote. This ensemble approach reduces variance and mitigates overfitting while handling non-linear relationships and feature interactions effectively [32].
- **Support Vector Machines** (SVM) find optimal hyperplanes to separate classes in high-dimensional feature space, with kernel functions enabling non-linear decision boundaries. SVMs excel with smaller datasets and feature interaction patterns [33].
- **Multivariate Adaptive Regression Splines** (MARS) iteratively build piecewise linear models, capturing non-linear relationships through basis functions and interactions. MARS provides interpretable models while accommodating non-linearities [34].

Models were assessed considering **Accuracy** (percentage of correct predictions across balanced test sets) and Area Under the Receiver Operating Characteristic Curve (**AUC**) (measuring discrimination ability across threshold values; perfect predictor = 100%, random predictor = 50% on balanced data). Variable importance rankings were computed for each algorithm iteration, with average importance scores across 100 iterations providing robust estimates.

4 Results

4.1 Full-Feature Model Comparison

RF demonstrated the strongest predictive performance across both metrics (Table 1). Mean accuracy reached 83% (SD = 0.8%, range: 81–85%), while mean AUC was 91% (SD = 0.5%, range: 90–93%). Variable importance analysis identified six key predictors: emotional attachment, conditioning, epistemic curiosity, intrinsic innovation orientation, intrinsic technology acceptance, and empathy.

SVM achieved slightly lower but comparable performance (Table 1). Mean accuracy was 81% (SD = 0.9%, range: 80–84%) and mean AUC was 91% (SD = 0.5%, range: 90–92%). Variable importance rankings differed slightly, identifying emotional attachment, conditioning, epistemic curiosity, empathy, intrinsic innovation orientation, and optimism orientation as predictive features.

MARS exhibited the most variability and lowest performance (Table 1). Mean accuracy was 80% (SD = 1.53%, range: 76–86%) with mean AUC of 88% (SD = 1.31%, range: 85–90%). This model identified only two important variables: emotional attachment and intrinsic innovation orientation.

RF achieved the highest mean accuracy (83%) with lowest variance (0.8%), indicating both superior performance and stability across random samples. Variable importance analysis identified functional value, emotional value, and consumer innovativeness as dominant predictors across algorithms.

Table 1. Classification Model Performance Comparison.

Model	Metric	Worst	Best	Mean (sd)
RF	Accuracy	81%	85%	83% (0.8%)
	AUC	90%	93%	91% (0.5%)
SVM	Accuracy	80%	84%	81% (0.9%)
	AUC	90%	92%	91% (0.5%)
MARS	Accuracy	76%	86%	80% (1.53%)
	AUC	85%	90%	88% (1.31%)

4.2 Reduced-Feature Model: The Parsimonious Solution

If a decision maker can identify which questions are sufficient to estimate the probability that a consumer will enter (or not enter) a gamification process, those questions should form a small yet informative set. Because evaluating consumers' willingness to engage in a gamification process may involve survey-based measurement, it is important to rely on a minimal but meaningful set of variables in order to reduce respondent burden and encourage participation. Accordingly, RF were tested to assess whether they could maintain or improve performance using only the three most important variables: functional value, emotional value, and consumer innovativeness. Furthermore, reducing the number of input variables in a RF classification problem can enhance predictive performance by minimizing noise, reducing overfitting, and improving generalization. Irrelevant or redundant features introduce unnecessary randomness into the tree-building process, weakening split quality and ultimately degrading model performance. By concentrating on the most informative variables, the model avoids learning spurious associations, leading to greater stability and reduced variance across trees. Moreover, removing features that are not contributing to the final outcome helps to diminish the curse of dimensionality, thereby preserving well-defined decision boundaries and improving computational efficiency. Empirical validation—such as comparing classification accuracy before and after feature reduction—strongly supports this approach. The obtained results show that feature reduction not only maintained performance but improved accuracy, as can be seen in Table 2.

Table 2. Reduced-Feature Model Performance.

Model	Metric	Worst	Best	Mean (sd)
RF	Accuracy	82%	87%	84% (0.88%)
	AUC	89%	92%	91% (0.47%)

Statistical significance testing confirmed these improvements were indeed relevant: Wilcoxon signed-rank test (Accuracy): $p = 3.014 \times 10^{-11}$; Paired t-test (AUC): $p =$

6.021×10^{-16}. Both differences are highly statistically significant ($p < 0.001$), indicating that the three-variable model generalizes better than the full-feature model. This improvement aligns with machine learning theory: eliminating irrelevant or redundant features reduces noise, minimizes overfitting, and decreases variance across decision trees, enabling the algorithm to identify more robust decision boundaries and avoid spurious correlations.

