Evidence-based HRM: a Global Forum for Empirical Scholarship

More than a game: gamification as a recruitment method and the attitude effect

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Abstract

Purpose – This study examined how individual drivers influence recruiters' behavioral intention to use gamification in recruitment. It also proposes that this relationship is mediated by recruiters' attitudes, encouraging the use of more playful and user-friendly techniques.
Design/methodology/approach – This article presents a theoretical and empirical model analyzing how recruiters' attitudes influence the relationship between individual drivers and their behavioral intention to use gamification. The model was tested among 203 recruiters using partial least squares structural equations and fuzzy set qualitative comparative analysis to explore factors contributing to high behavioral intention.
Findings – We empirically confirm that individual drivers positively influence recruiters' behavioral intentions. This effect intensifies when drivers directly influence attitudes, underscoring attitudes as a key mediator in the relationship between drivers and their attitudes.
Originality/value – The results increase confidence in applying gamification in recruitment, reinforcing the role of individual drivers as predictors of behavioral intention.

Keywords Gamification, Recruitment, Employee attitudes, Intention to use, Human resource management practices

Paper type Research article

1. Introduction

The current relevance of traditional recruitment methods is being debated (Henning *et al.*, 2025). Recruitment based on the publication of job advertisements, acceptance or rejection of resumés, etc., although intended to attract candidates and predict their potential performance, has become outdated.

A fundamental aspect of recruitment is its high impact on firms' growth and sustainability over time. If one of the key elements of a firm is its people, its growth is directly linked to the actions taken to attract, train, and retain the best talent (Obaid *et al.*, 2020).

In the workplace, gamification involves incorporating playful elements into non-recreational activities to improve the selection and evaluation of candidates in an organizational context (Georgiou *et al.*, 2019). The actions derived from gamification processes are characterized by increased interaction, which favors the generation of innovative

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and creative environments (Singh, 2022). In the case of recruiters, they must attract a sufficient number of candidates for a position. Gamification allows for the evaluation of skills such as time management, creativity, and innovative thinking (Shree and Singh, 2019).

In this paper, we model and contrast the positive and direct influence of individual drivers (ID) on the behavioral intention (BI) to use gamification by recruiters. However, this direct relationship will, in turn, be influenced by the mediating effect of attitude to use (AT). Therefore, the present study was guided by two research questions:

RQ1. Do individual drivers directly and positively contribute to recruiters' behavioral intention to use gamification?

RQ2. Does recruiter attitude mediate the influence of individual drivers on behavioral intention to use gamification?

This study addresses a current knowledge gap by examining the primary motivators and behaviors that influence attitudes towards gamification and the intention to use gamification-based resources by recruiters of firms and organizations when planning and developing recruitment processes.

The practical implications are also crucial for human resource managers and recruiters. Knowing which elements influence BI when using gamification as a valuable tool for recruitment processes and the mediating role of AT provides greater certainty and security when designing and implementing it.

Following the introduction, the second section presents theoretical concepts and hypotheses, while the third section describes the methodology, sample, and data. The fourth section presents the results and evidence, while the fifth discusses them and establishes the main conclusions. Finally, the sixth section examines the implications, limitations, and future research directions derived from this study.

2. Literature review

Gamification is linked to technological, economic, social, and cultural advances, transforming reality into more motivating, creative, and entertaining experiences (Hamari, 2019). In the context of our study, gamification can be defined, in line with Bhawna *et al*. (2025), as the application of game design elements and principles in non-game and professional contexts that fosters autonomy, skills, and competencies, as well as interaction among participants.

Promoting individuals' participation and involvement through gamification has enabled its expansion into various fields. The concept's relative topicality suggests that there remains no consensus on a single definition that explains the differences among existing definitions, depending on the reality to which they are linked (Tanouri *et al*., 2023).

2.1 Individual drivers to use gamification in the recruitment process

The Behavioral Intention to use gamification is influenced by different elements. According to Davis (1986), the Technology Acceptance Model (TAM), which encompasses Perceived Ease of Use (PE) and Perceived Usefulness (PU), influences the behavioral intention to use technology in the adoption process by individuals (Aydınlıyurt *et al*., 2021). As pointed out by Davis (1989), PE refers to the level of perceived ease regarding the use of a given system, such that, all things being equal, the ease of use of this relative to another will cause one to decant in one direction or the other (Madi *et al*., 2024). PU alludes to the extent to which an individual believes that using the system will improve the results of their task (Davis, 1989), thereby establishing a positive relationship between its use and the outcome.

According to Self-Determination Theory (SDT) of Ryan and Deci (2000), Intrinsic Motivation (IM) and Identified Regulation (IR) are two relevant predictors of behaviors. IM refers to behavior performed for the mere satisfaction of doing it, rather than for the expected consequence. When IM guides individuals' behaviors, they participate and become actively involved in those activities that interest them (Li *et al.*, 2024). In terms of IR, individuals act after evaluating their goals and the means to achieve them. It is the most autonomous form of extrinsic motivation, as the goal is perceived as integrated and consistent with one's values (Stiegemeier *et al.*, 2023).

The combination of elements of the TAM (Davis, 1989) and SDT (Ryan and Deci, 2017) theories has been used in various studies (Racero *et al.*, 2020). Therefore, from the theoretical perspectives of these two models, it can be established that PU, PE, IM, and IR are ID of the individual's behavioral intention, conforming to a unidimensional construct. According to the above description, and in the case of the use of gamification by recruiters, the following hypothesis can be established:

H1. Individual drivers directly and positively influence the recruiters' behavioral intention to use gamification.

2.2 The mediator effect of attitude

According to Deci (1975), attitude can be determined by the motivation to participate in an action. An individual's attitude is more likely to be positive when autonomously motivated (Li *et al.*, 2024). That is, through their intrinsic motivation. On the other hand, the perception of external factors when establishing autonomy in adopting a particular behavior (the so-called IR) also influences their attitude (Khan *et al.*, 2023) and, therefore, their intention to use technology, such as gamification.

