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Research article

The multidimensional influence structure of college students' online gamified learning engagement: A hybrid design based on QCA-SEM

Hongfeng Zhang [a], Fanbo Li [b,*]

[a] Faculty of Humanities and Social Sciences, Macao Polytechnic University, R. de Luís Gonzaga Gomes, China
[b] School of Social Sciences, Tsinghua University, China

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ABSTRACT

In the post-epidemic era, gamification is widely recognized for its potential to enhance the asynchronous nature of college students' online learning interactions and mitigate efficiency deficits. However, the intrinsic structure and core conditions influencing online gamified learning engagement remain unclear. The challenge lies in understanding the mechanisms through which gamification alters learning behaviors. This study employs fuzzy set qualitative comparative analysis (FSQCA) for core condition identification and robustness testing, innovatively combining it with structural equation modelling (SEM). Drawing on the extended technology acceptance model (TAM) theory, this research delves deeply into the structural relationships that influence student engagement in online gamified learning. The evaluation reveals that immersive experience and habit are core conditions fostering high engagement among college students in online gamified learning. A lack of immersive experience leads to non-high engagement results. Structural equation modelling confirms the mediating role of immersive experience and habit in the effects of performance expectations and perceived fun in student engagement. Furthermore, the study substantiates the moderating influence of learning style on perceptual factors and normalizing elements and describes an interactive relationship between perceived behavioral control, subjective norms, and online gamification behavior. This research extends our understanding of perceptions, norms, and structural factors within a gamified learning environment. It uncovers the mechanisms of engagement from perception to normalization factors, highlighting the positive bidirectional influence of subjective cognition and objective factors on gamified learning and emphasizing the moderating role of learning style between perceptual factors and normalization elements. These findings provide a solid foundation for future research and practice in online gamified learning.

1. Introduction

As a consequential pedagogical modality, online learning is no longer passive. It has evolved into an educational paradigm in which individuals discern and actively employ its immediacy, convenience, and temporal and spatial flexibility, concurrently with traditional offline learning endeavors [1]. Nevertheless, the deficiencies inherent in online learning are glaring, notably epitomized by the

* Corresponding author.
E-mail addresses: hfengzhang@mpu.edu.mo (H. Zhang), lifanbo0706@gmail.com (F. Li).

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human–machine–human isolation model, precipitating a diminution in the interactive and communicative dimensions of the learning experience. This, in turn, engenders a palpable sense of isolation among students, depriving them of meaningful social interaction [2,3]. However, cultivating self-discipline has helped to increase students' participation in online learning [4,5]. Consequently, scholarly investigations have gravitated towards filling the gaps in asynchronous interactions and efficiency that plague online education [6,7]. In this context, gamification has emerged as a keenly examined research avenue [8], captivating scholarly attention as a strategic response to the inherent deficiencies of online learning.

Gamified learning is an innovative pedagogical approach with the overarching aim of enhancing student engagement, motivation, and the overall efficacy of the learning process. Game elements such as competitions, achievements, rankings, tasks, storylines, and the like interweave seamlessly with the learning experience, encompassing virtual rewards, task-oriented pedagogy, role-playing, and gamified assessments. This renders the learning journey not only more intellectually stimulating but also fosters a heightened level of interactivity [9]. In recent years, the escalating corpus of research dedicated to gamified learning has led to the conceptualization of this approach as a robust theoretical framework. The crux of this theoretical framework lies in elucidating the elemental composition of game elements and constructing a model that delineates their impact on the efficacy of gamified learning [10,11]. Some other studies are grounded in theoretical foundations to explain why "gamification" works, probing the intricacies of learning engagement and its consequential effects. A pertinent study exemplifying this is one by Liu et al., which explored a gamified approach using Easter eggs to improve the learning performance of K-6 students. This approach demonstrated significant enhancements in student motivation and engagement by incorporating hidden rewards, thereby justifying the claimed motivation improvement in gamified learning environments. Such findings highlight the potential of specific gamification elements to foster a more interactive and motivating learning experience [12]. Most scholarly exploration in the realm of game-based learning converges on the latter, and the prevailing theoretical frameworks can be broadly categorized into three archetypes: those founded on emotional motivation (epitomized by flow theory and self-determination theory), those rooted in behavioral considerations (exemplified by the technology acceptance model and theory of planned behavior), and those anchored in learning-related theories (represented by the social learning theory and cognitive load theory) [13].

Various studies have explored the concept of structured gamification, highlighting how structured game elements can significantly improve learning performance. These findings underscore the potential of structured gamification elements in fostering a more interactive and motivational learning experience [14]. Most research about online learning is focused on behavior-oriented investigations, particularly those associated with the technology acceptance model (TAM), a framework intricately aligned with the nuanced dimensions of games as a technological entity [15,16].