Because we are able to construct a predictive model that relies on only three variables while maintaining reliable performance, firms can assess consumers' willingness to enter a gamification process by asking a very limited number of questions, specifically those measuring functional value (*"It will be useful to me"*, *"It will be easy to use"*, *"It will give me advantages"*), emotional value (*"It will excite me"*, *"It will provide me with varied enjoyment"*, *"It will be fun"*) and consumer innovativeness (*"Other people come to me for advice on new technologies"*, *"In general, I am among the first in my circle of friends to acquire new technology when it appears"*, *"I can usually figure out new high-tech products and services without help from others"*, *"I keep up with the latest technological developments in my areas of interest"*).

4.3 Decision Tree Interpretation

To interpret the predictive patterns of the reduced model, a decision tree was trained using the same subset of attributes previously selected for the RF model. While the RF served as the primary predictor due to its superior performance, the decision tree offers an interpretable representation of how the model differentiates between classes. Random forests perform very well considering their predictive performance because they combine hundreds of decision trees, each trained on a bootstrap sample with a random subset of features. This ensemble approach increases robustness to noise, allows random forests to be able to represent complex nonlinear relationships, and allows evaluation of feature importance. However, interpretability of the results is rather limited, since it is difficult to analyze and interpret the model as a whole. A single decision tree, by contrast, offers explicit if-then rules that can be visualized and communicated, although most of the time it is not able to reach the same level of classification accuracy obtained with RF. One possible compromise solution is to use RF to identify the most relevant attributes and then training a constrained decision tree on that reduced set. This strategy is especially valuable when stakeholders, like managers, prefer rule-based explanations and transparent decision logic. This is exactly what was done.

The resulting tree (Fig. 1) reveals the hierarchical relationships among key psychological and behavioral variables. The first split, based on the functionality score (*Func*), separates participants into two primary groups, showing that higher perceived functionality is strongly associated with the positive class. Subsequent splits refine the classification according to emotional engagement (*emot*) and innovation-related traits (*innovtr*). Participants with low functionality and emotional engagement are mostly classified in the negative class, while those with higher functionality or innovation scores are more likely to belong to the positive class. Actually, it is known that consumer innovativeness - an inherent personal characteristic reflecting one's willingness to pursue, accept, and adopt new products, services, ideas, or behaviors independently of peer influence – is able to consistently predict adoption of market innovations [19]. Prior research shows that

highly innovative consumers are more receptive to novel marketing approaches, including gamification. This personality trait complements consumption value dimensions by capturing autonomous decision-making regarding innovation adoption.

Terminal nodes in the tree display the number of observations per class and the proportion of correctly classified cases, confirming that the positive class is more prevalent among participants with higher scores on these dimensions. Overall, the decision tree represents functionality, emotional engagement, and innovation as very important factors for distinguishing participants likely to engage (positive class) from those less likely (negative class). Functional value serves as the primary decision node: participants with low perceived functionality are generally classified as non-engaging, whereas those with high functionality are further evaluated on emotional engagement. High scores on both functionality and emotional engagement correspond to a very high probability of gamification acceptance. Consumer innovativeness plays an important role in reaching a classification in lower levels of the decision tree.

This hierarchical structure provides managers with an intuitive and transparent assessment tool. By querying participants on these three dimensions through a brief questionnaire, organizations can make rapid, confident predictions regarding gamification suitability.

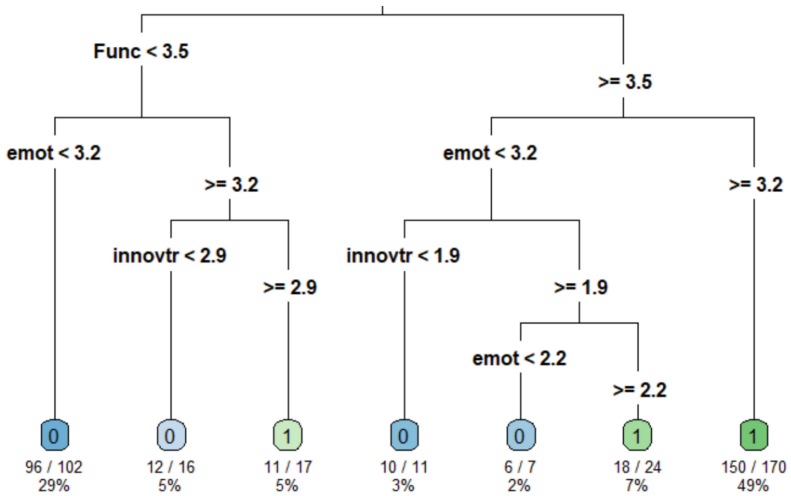

Fig. 1. Decision tree classifying participants based on functionality, emotional engagement, and innovativeness, with terminal nodes showing class proportions