As Buil *et al.* (2020) point out, in various contexts, the attitude toward the use of technology depends on the PE and PU perceived by the individual. Therefore, these dimensions are valid for studying the acceptance and use of technologies such as gamification, as they influence attitude and mediate behavioral intention to use (Yang *et al.*, 2017).

The fundamental role played by an individual's attitude, derived from their perceptions, in influencing their intention to behave has not only been highlighted in TAM (Yen *et al.*, 2023). Other theories on the behavior of individuals consolidated in the literature, such as the Theory of Planned Behavior (TPB) by Ajzen (1991), shows attitude as one of the main predictors of behavioral intention.

Literature indicates that attitude mediates the positive relationship between individual factors and recruiters' intention to use gamification. This relationship is reinforced by the influence of these factors on their attitudes, which allows us to formulate the following general hypothesis: (Figure 1)

H2. Attitude positively mediates the effect of individual drivers on the recruiters' behavioral intention to use gamification.

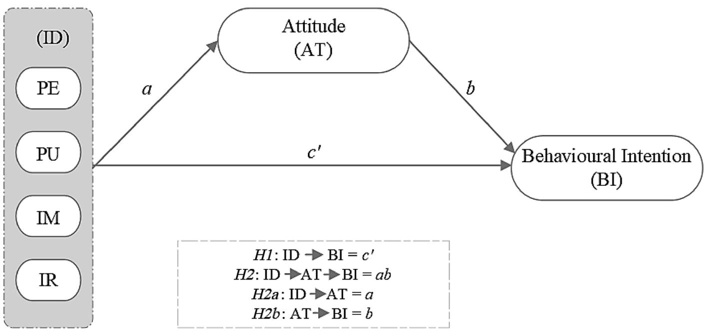

Figure 1. Research model. Note: ID: Individual Drivers; PE: Perceived Ease of Use; PU: Perceived Usefulness; IM: Intrinsic Motivation; IR: Identified Regulation. Source: Authors' own work

From this general hypothesis, the following two specific hypotheses can be deduced:

H2a. Individual drivers are positively related to attitude.

H2b. Attitude is positively related to behavioral intention to use.

3. Methodology

3.1 Sample

The study population includes human resources professionals involved in recruitment. The final sample included 203 firms, whose participants met the sociodemographic criteria in Table 1.

According to Blackwood *et al*. (2015), all human-subject studies must meet the requirements of the Institutional Review Board. Accordingly, participants were informed about the purpose of the study, the data processing procedure, and measures to ensure their anonymity. Informed consent and ethical approval were obtained before participation.

G*Power was used to calculate statistical power. The parameters introduced were effect size $f^2 = 0.15$; $\alpha_{\text{error prob.}}$ 0.05; Power (1-β err prob) = 80%; and number of predictors = 9. The results obtained required a total sample size of 114 cases. Our study meets the minimum requirement by having a sample of 203 companies, which guarantees its reliability.

3.2 Measures and data collection

The items to measure PE and PU were adapted from those of Buil *et al*. (2020) and Davis (1989). The IM items are based on Buil *et al*. (2019) and Neys *et al*. (2014). Finally, the items to measure IR are based on the proposals of Buil *et al*. (2020) and Neys *et al*. (2014). In the case of AT, the items have been adapted from Taylor and Todd (1995) and Verkijika and De Wet (2018). Lastly, the measurement of BI was performed based on the work of Dwivedi *et al*. (2017) and Taylor and Todd (1995).

The constructs were measured by a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). Table 2 presents all variables used in this model. The independent variable ID was structured as a unidimensional construct comprising PU, PE, IM, and IR to enhance interpretation and analysis.

3.3 Data analysis

The proposed research model was tested through the second-generation multivariate method called Partial Least Squares Structural Equation Modeling (PLS-SEM), specifically standard

Table 1. Respondent demographics

		Frequency	(%)
Age	20 to 30	84	41.38%
	31 to 40	81	39.90%
	41 to 55	36	17.73%
	Over 55	2	0.99%
Gender	Male	77	37.93%
	Female	126	62.07%
Years of professional experience	1 to 5	77	37.93%
	5 to 10	57	28.08%
	10 to 20	49	24.14%
	Over 20	20	9.85%
Educational level	Degree	58	28.57%
	Masterś Degree	138	67.98%
	Doctorate	7	3.45%

Source(s): Authors' own work

Table 2. Description of the variables

Individual drivers (ID)		
Intrinsic Motivation (IM)		
IM1	Opinion on gamification	Buil *et al*. (2019), Neys *et al*. (2014)
IM2	Opinion on gamification activities	
IM3	Sentiment when participating in gamification actions	
Identified Regulation (IR)		
IR1	Opinion on the usefulness of gamification activities in one's case	Buil *et al*. (2020), Neys *et al*. (2014)
IR2	Autonomy when deciding to participate in gamification actions	
IR3	Opinion on the usefulness of self-participation in gamification activities	
Perceived Ease Of Use (PE)		
PE1	Ease of gamification activities	Buil *et al*. (2020), Davis (1989)
PE2	Ease of use of gamification in general	
PE3	Ease interaction in gamification activities	
Perceived Usefulness (PU)		
PU1	Demonstration of one's skills through gamification	Buil *et al*. (2020), Davis (1989)
PU2	Demonstration of one's decision-making ability through gamification	
PU3	Knowledge of one's professional talent through gamification	
Attitude (AT)		
AT1	Gamification as an innovative idea	Taylor and Todd (1995), Verkijika and De Wet (2018)
AT2	Competitions based on gamification are a good idea	
AT3	Tendency to participate in competitions based on gamification	
Behavioral Intention to Use (BI)		
BI1	Intention to use gamification in recruitment processes	Dwivedi *et al*. (2017), Taylor and Todd (1995)
BI2	Likelihood to use gamification in recruitment processes	
BI3	Planning to use gamification in recruitment processes soon	

Source(s): Authors' own work

PLS-SEM, since it better fits the purpose of our research, where the obtained sample is intended to represent the mean of a population, showing the dispersion of the sample means around the population mean (Hair *et al*., 2022).