This inquiry embarks upon an exploration rooted in an expanded TAM, poised to delve into the structural relationships that influence online gamified learning engagement (OGLE) among college students. Nevertheless, despite the evolutionary trajectory of TAM, the constructs mentioned above are habitually perceived as direct influencers on OGLE, with scant attention devoted to unraveling the mediating dynamics between these constructs. For instance, the inclusion of habit (HA) into the model, displacing behavioral attitude [17], has been crafted to align with the perspectives of prior behavior [18] and automatic awareness [19]. However, the precise positioning of habit within the model warrants meticulous scrutiny, particularly of whether the perceived variables of technology acceptance necessitate an impact on OGLE through the conduit of habit. These nuanced intricacies constitute the focal points that this study seeks to elucidate. The envisaged contribution of this inquiry is twofold. Firstly, by introducing modifications or adjustments to certain novel constructs within the milieu of game-based learning, it aims to expansively augment the domain of soft technology acceptance and verify and discover the influence mechanism of OGLE for college students. Secondly, in a methodological departure, the research endeavors to transcend the conventional confines of literature review and logical deduction. It proposes to introduce a fusion of qualitative comparative analysis (QCA) and structural equation modelling (SEM) as a means of cultivating and substantiating the structural relationships within the identified constructs.

2. Theoretical foundation and research design

2.1. Theoretical development

Over the course of more than a decade, TAM has undergone a metamorphosis, giving rise to iterations such as the expanded TAM, the unified theory of acceptance and use of technology (UTAUT), and UTAUT2. The original constituents, encompassing perceived usefulness—perceived ease of use, behavioral attitude, participation intention, and behavior—have amalgamated with the theory of planned behavior and the flow theory, thereby ushering in a substantial transformation in the variable structure [20]. The names of some variables have changed in the third-generation model, for example, perceived usefulness and perceived ease of use are now performance expectancy and effort expectancy, respectively [17]. Additionally, variables such as subjective norms, perceived behavioral control [21], habit [17], immersive experience [22], and perceived entertainment [23,24] have assumed prominence in this evolution. The empirical validation of diverse construct models has been undertaken across an array of technological typologies, user populations, and cultural contexts. While acknowledging the criticality of the historical context and the deductive progression of research in the gamified learning domain, the subsequent in-depth development of research endeavors necessitates a dual consideration. Firstly, it must be anchored in well-established models, and secondly, it should consider the characteristics of the theme itself and the structural relationships and functions of the constructs in new contexts.

In emerging educational paradigms, gamification assumes a dual role as both a technological innovation and a form of edutainment [25,26]. This novel milieu necessitates profound adjustments at the theoretical level. Notably, the conceptual landscape witnesses the ascendancy of perceived fun (PF) as a novel perceptual variable, supplanting the erstwhile perceived ease of use or effort expectancy

[27]. Pedagogically designed games are inherently simplistic, so the students' receptivity to learning hinges upon their perceptual experience of the inherent entertainment value of these educational games [28]. Furthermore, within the second and third generations of technology models, performance expectancy (PE) supersedes the conventional perceived usefulness [17]. This realignment aligns seamlessly with the overarching objectives of gamified learning, transcending a mere scrutiny of the utilitarian facets of game-based learning. Instead, it delves into the nuanced terrain of expectations of performance outcomes [28].

The theory of flow assumes particular relevance in the realm of gamified learning [29], as evidenced by the profound captivation observed in gamers immersed within the realm of online gaming [30]. Consequently, the construct of immersive experience (IE) emerges as a salient consideration within specific contexts. In the evolutionary trajectory of the third-generation technology model, HA is posited as a variable that supplants behavioral intention [19,31]. The engagement of college students in online gamified learning is delineated less by behavioral attitudes or intentions than by behavioral patterns entrenched in habituation, as underscored by the emphasis placed by behaviorism [31]. HA and IE denote two states, implying that the extension of the TAM model is more concerned with the normalization of behavior. Although the mediating effect of normative factors was not proposed in the TAM extension model, some research unveiled that perceived fun significantly influenced immersive experience and habit respectively [32,33]. Similarly, the conceptualizations of subjective norm (SN) and perceived behavioral control (PBC) posited by the theory of planned behavior (TPB) transcend the realm of mere expansion within TAM [21]. They serve to elucidate the structural elements that underscore the direct influence of external norms upon the subject's cognitive and behavioral processes [34]. In this study, the behavioral variable of the TAM extension model is OGLE. The previous six variables are all influence variables of OGLE in the model, and the mediating factors are not explicitly identified. Consequently, the current inquiry is poised to delve into the theoretical models and articulate intricate structural relationships that are grounded in the evolutionary trajectory of TAM.

2.2. Research design

Online gamified learning is a multifaceted and complex phenomenon involving a constellation of constructs such as PE, PF, HA, IE, PBC, and SN. While a solitary SEM proves instrumental in navigating the intricate web of structural relationships, the elucidation of the underlying mechanism often necessitates a reliance on antecedent theoretical frameworks and literature to postulate path assumptions for the model [35]. Past attempts at synergizing SEM with QCA have tended to relegate QCA to a position of merely "expanding and fortifying the PLS-SEM results" [36], with QCA's introduction failing to manifest a substantive contribution to the study design. However, this study endeavors to effect a methodological breakthrough.