5 Managerial Implications

This research offers several practical insights for marketing practitioners:

- **Pre-Implementation Market Assessment:** Before investing resources in gamification development, managers can use a brief survey to assess functional value, emotional value, and consumer innovativeness. Based on these three dimensions, our model predicts whether individual clients are likely to adopt gamification with an

accuracy of 84%, supporting more informed go/no-go decisions and helping identify segments with lower adoption potential.

- **Market Segmentation and Targeting:** Rather than implementing broad, organization-wide gamification strategies, managers should identify customer segments exhibiting high functional value perception, high emotional value orientation, and high consumer innovativeness. This targeted approach concentrates resources on customers with a high-probability of engaging in the gamification strategy, maximizing return on investment.
- **Gamification Design Strategy:** For identified high-probability segments, gamification design should emphasize both functional benefits (efficient reward accumulation, clear progression paths, ease of use) and emotional appeal (entertainment, enjoyment, fun narratives). On the other hand, for lower-probability segments, alternative engagement strategies may prove more cost-effective than gamification strategies.
- **Risk Mitigation:** Implementing gamification prematurely and without previously studying the potential impact on customers may harm the brand, namely if customers perceive its mechanics as intrusive or poorly aligned with their preferences. By segmenting audiences according to their demonstrated receptivity, organizations can reduce this reputational risk while improving campaign effectiveness.

6 Discussion

The work developed presents interesting results considering the adoption of gamification within a marketing context, since it allows organizations to base their decisions regarding the development of gamification strategies grounded on data-driven models able to robustly predict the potential customer engagement. Although the questionnaire data could have been analyzed using a classical structural equation modeling approach, this work adopts a practical perspective, using the questionnaire as an operational tool to identify consumers' willingness to engage in a gamification process. Most of existing research works document gamification's benefits for engaged consumers, whilst the current work is focused on providing guidance for ex-ante evaluation of adoption likelihood within specific markets.

The theoretical contribution lies in demonstrating that consumption value theory - functional and emotional dimensions - combined with consumer innovativeness provides a simple yet powerful framework for predicting gamification adoption. These constructs capture the existing heterogeneity in how consumers evaluate novel marketing approaches, explaining the differences that can be observed in gamification effectiveness. This work contributes methodologically by showing that, with just a very small set of carefully selected questions, it is possible to achieve highly accurate predictions of consumer behavior. By reducing features to only three key variables, the RF model attains superior classification performance - higher AUC and lower variance - compared to the full six-variable model, highlighting both the practical efficiency and predictive power of the method. The practical contribution is a lightweight, implementable tool: a small questionnaire that feeds a trained RF model able to output an accurate assessment of whether gamification aligns with individual or segment-level customer preferences. This represents a substantial advance over existing practice, where such decisions typically rely on intuition rather than evidence.

Although the results presented are interesting and useful, it is also important to acknowledge some existing limitations. Firstly, the sample (N = 347) is moderate in size; validation on larger, more diverse contexts and populations would strengthen generalizability. Secondly, this study measures *stated* willingness to engage via questionnaire; actual behavioral response to deployed gamification may differ due to implementation quality and contextual factors. Thirdly, while we tested three classes of algorithms, exploration of deep learning architectures might reveal further performance improvements, although requiring larger datasets. Fourthly, this cross-sectional analysis does not capture temporal dynamics: consumer preferences and technology adoption propensity evolve over time. Future research should examine whether the three-variable model generalizes across different contexts and demographic populations, validate its predictive power in real-world settings by comparing predicted and actual gamification adoption behavior, integrate external variables such as the competitive landscape, media exposure, and social influence into the predictive framework, and conduct longitudinal studies to analyze how innovativeness and value perceptions evolve alongside technological change.