This method was selected based on three reasons: (1) it is used in management studies aimed at predicting dependent variables (Chin, 2010); (2) when no prior knowledge is available (Wold, 1980), and when the sample size is small ($n = 203$). PLS-SEM can be used when the number of observations exceeds 100, as is the case in our study. PLS-SEM offers advanced prediction techniques suitable for prediction-oriented purposes (Chin *et al*., 2020), outperforming other approaches by evaluating complex models that incorporate High Order Constructs (Sarstedt *et al*., 2019).

3.3.1 Common method bias. Common method bias (CMB) may compromise the validity of this study, as respondents' answers may be influenced by the formulation of the question, affecting the instrument more than their actual beliefs, thereby impacting the research results. The detection in our research was carried out in two steps. Firstly, we applied some of the recommendations proposed by Podsakoff *et al*. (2003, 2012): (1) in the design of the questionnaire, we separated the measurement of the dependent variables from that of the independent variables; (2) measurement scales validated in the reference literature were used to ensure the accuracy and reliability of the measures; (3) the confidentiality and anonymity of the participants was guaranteed to avoid conditioning their responses; and (4) a paragraph explaining the research objectives was included in the questionnaire.

Secondly, possible collinearity, based on variance inflation factors, was assessed to detect a possible CMB situation. Works such as those of Kock (2015) have demonstrated that Harman's Single Factor Test in PLS-SEM is an appropriate test for examining the contamination of the data set that constitutes an investigation. In this sense, Kock (2015) indicates that when a VIF exceeds 3.3, there are indications of collinearity within the obtained data. Our model yields a maximum VIF of 2.663; therefore, we can consider our research to be free of CMB. Likewise, the results show that the first factor explained 37.643% of the variance. This result is below the 50% threshold established by Harman (1980). The results of both tests confirmed the non-existence of collinearity in our investigation.

3.3.2 Fuzzy set qualitative analysis. This study also includes a comparative analysis of the qualitative nature of fuzzy sets (*fs*-QCA). The use of *fs*-QCA has proved to be a relevant analysis complement for the case of complex phenomena (Pappas and Woodside, 2021) furthermore, it has specific features that distinguish it from traditional quantitative and qualitative methods (Del Sarto *et al.*, 2020), since, instead of estimating the net effects of the independent variables, it employs the logic of Boolean algebra to analyze the relationship between an outcome and all binary combinations of the independent variables (Kraus *et al.*, 2018). As noted by Pappas and Woodside (2021), *fs*-QCA identifies the sufficient and necessary conditions that explain the outcome, as well as those that are insufficient but are essential components of the solutions.

4. Results

4.1 Measurement model

The existing literature (Hair *et al.*, 2022) suggests that to assess the validity of the constructs specified in Mode A, the individual validity of the indicators (e.g. loadings) and the internal consistency, reliability, and discriminant validity of the construct should be examined (Tables 3 and 4). Table 3 displays all indicators and dimensions (second-order constructs) with loadings exceeding the recommended threshold of 0.7. The internal consistency reliability, ρc, results show levels above the 0.7 threshold, and the ID construct demonstrates convergent validity (above 0.5) through the average variance extracted.

Regarding the constructs specified in Mode B, the literature indicates that the assessment should be approached at two levels: (1) at the construct level, by measuring convergent validity, and (2) at the dimension level, by assessing multicollinearity and weights. As shown in Table 4, the results of the BI and AT constructs are within the recommended limits for the assessment levels of Mode B constructs (Sarstedt *et al.*, 2019). At the indicator level, the VIF values are all below the threshold of 3. For assessing the weights and loadings, we employed a two-tailed bootstrap procedure (10,000 samples) to determine the significance of the dimensions.

Subsequently, the model fit assessment was analyzed (Henseler *et al.*, 2016). To this end, we employed a two-tailed bootstrap approach to obtain the appropriate measures of the standardized root mean square ratio, the unweighted least squares discrepancy, and the geodesic discrepancy for the estimated model. The results confirmed that our model falls below the 99th percentile (HI99) (Table 4). The data show that our model is reliable and fits the research data.

4.2 Structural model

Following the steps established in the literature (Hair *et al.*, 2011) for measuring structural models, we first examined the absence of possible collinearity problems in the internal model

Table 3. Estimated model results and

Construct/dimension/ indicator	Weights	Loadings	Consistent reliability ρ_A	Composite reliability ρ_c	Convergent validity AVE	Full collinearity VIF
Individual Drivers (01_ ID) (composite mode A)			0.860	0.901	0.696	
Intrinsic Motivation						
IM1	0.463	0.885				
IM2	0.173	0.790				
IM3	0.500	0.907				
Identified Regulation						
IR1	0.614	0.954				
IR2	0.385	0.901				
IR3	0.094	0.715				
Perceived Ease Of Use						
PE1	0.184	0.596				
PE2	0.486	0.752				
PE3	0.786	0.946				
Perceived Usefulness						
PU1	0.270	0.786				
PU2	0.545	0.933				
PU3	0.354	0.791				
Attitude (02_AT) (composite mode B)			n.a	n.a	n.a	1.962
AT1	0.422	0.781				
AT2	0.140	0.706				
AT3	0.624	0.915				
Behavioral Intention to Use (03_BI) (composite mode B)			n.a	n.a	n.a	1.032
BI1	0.378	0.882				
BI2	0.389	0.929				
BI3	0.351	0.870				

Note(s): CR: composite reliability. AVE: Average variance extracted. MC: Multidimensional construct. n.a.: non-applicable,
n.s./*/**/***: non-significant/significant at p-value <0.05/0.01/0.001 (2 tails)

Source(s): Authors' own work

by determining whether all VIF values are equal to or below the threshold of 3 (Hair *et al.*, 2019). The highest VIF was 1.962, remaining below the accepted threshold. Table 5 presents the direction, magnitude, and significance of the path coefficients. A one-tailed bootstrap of 10,000 samples provided t-statistics and confidence intervals confirming support for hypotheses H1, H2a, and H2b.

Figure 2 illustrates the coefficient of determination (R^2), which represents the proportion of the dependent variable's variance that the independent variables can explain, with the dependent variable (BI) achieving moderate predictive power.