Primarily, through the configurational analysis of diverse condition variables within QCA, the study endeavors to pinpoint core conditions or factors wielding a decisive impact on the outcomes. Core conditions denote the presence or specific configuration of factors deemed sufficient to precipitate the outcome, irrespective of changed in other conditions [37]. Given the intricate interplay of multiple factors during the process of online gamified learning, the threshold effect of these core conditions tends to be low. Once manifested, they can exert a significant influence on the outcomes [38,39], thereby holding methodological significance in delineating their positioning and role within the SEM. Subsequently, grounded in the factors identified through QCA, the study endeavors to quantitatively expound upon the relationship between these factors and learning engagement. This entails a nuanced exploration of direct effects, indirect effects (in the form of mediating variables), and moderating effects. Through a synthesis of theoretical underpinnings and logical deduction, a hypothetical model probing the intricacies of OGLE is proffered. Lastly, SEM assumes the mantle of testing this intricate theoretical model, which encompasses independent variables, mediating variables, and dependent variables. This rigorous evaluation seeks to identify the alignment between the hypothesized model and the empirical data [40], thereby validating the model's robustness and the viability of the underlying theory. Concurrently, a process of iterative refinement optimizes and enhances the model in tandem with empirical insights.

3. Literature review and QCA conditional variable selection

Founded upon the amplification of the TAM, this study incorporates six conditional variables within its purview, specifically PE, PF, HA, IE, PBC, and SN. Based on the essential understanding that these conditional variables affect learners' behavior, the study classified them into three broad categories: perceptivity, normalization, and structuration, to reflect how different types of motivations and constraints work together in OGLE.

3.1. Perceptual factors and OGLE

PE and PF are initial perceptual elements for the study of online gamified learning. PE refers to college students' perception of the expected educational outcomes that can be achieved through the use of gamified learning platforms [41]. Consistent with the findings of Venkatesh et al.'s research, college students' propensity to engage in gamified learning experiences registers a significant increase when they hold the belief that such pedagogical tools effectively enhance their academic skills or abilities [42]. Given that gamified learning platforms combine gaming elements with the overarching goal of advancing learning objectives [43], learning achievement becomes paramount. It emerges as a prerequisite for students' cognitive, emotional, and behavioral engagement [44]. Moreover, students' subjective evaluations of the captivating appeal and satisfaction derived from learning activities can increase cortical arousal and sensitivity [45,46]. This captivating and entertaining dimension emerges as a linchpin for gamification in igniting learning motivation [47]. As confirmed by the findings of Hamari & Koivisto, learning activities that are steeped in deep interest and entertainment have a profound impact and significantly increase student engagement [48].

3.2. Normalization factors and OGLE

HA and IE are central determinants that profoundly influence the depth of students' learning engagement [33]. These constructs embody the habitual nature of learning efforts and the importance of capturing students' attention. On the one hand, HA is aligned with previous behavior [18], while on the other hand, it is conceived as the measure of automaticity [49]. Given that a learner's historical behavior exerts an indelible influence on current and future patterns of learning behavior, HA emerges as a central protagonist in the pedagogical narrative [50]. To some extent, HA encapsulates a cultural facet of behavior that drives individuals towards a trajectory of continuous development in a predetermined direction [51]. As noted by Limayem et al. [49], cultivating a positive learning HA within a gamified learning milieu significantly increases students' willingness and frequency to engage in analogous learning activities in the future. This underscores that encouraging and reinforcing constructive learning habits can profoundly enhance students' sustained use and deep engagement with gamified learning platforms.

IE, which is synonymous with the absolute immersion and concentration of the learner in the learning process, is another key determinant that enriches the landscape of learning engagement. Flow theory [52] posits that individuals achieve optimal learning and performance when they reach a state of deep concentration and absorption in an activity. Online gamified learning environments promote immersion by providing challenging and interactive learning tasks that enhance motivation and effectiveness [48].

3.3. Structuration factors and OGLE

SN and PBC, as structuration factors, elucidate the influence of the external social milieu and individual beliefs on learning behavior. SN encapsulates students' perceptions of the attitudes of influential others (such as peers, family members, educators, and external recommendations) towards the use of gamified learning platforms [53]. These perceptions create social pressures that compel students to change their behavior to conform with the expectations of their immediate social environment [54]. Consistent with Ajzen's theory of planned behavior [55], individuals are more likely to engage in a particular behavior when they perceive support for that behavior from significant others. In the area of online gamified learning, students' propensity to engage with these platforms is significantly increased when they perceive that their social circles are supportive of adopting such platforms in the pursuit of learning.

On the other hand, PBC reflects students' confidence in their ability to actively participate in and successfully complete gamified learning activities [56]. This goes beyond personal efficacy beliefs to include perceptions of the accessibility of necessary resources and opportunities, which is a form of subjective cognition [57]. In line with Bandura's self-efficacy theory [58], an individual's belief in their competencies emerges as a central determinant that drives behavioral choices. Findings from research on online gamified learning highlight that students' learning engagement increases significantly when believe they have the necessary skills and resources to engage in these learning activities [59].

In summation, the perception category encompasses factors wielding a direct impact on learners' motivation and choices, the normalization category delves into the ramifications of enduring behavioral patterns and learning experiences, and the structuration factors shed light on the social and psychological dimensions necessitating consideration for the facilitation of learning engagement. On this foundation, we formulate the theoretical model as shown in Fig. 1.