7 Conclusion

This research demonstrates that machine learning classification models can reliably predict consumer willingness to adopt gamification using a parsimonious set of theoretically grounded variables: functional value, emotional value, and consumer innovativeness. RF achieved 84% prediction accuracy with an AUC of 0.91, clearly better than random guessing (50% on balanced data) and providing actionable guidance for managers. The practical payoff is significant: organizations can conduct rapid, evidence-based market assessment before spending substantial resources with gamification development. By segmenting audiences and targeting gamification to high-probability adopters, companies enhance return on investment, minimize brand misalignment risk, and concentrate efforts on customer segments with a higher probability of engaging. Machine learning predictions can be converted into decision rules that managers can more easily understand, making them more useful in practice.

As the adoption of marketing gamification strategies continues to grow, especially across digital markets, data-driven approaches capable of predicting customer adoption become increasingly valuable. This work provides both theoretical understanding of customer adoption or rejection of gamification strategies as well as an example of a practical tool that can be used for market assessment, enabling organizations to make informed, risk-mitigated decisions regarding this powerful yet costly marketing innovation.

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Disclosure of Interests. The authors have no competing interests.

Appendix 1

STUDY ABOUT ONLINE SHOPPING BEHAVIOR

I. The following statements refer to your perception of the company.

	Please indicate your degree of agreement with the following statements:	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
1	I trust this company.	1	2	3	4	5
2	I rely on this company.	1	2	3	4	5
3	This is an honest company.	1	2	3	4	5
4	This company is safe.	1	2	3	4	5

II. Please read the following scenario carefully:

Suppose that the company's website/application provides you an interactive, enjoyable and totally free gaming experience. By creating a user profile, you become part of a community that allows you to interact with other users, exchange information and recommendations and add friends from your social networks. You will also be able to participate in the improvement and creation of products/services and in the development of solutions offered by this organization. Over the course of time, you will be invited to fulfill various challenges which, in addition to improving your shopping experience, making it even more rewarding, will give you points. These challenges include, for example: (1) sharing the website link with your family and friends; (2) evaluating and commenting on the products and/or services you have purchased; (3) reaching a certain amount in purchases per month, among others.

The more points you gain, the more benefits you will have, achieving new heights as a customer. Through your involvement, you will have access to exclusive promotions, priority access to new products, surprise gifts, among others. You can also obtain badges that symbolize your achievements and challenge your friends to a competition or to cooperate towards a certain objective. On your profile you will be able to track your progress and compare it with that of other users. Moreover, you will be able to share your achievements on social media.

III. Assuming that the previously described gaming experience is currently available to you. Please indicate your degree of agreement with the following statements:

	It seems to me that integrating this gaming experience:	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
1	It will be useful to me.	1	2	3	4	5
2	It will be easy to use.	1	2	3	4	5
3	It will give me advantages.	1	2	3	4	5
4	It will excite me.	1	2	3	4	5
5	It will provide me with varied enjoyment.	1	2	3	4	5
6	It will be fun.	1	2	3	4	5
7	It will help me to feel acceptable.	1	2	3	4	5
8	It will improve the way that I am perceived.	1	2	3	4	5
9	It will make a good impression on other people.	1	2	3	4	5
10	It will give social approval.	1	2	3	4	5
11	It will arouse my curiosity for novelty.	1	2	3	4	5
12	It will provide me with a new experience.	1	2	3	4	5
13	It will help me acquire new knowledge.	1	2	3	4	5
14	It will make my purchasing process easier.	1	2	3	4	5
15	It will help me to find information easily.	1	2	3	4	5
16	It will help me to achieve information quickly.	1	2	3	4	5

IV. Continue to assume that the gaming experience described above is currently available to you. Please indicate your degree of agreement with the following statements:

		Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
1	I plan to enter in this experience in the future.	1	2	3	4	5
2	I intend to enter in this experience in the future.	1	2	3	4	5
3	I predict I will enter in this experience in the future.	1	2	3	4	5

V. Next, you will find a list of statements about how you perceive TECHNOLOGY.

	Indicate your level of agreement with each of the statements:	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
1	New technologies contribute to a better quality of life.	1	2	3	4	5
2	Technology gives me more freedom of mobility.	1	2	3	4	5
3	Technology gives people more control over their daily lives.	1	2	3	4	5
4	Technology makes me more productive in my personal life.	1	2	3	4	5
5	Other people come to me for advice on new technologies.	1	2	3	4	5
6	In general, I am among the first in my circle of friends to acquire new technology when it appears.	1	2	3	4	5
7	I can usually figure out new high-tech products and services without help from others.	1	2	3	4	5
8	I keep up with the latest technological developments in my areas of interest.	1	2	3	4	5
9	People are too dependent on technology to do things for them.	1	2	3	4	5
10	Too much technology distracts people to a point that is harmful.	1	2	3	4	5
11	Technology lowers the quality of relationships by reducing personal interaction.	1	2	3	4	5
12	I do not feel confident doing business with a place that can only be reached online.	1	2	3	4	5
13	When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do.	1	2	3	4	5
14	Technical support lines are not helpful because they don't explain things in terms I understand.	1	2	3	4	5
15	Sometimes, I think that technology systems are not designed for use by ordinary people.	1	2	3	4	5
16	There is no such thing as a manual for a high-tech product or service that's written in plain language.	1	2	3	4	5