4.2.1 Mediator effect. As has been argued, we believe that the ID variable may have positive indirect effects on the BI variable. The mediation study (Roldán, 2021) employed a one-tailed bootstrap (10,000 samples) to confirm a significant indirect impact on BI. To assess their type and magnitude, the Variance Accounted For (VAF = Indirect Effect/Total Effect) was applied, showing an indirect impact exceeding the 20% threshold (Table 6). We can conclude that the indirect effects of the ID variable on the BI variable are relevant. This allows accepting H2.

Table 4. Discriminant validity, convergent validity, and tests of model fit

Mode A composite constructs assessment		Individual drivers	Age	Sector	Gender
Individual drivers	Mode A	*n.a*	−0.129	0.058	−0.001
Age		0.140	*n.a*	−0.064	0.044
Sector		0.068	0.064	*n.a*	−0.009
Gender		0.018	0.044	0.009	*n.a*

Mode B composite construct assessment convergent validity	
Construct (≥0.8)*	Path coefficient
Behavioral intention	0.7999
Attitude	0.6557

Estimated model		
	Value	HI99
SRMR	0.052	0.072
d_{ULS}	0.246	0.878
d_G	0.127	0.317
Saturated model		
SRMR	0.044	0.067
d_{ULS}	0.179	0.277
d_G	0.177	0.285

Note(s): SRMR stands for standardized root mean squared residual. dULS stands for unweighted least squares discrepancy. dG stands for geodesic discrepancy. HI99 stands for the 99th percentile bootstrap base. Fornell-Larker criterion for all constructs below the diagonal (included). HTMT ratio for Mode A constructs above the diagonal. *n.a.*: non-applicable. HTMT inference confidence intervals (2.5%–97.5%) underneath HTMT values, extracted from a two-tailed bootstrapping procedure. * (Hair *et al*., 2017)

Source(s): Authors’ own work

It is observed that when the AT variable comes into play in the relationship between ID and BI, a positive and significant interaction occurs, indicating that the final variable receives more information when it interacts with the mediating AT variable (Table 6).

4.2.2 The model’s predictive power. Finally, we evaluated the predictive capacity of the model using the procedure outlined by Shmueli and Koppius (2011) via an out-of-sample test. According to Roldán *et al*. (2018), and the sample size was divided into six sections (K = 6) of 30 cases each ($n = 30$). The steps proposed by Shmueli *et al*. (2016) were followed. Firstly, we confirmed that all the $Q^2_{predict}$ values of the dependent variables are positive and more significant than zero ($Q^2_{predict} > 0$), which means that the PLS prediction errors are smaller than those used in the linear regression model; this guarantees that the PLS model has a higher predictive ability. Secondly, we observe that all RMSE values are less than 1 (RMSE – PLS LM < 1), indicating a symmetrical distribution of errors. Thirdly, most show a negative difference in RMSE errors. These results allow us to conclude that the model has moderate predictive power and can make accurate predictions.

4.3 Fuzzy-set qualitative comparative analysis

The *fs*-QCA analysis requires calibrating data, constructing the truth table, and analyzing conditions. Average scores were calculated for each item and calibrated on a five-point fuzzy scale, with thresholds at 4, 3, and 2 (Pappas and Woodside, 2021). The membership of each causal condition ranged from 0 to 1.

Table 5. Effects on endogenous variables

Hypothesis	Direct effect	*p*-value	Correlations	CI 5%	95%	Support	VIF	Explained variance
H1 (+): Individual Drivers – Behavioral Intention to Use *(c')*	0.597	0.001	0.611	[0.491	0.696]	Yes	1.915	35.38% (High)
H2a (+): Individual Drivers – Attitude *(a)*	0.685	0.001	0.685	[0.602	0.755]	Yes	1.000	46.92% (High)
H2b (+): Attitude – Behavioral Intention to Use *(b)*	0.724	0.001	0.813	[0.596	0.829]	Yes	1.962	58.86% (High)
Control variables	Two-tailed bootstrapping							
Sector	Direct effect	*p*-value	*t*-value					
	0.047	0.170^{ns}	1.371					
Age	−0.803	0.030	2.175					
Gender	0.074	0.405^{ns}	0.089					

Note(s): VIF: variance inflation factor; CI: confidence interval. ^{ns}: non-significant

Source(s): Authors' own work

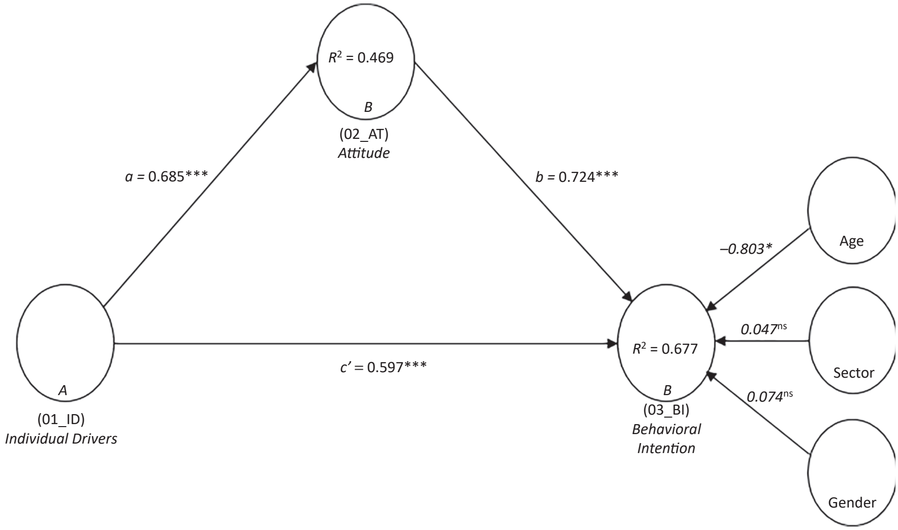

Figure 2. Structural model results. Source: Authors' own work

Table 6. Summary of mediating effect test

	Coefficient		*t*-statistics	*p*-values	Bootstrap 90% CI percentile		VAF
Direct effects							
ID à BI	0.101		1.286	0.113	[−0.015	0.235]	
ID à AT	0.685		17.347	0.001	[0.602	0.755]	
AT à BI	0.724		12.222	0.001	[0.596	0.829]	
Total effects							
H1 (+): *c'*	0.597	*sig******	11.341	0.001	[0.491	0.696]	16.92%
H2a (+): *a*	0.685	*sig******	17.347	0.001	[0.602	0.755]	
H2b (+): *b*	0.724	*sig******	12.222	0.001	[0.596	0.829]	
Total indirect effect	*Point estimate*						
H2 (+): *a* x *b*	0.496	*sig******	10.021	0.001	[0.396	0.589]	20.36%
					Partial sequential mediation 20%<VAF<80%)****		