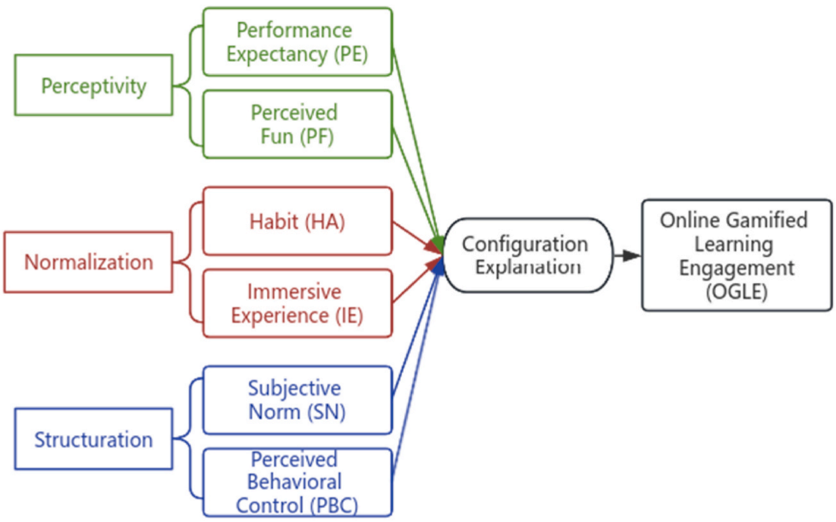

Fig. 1. OGLE influence mechanism configuration analysis model.

Table 1
Origins of survey measures.

Variables	Source of measurement items
SN	[21,65]
HA	[17]
IE	[66,67]
PBC	[21,65]
PE	[17,42]
PF	[68,69]
LS	[70]
OGLE	[71]

Note: SN represents subjective norm, HA represents habit, IE represents immersive experience, PBC represents perceived behavioral control, PE represents performance expectancy, PF represents perceived fun, LS represents learning style, and OGLE represents online gamified learning engagement.

4. Research methods

4.1. Measurement

4.1.1. Survey design

To guarantee the reliability and accuracy of the survey method employed in this research, its measurement components were meticulously modified, drawing inspiration from existing, authoritative scales. The modifications mainly addressed the following aspects. First, the measurement items were linked with the keywords of online gamified learning. Second, gamified learning, as a soft technology, was differentiated from the acceptance of hard technology, so the scale design was modified to address the characteristics of learning behaviors. For example, the former PF scale emphasized the entertainment level of the technology, while the modified scale added the measurement of curiosity and imagination, which are more in line with the characteristics of learning. The scale design differentiates between gamification and online learning, rather than merely accepting the technology. For example, in the OGLE, “If online learning incorporates gamification elements, I will be more actively engaged” was highlighted.

Table 1 presents the variables and the origins of the items selected for this investigation. In addition to the six variables identified for the QCA, the role of Learning Style (LS) as a critical moderating factor in the context of online gamified learning is emphasized [60, 61]. Given that independent variables typically exert no influence on moderating variables [62], this research delineates moderating elements as separate entities to prevent any overlap with the set theory-based configurational analysis and the linear regression-based moderating analysis, integrating them into the study’s structural equation model.

The first part of the survey gathers demographic information about the participants, and the following sections align with the study’s model construction. Responses are gathered using a five-point Likert scale, ranging from "1 Strongly Disagree" to "5 Strongly Agree," to measure each questionnaire item accurately. The survey was originally crafted in English and then carefully translated into Chinese paying particular attention to the nuances of online gamification. Three local educational experts reviewed the first version and gave constructive feedback to strengthen its content validity [63]. After the survey, the Chinese scale was translated back into English to maintain equivalence in translation [64].

4.1.2. Pilot test

Using a convenience sampling strategy, we undertook an initial evaluation of the survey by administering it to 100 students at our institution. Of these, 94 participants returned fully completed surveys, yielding an effective response rate of 94 %. We rigorously evaluated the reliability of each item, using Cronbach’s alpha for reliability assessment and factor analysis for construct evaluation and excluded those with reliability scores less than 0.7. Subsequent factor analysis demonstrated that each item loaded significantly on its intended factor while exhibiting minimal loading on unrelated factors. These findings underscore the survey’s strong convergent and discriminant validity.