VI. The following statements address your relationship with VIDEO GAMES.

	Indicate your level of agreement with each of the statements:	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
1	I like playing video games.	1	2	3	4	5
2	I often play video games.	1	2	3	4	5
3	Compared to people of my age, I spend more time playing video games.	1	2	3	4	5
4	I would describe myself as a gamer.	1	2	3	4	5
5	I play different types of video games.	1	2	3	4	5

VII. Now consider your way of being. Please indicate the degree to which you generally feel as follows:

		Very little or nothing	A little	Moderately	Quite	Extremely
1	Inspired	1	2	3	4	5
2	Attentive	1	2	3	4	5
3	Excited	1	2	3	4	5
4	Enthusiastic	1	2	3	4	5
5	Determined	1	2	3	4	5
6	Afraid	1	2	3	4	5
7	Upset	1	2	3	4	5
8	Nervous	1	2	3	4	5
9	Scared	1	2	3	4	5
10	Distressed	1	2	3	4	5

VIII. Think again about the way you are.

	Indicate your level of agreement with each of the statements:	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
1	I am a more melancholic person than others.	1	2	3	4	5
2	I am a temperamental person.	1	2	3	4	5
3	I am an envious person.	1	2	3	4	5
4	My emotions go way up and down.	1	2	3	4	5
5	I am more irritable than other people.	1	2	3	4	5
6	I am less shy person than others.	1	2	3	4	5
7	I am a daring person.	1	2	3	4	5
8	I am an extroverted person.	1	2	3	4	5
9	I feel I am a very creative person.	1	2	3	4	5
10	I always have new ideas.	1	2	3	4	5
11	I appreciate art.	1	2	3	4	5
12	I find new solutions to problems.	1	2	3	4	5
13	I am more original than other people.	1	2	3	4	5
14	I am kind to other people.	1	2	3	4	5
15	I am tenderhearted with others	1	2	3	4	5
16	I am sympathetic.	1	2	3	4	5
17	I am a precise person.	1	2	3	4	5
18	I am an organized person.	1	2	3	4	5
19	I am a sloppy person.	1	2	3	4	5
20	I am an orderly person.	1	2	3	4	5

	Indicate your level of agreement with each of the statements:	Totally disagree	Disagree	Neither agree nor disagree	Agree	Totally agree
1	I don't like to make decisions quickly.	1	2	3	4	5
2	I don't like to take part in really fast-paced conversations.	1	2	3	4	5
3	I don't like to do things quickly.	1	2	3	4	5
4	I try to avoid activities where I have to act without much time to think first.	1	2	3	4	5
5	I frequently make appointments without thinking about whether I will be able to keep them.	1	2	3	4	5
6	I often make up my mind without taking the time to consider the situation from all angles.	1	2	3	4	5
7	Many times the plans I make don't work out because I haven't gone over them carefully enough in advance.	1	2	3	4	5
8	I often get involved in projects without first considering the potential problems.	1	2	3	4	5

IX. Finally, we ask you for some information so that we can characterize the profile of the respondents.

1. Gender:
☐ Female
☐ Male
☐ Other

2. Age: _____ years

3. Nationality:
_____

4. Number of people in the household:
☐ 1 ☐ 2 ☐ 3
☐ 4 ☐ 5 ☐ 6 or more

5. Profession:
☐ Student
☐ Worker/student

6. What level of education do you attend?
☐ Degree
☐ Master's degree
☐ PhD
☐ Other. Which? _____

7. Please tell us the name of the course and year you are attending:
_____
_____

8. Net monthly income of the household:
☐ Less than €500
☐ €500-999
☐ €1000-1499
☐ €1500-2499
☐ €2500-4999
☐ €5000 or more

9. In the last 12 months, how many times have you purchased products/services online?
☐ Never
☐ 1 to 3 times
☐ 4 to 6 times
☐ 7 to 9 times
☐ 10 to 12 times
☐ 13 or more times

Thank you for your cooperation.

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