Note(s): Total direct and indirect effects were estimated using control variables — Age, Sector, and Gender —as they relate to BI. Coefficient, *t-statistics*, *p-values*, and percentiles were determined by a percentile bootstrap confidence interval of 90% (one tail), based on $n = 10{,}000$ subsamples. */**/***: significant at *p*-value <0.05/0.01/0.001; Abbreviations: ID: Individual Drivers; AT: Attitude; BI: Behavioral Intention to Use. VAF: Variance Accounted For

Source(s): Authors' own work

The next step was to run the fuzzy set algorithm, generating the truth table which included all possible background configurations. A minimum consistency of 0.80 (Krogslund *et al.*, 2015) was determined in the table to exclude the least essential configurations. Two truth tables were developed: 1) outcome variable "BI" and 2) outcome variable "negation of BI" (∼BI) (Figure 3).

The *fs*-QCA solution typically includes one or more causal configurations that are sufficient to generate the result (Fainshmidt *et al.*, 2020). Of the three possible solutions

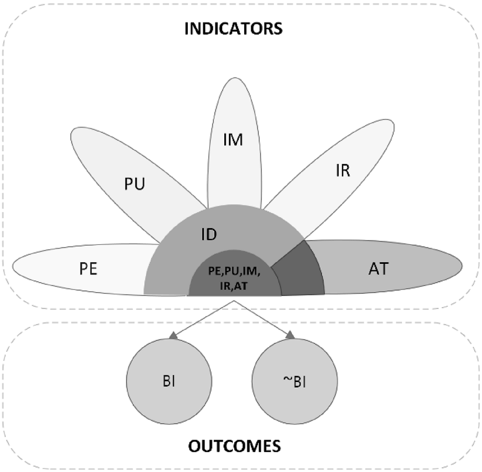

Figure 3. *fs*-QCA configurational model. Note: ID: Individual Drivers; PE: Perceived Ease of Use; PU: Perceived Usefulness; IM: Intrinsic Motivation; IR: Identified Regulation, AT: Attitude, BI: Behavioral Intention. Source: Authors' own work

(complex, parsimonious, and intermediate), the most conservative option prioritizes the complex one, avoiding empirically unsupported claims (Vis, 2012) (Table 7).

The conditions of each solution may be present, absent, or irrelevant if they do not influence a specific configuration. They may be necessary or sufficient, and act as central or peripheral elements. (Pappas and Woodside, 2021). A comparison of the intermediate and parsimonious solutions allows identifying the central conditions (IM, PE, and PU) from the peripheral ones (IR and AT).

Necessary conditions analysis emphasizes the cases that influence the outcome, which are then used to test propositions. The first step of the essential conditions analysis examines whether a single condition is continuously present or absent when the outcome is present (or lacking).

The overall solution achieves consistency levels of 0.949 and 0.546 for the BI and ~BI results, respectively. This enables us to assert that the resulting solution yields robust results.

The results indicate an overall consistency of solutions of 94.22% and a coverage of 94.93%, suggesting that the identified solutions consistently cover a substantial proportion of the outcome. A total of 94.22% of the cases with high BI include all three combinations of causal conditions. IM is the central condition along with PE, while the other factors are peripheral conditions.

Solution number 1 has the highest consistency, with IM present, which is a necessary condition in all three solutions. AT is present in the two solutions with the highest consistency, and IR is in the second solution with the highest consistency. The combination of PE, IM, and AT, along with the absence of PU, is the second solution with the highest consistency.

Three different pathways are identified in the absence of BI (~BI). The results showed an overall coverage for ~ BI of 54.64%. The three combinations of causal conditions accounted for 83.19% of the cases. Solution number 2, which combines the presence of PU and IM with the absence of IR and AT, yielded the highest consistency.

5. Discussion and conclusions

The results, and therefore, the similar behavior of the four dimensions within the ID, demonstrated the positive influence of IDs (based on PE, PU, IM, and IR) on recruiters' BI

Table 7. Necessary conditions and solutions for high/low behavioral intention to use

Condition tested	BI Consistency	Coverage	~BI Consistency	Coverage
PEc	0.764865	0.915893	0.723188	0.160675
~PEc	0.299079	0.859032	0.616731	0.324627
PUc	0.914025	0.936291	0.724263	0.135956
~PUc	0.156505	0.755912	0.660624	0.584741
IMc	0.984087	0.900811	0.867366	0.145502
~IM	0.066507	0.732349	0.408716	0.824775
IRc	0.955118	0.938165	0.664122	0.119546
~IRc	0.103637	0.627382	0.656489	0.728299
ATc	0.981289	0.926577	0.715330	0.123782
~ATc	0.072045	0.580010	0.575701	0.849366

Configuration	BI 1	2	3	~BI 1	2	3
PEc		●	⊗	•		⊗
PUc		⊗	●	⊗	•	⊗
IMc	●	●	●	●	●	⊗
IRc	•		⊗	⊗	⊗	⊗
ATc	•	•	⊗		⊗	⊗
Consistency	0.956102	0.892478	0.837336	0.82501	0.934189	0.914383
Raw coverage	0.940721	0.122406	0.0447075	0.395993	0.37023	0.254771
Unique coverage	0.817149	0.00268126	0.00320584	0.123728	0.0896947	0.0435749
Overall solution consistency	0.942207			0.831961		
Overall solution coverage	0.949347			0.546439		

Note(s): Black circles (●) indicate existence, while dashed circles (⊗) indicate lack. Larger circles represent central elements, and smaller circles represent peripheral elements. In the blanks, the causal element may be present or absent

Source(s): Authors' own work

when using gamification in recruitment processes. This first result generally aligns with Li *et al.* (2024), who noted that the elements influencing an individual's behavioral intention regarding gamification are varied.