4.2. Sample selection and data collection

4.2.1. Sampling procedures

The study was ethically approved by the research committee of the researcher’s institution prior to the start of the survey. Firstly, recognizing the unique aspects of online gamified learning, the research team conducted an initial survey in Macau, Guangdong, and Shanghai. This survey aimed to assess the extent of gamification’s incorporation into educational practices at universities and classrooms. We used classes in colleges and universities that had implemented gamified teaching and learning in these more developed provinces or special administration region as our sample frame. Because gamified learning is not widely applicable in all disciplines, the study did not limit the sample frame by discipline. The selection of the sample frame was driven by several critical factors. For example, the application of online gamified teaching approaches is limited in the less affluent central and western regions of China, so we did not include students from these areas to prevent any potential misinterpretation of data [72]. Our sampling strategy was informed by the diverse cultural environments of the chosen regions. Specifically, Macau's diverse cultural fabric, marked by its rich heterogeneity, was selected to enhance the study's wider applicability [73]. Furthermore, the universities in these selected areas provided access to a network of researchers and experts in relevant disciplines, offering essential insights and support. This approach was carefully designed to not only engage participants actively but also to reduce the potential effects of common method variance (CMV). Secondly, this study adopted the cluster typicality sampling method to address the specificity of the sample frame and select 11 higher education institutions (five in Guangdong, three in Macao, and three in Shanghai) as the sampling institutions. We selected 55 classes (33 in Guangdong, 8 in Macao, and 14 in ShangHai) that regularly used gamification. The participants were mainly undergraduates (see the descriptive analyses for detailed characteristics). We asked faculty or administrators in the relevant HEIs to distribute the questionnaires and ensure that the participating students gave informed consent.

4.2.2. Data collection

The questionnaire survey was conducted online between October 2023 and December 2023. To maximize response rates, the research team asked the commissioned agents of each HEI to distribute the questionnaire link to students so they could fill them in during class or at formal events. Before distributing the link the purpose of the study and the precautions for filling in the questionnaire were specifically explained to the participating students to ensure that they filled the questionnaires as effectively as possible.

Finally, 1910 of the 2210 selected students filled out the questionnaires. After a rigorous review process, which weeded out incomplete submissions and responses flagged for unusually quick completion times, a final tally of 1716 valid questionnaires remained—an 89.8 % effective response rate. The demographic makeup of respondents was closely balanced in terms of gender, with 47.2 % identifying as female and 52.8 % as male. In terms of place of origin, 15.4 % were from Macau, 51.2 % from Guangdong, 25.6 % from other areas, and 8.8 % from Shanghai. Most respondents were undergraduates aged 19–29 years. Regarding their field of study, 53.3 % studied the humanities, 39.5 % social sciences, and 4.3 % natural sciences (See Fig. 2.). The survey gathered data on previous exposure to gamified learning, with most participants reporting varying levels of familiarity, which could potentially influence their engagement levels in this study.

4.3. FSQCA and mplus

We employed a novel methodological blend specifically crafted to meet the study's objectives, combining a comprehensive approach and detailed methodologies. Key to this approach was the application of FSQCA, which is very well suited to analyzing the complex phenomena of students' experiences with OGLE. FSQCA applies a configurational logic to understand entities by examining how different elements interact within systems rather than in isolation [74]. By utilizing Boolean algebra, FSQCA effectively navigates around the issue of omitted variable bias, eliminating the need for variable control measures [75]. Its strength lies in shifting the analytical focus from the singular effects of variables to understanding how various combinations of conditions impact outcomes [76]. This highlights the role of conditions when they serve as critical components within these combinations without their being masked by the influence of other variables [77,78].

To augment our analysis, the preliminary insights gained from FSQCA were seamlessly integrated with the advanced structural equation modeling (SEM) approach, executed via Mplus software. SEM excels in examining the intricate interrelations between multiple variables within a cohesive model, allowing for a deeper investigation into the latent dynamics unveiled by FSQCA. This sophisticated integration leverages the configurational insights provided by FSQCA, enabling SEM to refine and validate these insights

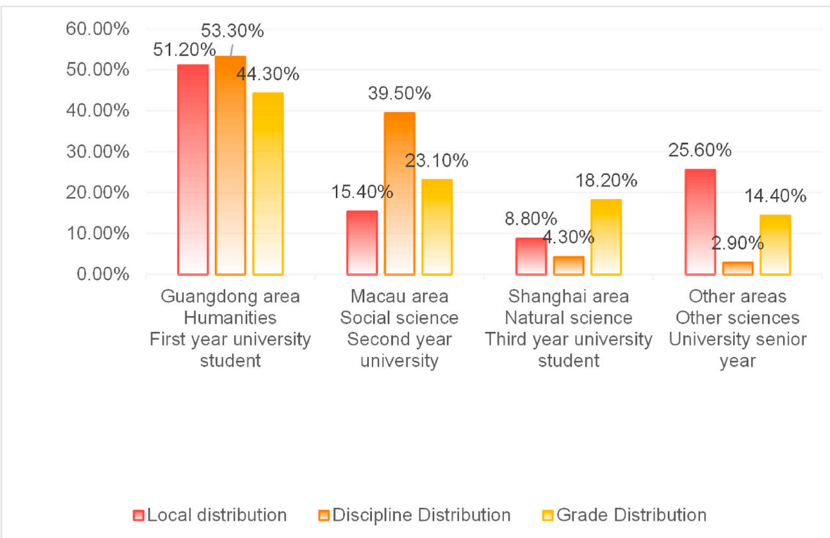

Fig. 2. Sample feature distribution.

Table 2
Defining variable calibration points.