Regarding the research questions posed, in the case of RQ1, this relationship has been demonstrated in a positive sense, and it can be established that the higher the PE, PU, IM, and IR, the higher the BI of gamification use by recruiters. These results coincide with those proposed by Davis (1989) and Ryan and Deci (2000) through TAM and SDT, respectively. The PE and PU cases are similar, as pointed out by Aydınlıyurt *et al.* (2021). PU shows no positive influence on BI in this case. However, our findings align with studies that confirm the relationship between PE, PU, and BI. This may stem from the importance of ease of use and utility in task performance, especially for recruiters. Regarding IM and IR, our results mirror recent research emphasizing their role as behavioral predictors (e.g. Stiegemeier *et al.*, 2023). As in our study, this work also analyzes the behavior of predictors from different theories, as reported by previous studies (e.g. Racero *et al.*, 2020).

Regarding RQ2, the results show that when the AT variable comes into play in the relationship between ID and BI, it produces a positive and significant interaction, indicating that BI receives more information and is greater. The findings of this effect are new, as it has not been addressed to date in the literature on BI gamification by recruiters. This mediating effect has been discussed in other areas, but not in the specific case of the connection between gamification and recruitment, where attitude appears as a significant predictor of particular behavior. Works such as those of Buil *et al*. (2020) and Hsu *et al*. (2017) yield results that align with the general behavioral theories of SDT (Ryan and Deci, 2000) and TPB (Ajzen, 1991).

The primary contribution of this article lies in the impact of recruiters' attitudes toward gamification in the recruitment process. Although organizations have the tools to gamify, the effective use of these tools depends on employee perception. The data show that adoption increases when recruiters believe that gamification enhances efficiency and facilitates a more accurate assessment of candidates' skills.

6. Implications and limitations

6.1 Theoretical implications

From a theoretical perspective, this research improves knowledge about the factors that positively influence recruiters' BI regarding the use of gamification.

Empirically, our study provide evidence on factors that influence the intention to use gamification, highlighting the mediating role of attitude concerning the direct influence of individual elements. Although adopting technology in different domains has been analyzed through TAM, Unified Theory of Acceptance and Use of Technology, or its extended version, no studies have examined the mediating effect of attitude on individuals' behavioral intention. The findings of our work expand the understanding of the intention to use technologies, which, as in the case of gamification, are increasingly prevalent in various aspects of daily human life.

6.2 Practical implications

The practical implications are relevant. The results of the proposed model are beneficial for business management, particularly in the areas of recruitment and selection. Understanding the benefits of these technologies is crucial to enhancing processes and achieving sustainable competitive advantages.

In recruitment, understanding which elements positively influence the perception of gamification is key for organizations. This study demonstrates that when designing and implementing gamification, it is crucial to focus on the users, identifying factors that influence their intention to use it and promoting collaboration among all relevant actors. It is also essential to highlight the mediating role of these recruiters' attitudes in this direct and positive relationship between ID and BI.

In short, gamification techniques in recruitment can be recommended to attract potential employees, especially those from the millennial generation, by increasing their interest in developing within the company and reducing boredom and monotony associated with the ordinary recruitment process (Saleh *et al*., 2020).

6.3 Limitations and future lines of research

This study has limitations. First, although the sample is representative, it was collected only in Spain; therefore, caution should be exercised when extrapolating the results to other countries with different regulations and organizational cultures. Second, the cross-sectional design prevents the establishment of causal relationships or confirmation of actual behaviors following the use of gamification.

Future research should overcome these limitations. Replicating the study in other regions would allow for the identification of contextual differences and the validation of the model using larger samples. This would strengthen methodological rigor and help distinguish universal principles. In addition, a longitudinal design would better capture the evolution of recruiters' intentions regarding gamification. Finally, future research should incorporate organizational factors such as corporate culture, hiring strategies, and prior experience with gamification.

References

Ajzen, I. (1991), "The theory of planned behavior", *Organizational Behavior and Human Decision Processes*, Vol. 50 No. 2, pp. 179-211, doi: 10.1016/0749-5978(91)90020-T.

Aydınlıyurt, E.T., Taşkın, N., Scahill, S. and Toker, A. (2021), "Continuance intention in gamified mobile applications: a study of behavioral inhibition and activation systems", *International Journal of Information Management*, Vol. 61, 102414, doi: 10.1016/j.ijinfomgt.2021.102414.

Bhawna, B., Dogra, P., Akram, U. and Sharma, S.K. (2025), "Enhancing employer branding in startups through job autonomy and intrinsic motivation: the role of gamification", *Business Process Management Journal*. doi: 10.1108/BPMJ-12-2023-0934.

Blackwood, R.A., Maio, R.F., Mrdjenovich, A.J., VandenBosch, T.M., Gordon, P.S., Shipman, E.L. and Hamilton, T.A. (2015), "Analysis of the nature of IRB contingencies required for informed consent document approval", *Accountability in Research*, Vol. 22 No. 4, pp. 236-244, doi: 10.1080/08989621.2014.956866.

Buil, I., Catalán, S. and Ortega, R. (2019), "Gamification and motivation: new tools for talent acquisition", *UCJC Business and Society Review*, Vol. 16 No. 3, pp. 146-179, doi: 10.3232/UBR.2019.V16.N3.04.

Buil, I., Catalán, S. and Martínez, E. (2020), "Understanding applicants' reactions to gamified recruitment", *Journal of Business Research*, Vol. 110, January, pp. 41-50, doi: 10.1016/j.jbusres.2019.12.041.

Chin, W.W. (2010), "How to write up and report PLS analyses BT", in Esposito, V., Chin, W.W., Henseler, J. and Wang, H. (Eds), *Handbook of Partial Least Squares: Concepts, Methods and Applications*, Springer Berlin Heidelberg, pp. 655-690, doi: 10.1007/978-3-540-32827-8_29.

Chin, W., Cheah, J.H., Liu, Y., Ting, H., Lim, X.J. and Cham, T.H. (2020), "Demystifying the role of causal-predictive modeling using partial least squares structural equation modeling in information systems research", *Industrial Management and Data Systems*, Vol. 120 No. 12, pp. 2161-2209, doi: 10.1108/IMDS-10-2019-0529.

Davis, F.D. (1986), "A technology acceptance model for empirically testing new end-user information systems: theory and results". doi: 10.1126/science.146.3652.1648.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly: Management Information Systems*, Vol. 13 No. 3, pp. 319-339, doi: 10.2307/249008.

Deci, E.L. (1975), "Conceptualizations of intrinsic motivation", *Intrinsic Motivation*, pp. 23-63, doi: 10.1007/978-1-4613-4446-9_2.

Del Sarto, N., Isabelle, D.A. and Di Minin, A. (2020), "The role of accelerators in firm survival: an fsQCA analysis of Italian startups", *Technovation*, Vols 90-91, 102102, doi: 10.1016/j.technovation.2019.102102.

Dwivedi, Y.K., Rana, N.P., Janssen, M., Lal, B., Williams, M.D. and Clement, M. (2017), "An empirical validation of a unified model of electronic government adoption (UMEGA)", *Government Information Quarterly*, Vol. 34 No. 2, pp. 211-230, doi: 10.1016/j.giq.2017.03.001.

Fainshmidt, S., Witt, M.A., Aguilera, R.V. and Verbeke, A. (2020), "The contributions of qualitative comparative analysis (QCA) to international business research", *Journal of International Business Studies*, Vol. 51 No. 4, pp. 455-466, doi: 10.1057/s41267-020-00313-1.

Georgiou, K., Gouras, A. and Nikolaou, I. (2019), "Gamification in employee selection: the development of a gamified assessment", *International Journal of Selection and Assessment*, Vol. 27 No. 2, pp. 91-103, doi: 10.1111/ijsa.12240.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011), "PLS-SEM: indeed a silver bullet", *Journal of Marketing Theory and Practice*, Vol. 19 No. 2, pp. 139-151, doi: 10.2753/MTP1069-6679190202.

Hair, J.F., Sarstedt, M., Ringle, C.M. and Gudergan, S.P. (2017), *Advanced Issues in Partial Least Squares Structural Equation Modeling*, SAGE Publications.

Hair, J.F., Hult, G., Ringle, C.M., Sarstedt, M., Castillo-Apraiz, J., Cepeda-Carrión, G.A. and Roldan, J.L. (2019), *Manual de Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2 ed., Sage, doi: 10.3926/OSS.37.

Hair, J.F., Hult, G.T., Ringle, C.M. and Sarstedt, M. (2022), "A primer on partial least squares structural equation modeling (PLS-SEM)". doi: 10.1007/978-3-030-80519-7.

Hamari, J. (2019), "Gamification", in *The Blackwell Encyclopedia of Sociology*, pp. 1-3, doi: 10.1002/9781405165518.wbeos1321.

Harman, H.H. (1980), *Análisis Factorial Moderno*, Saltés.

Henning, M., Eriksson, R., Garefelt, P., Martin, H. and Elekes, Z. (2025), "Job relatedness, local skill coherence and economic performance: a job postings approach", *Regional Studies, Regional Science*, Vol. 12 No. 1, pp. 95-122, doi: 10.1080/21681376.2025.2459148.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2016), "Testing measurement invariance of composites using partial least squares", *International Marketing Review*, Vol. 33 No. 3, pp. 405-431, doi: 10.1108/IMR-09-2014-0304.

Hsu, C.L., Chen, Y.C., Yang, T.N. and Lin, W.K. (2017), "Do website features matter in an online gamification context? Focusing on the mediating roles of user experience and attitude", *Telematics and Informatics*, Vol. 34 No. 4, pp. 196-205, doi: 10.1016/j.tele.2017.01.009.

Khan, Y., Hameed, I. and Akram, U. (2023), "What drives attitude, purchase intention and consumer buying behavior toward organic food? A self-determination theory and theory of planned behavior perspective", *British Food Journal*, Vol. 125 No. 7, pp. 2572-2587, doi: 10.1108/BFJ-07-2022-0564.

Kock, N. (2015), "Common method bias in PLS-SEM: a full collinearity assessment approach", *International Journal of E-Collaboration (Ijec)*, Vol. 11 No. 4, pp. 1-10, doi: 10.4018/ijec.2015100101.

Kraus, S., Ribeiro-Soriano, D. and Schüssler, M. (2018), "Fuzzy-set qualitative comparative analysis (fsQCA) in entrepreneurship and innovation research – the rise of a method", *International Entrepreneurship and Management Journal*, Vol. 14 No. 1, pp. 15-33, doi: 10.1007/s11365-017-0461-8.

Krogslund, C., Choi, D.D. and Poertner, M. (2015), "Fuzzy sets on shaky ground: parameter sensitivity and confirmation bias in fsQCA", *Political Analysis*, Vol. 23 No. 1, pp. 21-41, doi: 10.1093/pan/mpu016.

Li, L., Hew, K.F. and Du, J. (2024), "Gamification enhances student intrinsic motivation, perceptions of autonomy and relatedness, but minimal impact on competency: a meta-analysis and systematic review", (Issue 0123456789), in *Educational Technology Research and Development*, Springer US. doi: 10.1007/s11423-023-10337-7.

Madi, J., Al Khasawneh, M. and Dandis, A.O. (2024), "Visiting and revisiting destinations: impact of augmented reality, content quality, perceived ease of use, perceived value and usefulness on E-WOM", *International Journal of Quality and Reliability Management*, Vol. 2015 No. 6, pp. 1550-1571, doi: 10.1108/IJQRM-10-2023-0314.