Variables	Fully in	Crossover	Fully out
SN	4.4	3.4	2.4
HA	4.5	3.5	2.2
IE	4.3	3.3	2.1
PBC	4.4	3.4	2.3
PE	4.4	3.3	2.2
PF	4.3	3.4	2.4
OGLE	4.4	3.4	2.3

through its robust statistical modeling capabilities. By doing so, we can capture and analyze the multifaceted interplay between various factors influencing students' engagement with OGLE. Mplus was selected for its advanced features that facilitate testing complex mediation models efficiently and accurately, taking into account measurement error, which is critical for the investigation of the sophisticated relationships at the heart of our study [79]. We focused on assessing the model's fit to ensure accuracy in parameter estimation, thereby enhancing the model's overall validity [80]. Model fit was evaluated through various metrics, including chi-square degrees of freedom, root mean square error of approximation, comparative fit index, non-standard fit index, and standardized root mean square residual. This comprehensive methodological framework offers a rich, layered analysis of OGLE's impact mechanisms, laying a solid foundation for understanding the domain.

5. QCA analysis results

5.1. FSQCA analysis

Research has illuminated the complex effects that conditional variables exert on student participation within online gamified learning environments, highlighting the intricate dynamics that emerge from their interplay. Building on these insights, our research initially examined the configuration effects that govern their influence mechanisms.

We leveraged FSQCA, which is distinct from many quantitative methods due to its non-reliance on the assumption of normal data distribution. Central to FSQCA is the assumption of configuration and causality, suggesting that outcomes are derived from specific combinations of conditions rather than from single causal factors. To accommodate this assumption, we calibrated raw data into fuzzy-set scores. Utilizing Ragin's direct calibration method, we established distinct benchmarks for the outcome variable's conditions, designated as "full inclusion" (0.90), "midpoint crossover" (0.50), and "complete exclusion" (0.10) [81]. The results of the calibration are shown in Table 2. This calibration transformed the observed data values into a scale ranging from 0 to 1, in which the maximum, mean, and minimum values correspond to full inclusion, midpoint crossover, and complete exclusion, respectively.

To ensure the robustness and consistency of our calibrated data, we conducted a series of robustness checks by slightly adjusting these threshold values to observe potential impacts on the outcome configurations. This rigorous testing confirmed the stability of our initial calibration settings, as alternative adjustments did not result in significant changes to the core configurations that contribute to high engagement in gamified learning. Furthermore, FSQCA assumes the independence of cases, meaning that each case is analyzed based on its unique configuration of conditions, without presupposing any dependence on other cases. This assumption was critical in ensuring the integrity and validity of our analysis, allowing us to confidently interpret the configurational effects contributing to the phenomena being studied.

5.2. Single variable necessity analysis

We began by assessing the critical role and explanatory capacity of each variable through the application of consistency and coverage metrics for quantitative analysis. The consistency metric evaluates how reliably a variable explains the outcome, acting as a measure of its explanatory validity, while the coverage metric determines the degree to which a condition, or a combination of conditions, accounts for the observed outcome. A value approaching 1 for these metrics indicates a strong explanatory influence of the condition on the outcome [74].

Table 3 reveals that the consistency values for all examined variables do not reach the threshold of 0.8, indicating that these variables alone cannot be considered as sole explanatory elements. Therefore, it was essential to analyze the interplay and configurational effects between these conditional variables to understand their collective impact.

5.3. Sufficiency analysis of the combination of conditions

In Qualitative Comparative Analysis (QCA), a truth table is a systematic matrix that lists all possible combinations of causal conditions and their corresponding outcomes. It serves to identify and analyze the patterns and relationships between variables to determine causal configurations that lead to a specific outcome. The truth table analysis required that we set appropriate thresholds to examine the variable configurations. We established a frequency threshold of 10 and a consistency threshold of 0.8 for the analysis. Following the removal of essential conditions from the dataset, we proceeded to calculate complex, simple, and intermediate solutions. Our decision to focus on the analysis of intermediate solutions was influenced by their alignment with theoretical predictions and the

Table 3
Variable consistency and coverage analysis.

Conception	Result variables			
	OGLE		~OGLE	
	Consistency	Coverage	Consistency	Coverage
SN	0.660001	0.652337	0.440497	0.466735
~SN	0.460467	0.434294	0.671885	0.679330
HA	0.619008	0.636153	0.452031	0.498006
~HA	0.511530	0.465464	0.669745	0.653318
IE	0.703036	0.639417	0.489731	0.477490
~IE	0.425498	0.437522	0.630175	0.694645
PBC	0.669816	0.663138	0.433658	0.460253
~PBC	0.454817	0.428287	0.682610	0.689083
PE	0.681662	0.646082	0.457392	0.464737
~PE	0.435256	0.428004	0.651679	0.696969
PF	0.657261	0.655319	0.422632	0.451729
~PF	0.450106	0.421033	0.677526	0.679402

Note: "~" represents negation.

Table 4
High OGLE.

Conception	Paths				
	I	II	III	IV	V
SN	•	●	•	●	
HA		●	●	●	•
IE		●	●	●	•
PBC	•	•	●		●
PE	•	•		●	•
PF	●		•	•	●
Consistency	0.867487	0.898012	0.89633	0.892026	0.894898
Original coverage	0.375473	0.329589	0.318903	0.320714	0.331774
Unique Coverage	0.0784616	0.0325776	0.0218911	0.0237032	0.0347632
Consistency of solution	0.828092				
Coverage of solution	0.488407				

Note: ● signifies a core condition is present, ⊗ indicates a core condition is absent, • marks the presence of a marginal condition, and ⊗ signifies the absence of a marginal condition

support of empirical evidence for logical residuals. By combining the simple and intermediate solutions, we were able to identify the primary conditions contributing to the configurations [81], as detailed in Table 4, which showcases the pathways leading to elevated levels of OGLE.

The data presented in Table 4 highlight that all identified configurations exhibit consistency values above the 0.8 threshold, confirming their role in creating environments that foster high OGLE among students. The coverage values for these configurations are greater than zero, demonstrating the substantial explanatory value of each configuration and laying the groundwork for further investigations into this area.

In the realm of empirical research, one often encounters the concept of causal asymmetry, in which different factors may lead to the presence or absence of certain outcomes. This principle, embedded in the methodology of QCA, posits that the conditions precipitating

Table 5
Non-high OGLE.

Conception	Paths						
	I	II	III	IV	V	VI	VIIV
SN		⊗	⊗	●	⊗	⊗	
HA	●	•	⊗		•		⊗
IE	⊗	⊗	●	⊗		⊗	⊗
PBC		⊗	•	⊗	⊗	•	⊗
PE	⊗			•	●		
PF	⊗		⊗	⊗	⊗	⊗	•
Consistency	0.876805	0.872131	0.893222	0.922612	0.898826	0.8914	0.879381
Original coverage	0.205863	0.204196	0.132099	0.116961	0.128483	0.12037	0.11472
Unique coverage	0.034658	0.0193507	0.0403575	0.0218289	0.0108919	0.0200942	0.0272917
Consistency of solution	0.830017						
Coverage of solution	0.444607						

Note: ● signifies a core condition is present, indicates a core condition is absent, • marks the presence of a marginal condition, and signifies the absence of a marginal condition

an outcome do not always mirror those responsible for its non-occurrence [78]. To explore this notion of causal asymmetry further, our study extended its analysis to configurations associated with lower levels of OGLE, identifying condition combinations in which students did not exhibit high engagement. The detailed outcomes of this analysis are presented in Table 5.

6. Structural relationship assumptions and Mplus analysis results

6.1. Hypotheses and models

The results from the FSQCA reveal that HA and IE both emerge as core conditions in the three configurations influencing high levels of OGLE. Consequently, based on the inferential framework of the research design, these two latent variables exert a direct impact on OGLE when normalized. Prior studies demonstrate the impact of PF on gamified learning and education among college students, but

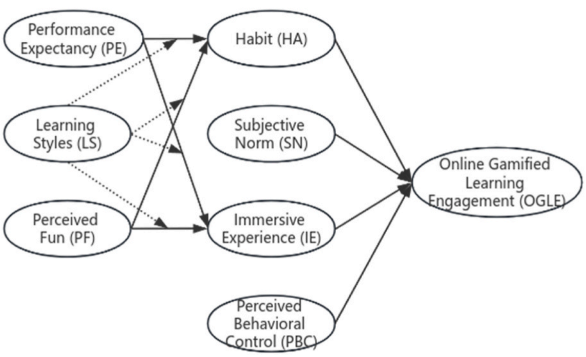

Fig. 3. OGLE influence mechanism structural relationship model.

Table 6
Table of factor loadings.

	Items	Factor Loadings	S.E.	Multi-Related Squares	CR	AVE
SN	SN1	0.789	0.011	0.623	0.878	0.644
	SN2	0.815	0.010	0.664		
	SN3	0.795	0.011	0.632		
	SN4	0.810	0.011	0.656		
HA	HA1	0.825	0.011	0.681	0.860	0.672
	HA2	0.837	0.011	0.701		
	HA3	0.797	0.012	0.635		
PF	IE1	0.817	0.010	0.667	0.888	0.665
	IE2	0.823	0.010	0.677		
	IE3	0.807	0.010	0.651		
	IE4	0.815	0.010	0.664		
PBC	PBC1	0.811	0.010	0.658	0.885	0.658
	PBC2	0.817	0.010	0.667		
	PBC3	0.816	0.010	0.666		
	PBC4	0.800	0.011	0.640		
PE	PE1	0.828	0.009	0.686	0.894	0.679
	PE2	0.833	0.009	0.694		
	PE3	0.820	0.010	0.672		
	PE4	0.815	0.010	0.664		
IE	PF1	0.830	0.010	0.689	0.892	0.674
	PF2	0.830	0.010	0.689		
	PF3	0.813	0.010	0.661		
	PF4	0.811	0.010	0.658		
OGLE	OGLE1	0.827	0.010	0.684	0.887	0.662
	OGLE2	0.824	0.010	0.679		
	OGLE3	0.792	0.011	0.627		
	OGLE4	0.812	0.010	0.659		

Table 7
Table of Pearson correlation coefficients.