Neys, J.L.D., Jansz, J. and Tan, E.S.H. (2014), "Exploring persistence in gaming: the role of self-determination and social identity", *Computers in Human Behavior*, Vol. 37, pp. 196-209, doi: 10.1016/j.chb.2014.04.047.

Obaid, I., Farooq, M.S. and Abid, A. (2020), "Gamification for recruitment and job training: model, taxonomy, and challenges", *IEEE Access*, Vol. 8, pp. 65164-65178, doi: 10.1109/ACCESS.2020.2984178.

Pappas, I.O. and Woodside, A.G. (2021), "Fuzzy-set qualitative comparative analysis (fsQCA): guidelines for research practice in information systems and marketing", *International Journal of Information Management*, Vol. 58, 102310, doi: 10.1016/j.ijinfomgt.2021.102310.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *The Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903, doi: 10.1037/0021-9010.88.5.879.

Podsakoff, P.M., MacKenzie, S.B. and Podsakoff, N.P. (2012), "Sources of method bias in social science research and recommendations on how to control it", *Annual Review of Psychology*, Vol. 63 No. 1, pp. 539-569, doi: 10.1146/annurev-psych-120710-100452.

Racero, F.J., Bueno, S. and Gallego, M.D. (2020), "Predicting students' behavioral intention to use open source software: a combined view of the technology acceptance model and self-determination theory", *Applied Sciences (Switzerland)*, Vol. 10 No. 8, p. 2711, doi: 10.3390/APP10082711.

Roldán, J.L. (2021), "Review of composite-based structural equation modeling: analyzing latent and emergent variables", *Structural Equation Modeling: A Multidisciplinary Journal*, Vol. 28 No. 5, pp. 823-825, doi: 10.1080/10705511.2021.1910038.

Roldán, J.L., Real, J.C. and Ceballos, S.S. (2018), "Antecedents and consequences of knowledge management performance: the role of IT infrastructure", *Intangible Capital*, Vol. 14 No. 4, pp. 518-535, doi: 10.3926/ic.1074.

Ryan, R.M. and Deci, E.L. (2000), "Intrinsic and extrinsic motivations: classic definitions and new directions", *Contemporary Educational Psychology*, Vol. 25 No. 1, pp. 54-67, doi: 10.1006/ceps.1999.1020.

Ryan, R.M. and Deci, E.L. (2017), "Self-determination theory basic psychological needs in motivation, development, and wellness", in *Self-determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness*.

Saleh, A.A., Endramanto, V. and Wang, G. (2020), "Gamification for recruitment: a new tool to attract talent", *International Journal of Advanced Trends in Computer Science and Engineering*, Vol. 9 No. 2, pp. 963-968.

Sarstedt, M., Hair, J.F., Cheah, J.H., Becker, J.M. and Ringle, C.M. (2019), "How to specify, estimate, and validate higher-order constructs in PLS-SEM", *Australasian Marketing Journal*, Vol. 27 No. 3, pp. 197-211, doi: 10.1016/j.ausmj.2019.05.003.

Shmueli, G. and Koppius, O. (2011), "Predictive analytics in information systems research", *MIS Quarterly*, Vol. 35, pp. 553-572, doi: 10.2139/ssrn.1606674.

Shmueli, G., Ray, S., Velasquez Estrada, J.M. and Chatla, S.B. (2016), "The elephant in the room: predictive performance of PLS models", *Journal of Business Research*, Vol. 69 No. 10, pp. 4552-4564, doi: 10.1016/j.jbusres.2016.03.049.

Shree, S. and Singh, A.S. (2019), "Exploring gamification for recruitment through actor network theory", *South Asian Journal of Human Resources Management*, Vol. 6 No. 2, pp. 242-257, doi: 10.1177/2322093719863912.

Singh, A.P. (2022), "Gamification: a new approach to facilitate recruitment", *ECS Transactions*, Vol. 107 No. 1, pp. 3581-3588, doi: 10.1149/10701.3581ecst.

Stiegemeier, D., Kraus, J., Bringeland, S. and Baumann, M. (2023), "Motivated to use: beliefs and motivation influencing the acceptance and use of assistance and navigation systems", *International Journal of Human-Computer Interaction*, Vol. 39 No. 14, pp. 2926-2941, doi: 10.1080/10447318.2022.2088658.

Tanouri, A., Kennedy, A.M. and Veer, E. (2023), "An implementation framework for transformative gamification services", *Behaviour and Information Technology*, Vol. 43 No. 10, pp. 1-33, doi: 10.1080/0144929X.2023.2241560.

Taylor, S. and Todd, P.A. (1995), "Understanding information technology usage: a test of competing models", *Information Systems Research*, Vol. 6 No. 2, pp. 144-176, doi: 10.1287/isre.6.2.144.

Verkijika, S.F. and De Wet, L. (2018), "E-government adoption in sub-Saharan Africa", *Electronic Commerce Research and Applications*, Vol. 30, February, pp. 83-93, doi: 10.1016/j.elerap.2018.05.012.

Vis, B. (2012), "The comparative advantages of fsQCA and regression analysis for moderately large-N analyses", *Sociological Methods \and Research*, Vol. 41 No. 1, pp. 168-198, doi: 10.1177/0049124112442142.

Wold, H. (1980), "Model construction and evaluation when theoretical knowledge is scarce", in *Evaluation of Econometric Models*, National Bureau of Economic Research, pp. 47-74, doi: 10.1016/b978-0-12-416550-2.50007-8.

Yang, Y., Asaad, Y. and Dwivedi, Y. (2017), "Examining the impact of gamification on intention of engagement and brand attitude in the marketing context", *Computers in Human Behavior*, Vol. 73, pp. 459-469, doi: 10.1016/j.chb.2017.03.066.

Yen, B.T.H., Mulley, C. and Meza, G. (2023), "Exploring the attitudes and perceptions influencing user participation in gamification schemes for TDM", *Research in Transportation Economics*, Vol. 99, April, 101300, doi: 10.1016/j.retrec.2023.101300.

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