	SN	HA	PF	PBC	PE	IE	OGLE
SN	0.802						
HA	0.361	0.820					
PF	0.433	0.341	0.816				
PBC	0.450	0.374	0.424	0.811			
PE	0.446	0.409	0.437	0.471	0.824		
IE	0.392	0.357	0.405	0.433	0.441	0.821	
OGLE	0.421	0.371	0.436	0.454	0.427	0.421	0.814

Note: Diagonal values represent the square roots of the AVE, while the lower triangle displays variable correlation coefficients.

focused more on IE as an external environmental condition [80,82] and less on its mediating role. The QCA analysis reveals that the direct effect of IE and HA on online gamified learning is greater with a lower threshold, i.e. the mere presence of the factors may lead to OGLE. Indeed, the ability of PF to influence OGLE lies in its capacity to induce a state of excitement or immersion among students, potentially becoming habit, and thereby fostering learning engagement [83]. When students exhibit positive PE in gamified learning, they are more likely to engage in repetitive learning activities, leading to the formation of HA, which further enhances their learning engagement [49]. Similarly, IE may initially form due to students' positive expectations of the effectiveness of gamified learning, subsequently deepening their involvement in learning activities [52]. Therefore, HA and IE respectively play mediating roles between PE, PF, and OGLE. Building upon the literature about QCA condition variables, the structural relationship assumes that SN and PBC exhibit a significant positive influence on OGLE.

Furthermore, LS is a preference pattern that individuals tend to adopt in receiving and processing learning-related information, so it plays a crucial moderating role in influencing relationships between PE, PF, and HA, IE. This role is illustrated by the fact that individuals with different LSs may respond differently to the same learning environment and stimuli due to their unique information-processing methods and learning preferences [84]. PE, denoting an individual's conviction in the efficacy of specific learning tools or strategies to yield anticipated learning outcomes, impacts HA and IE for individuals with distinct audiovisual learning inclinations

Table 8
Model fit evaluation results.

Indicators	χ^2/df	RMSEA	CFI	TLI	SRMR
Standard values	(1,5)	<0.08	>0.90	>0.90	<0.08
Actual values	1.27	0.013	0.997	0.997	0.014

[85]. PF describes an individual's subjective evaluation of the interest and enjoyment level of learning activities. Different LSs may result in variations in individuals' sensitivity and preferences for entertaining elements, thereby modulating the impact of PF on HA and IE. For instance, learners inclined towards exploration and experimentation may experience greater enjoyment in engaging in gamified learning tasks that involve interaction and higher levels of challenge, contributing to the formation of sustained learning HA and enhanced IE [86]. Hence, we posit that LS moderates the influence of the relationships between PE, PF, and HA, IE. The theoretical model is depicted in Fig. 3.

6.2. Reliability, validity analysis and CMV detection

We used Mplus software to conduct a detailed examination of our measurement model to establish a nuanced model that integrates and calculates factor loadings for various measurement items. The study measured the internal consistency of the measurement model using the composite reliability (CR) index, which calculates the collective variances and covariances of the measurement items associated with each construct, providing an assessment of the model's measurement reliability. To evaluate the model's validity, the study also computed the square root of the average variance extracted (AVE) for each construct based on Mplus outputs [87].

Analysis of the data presented in Tables 6 and 7 shows that the CR values for each construct are above 0.8, reflecting robust internal consistency within the model's constructs. Additionally, factor loadings for both primary and secondary measurement items are all above the threshold of 0.7, with AVE values surpassing 0.5. Significantly, the square roots of the AVEs exceed their respective Pearson correlation coefficients with other constructs, highlighting the model's strong discriminant validity. These findings collectively affirm the model's reliability and validity.

To validate the assumptions of the model and ensure the validity of the results, this study conducted the Durbin-Watson test on the residuals of the regression model to check for data independence. The Durbin-Watson test is a statistical method used to detect autocorrelation in the residual sequences of regression analysis. The result of the test yielded a Durbin-Watson statistic of 2.03 and a corresponding p-value of 0.56, which is significantly higher than the commonly used significance level (0.05). Therefore, we do not have sufficient evidence to reject the hypothesis of independence, indicating that there is no autocorrelation among the model residuals, thereby validating the applicability of the model and the rationality of the data processing.

In our SEM analysis, we meticulously tested the assumptions that are critical for valid inference. For normality, both skewness and kurtosis were within acceptable limits, confirming the suitability of the data for SEM. Assessing multicollinearity using the variance inflation factor (VIF) gave a maximum VIF of 4 among the predictors. This is significantly below the commonly accepted threshold of 5, indicating that multicollinearity does not distort the estimations. To further address potential concerns about CMV, we developed and analyzed a single-factor model hypothesizing that a common method factor influences all measurement items. A chi-square difference test comparing this single-factor model with the theoretical model revealed a statistically significant difference ($p < 0.05$) in fit, as indicated by the Mplus results. This significant chi-square difference between the theoretical and single-factor models suggests that CMV does not pose a significant concern in this study's findings, reinforcing the robustness of our analytical approach. Furthermore, the analysis of the correlation matrix also shows that the inter-variable correlations are appropriate, with no two variables displaying excessively high correlations (i.e., correlation coefficients close to ± 1). These test results confirm the independence and applicability of the model.

6.3. Model fitness test

The model's compatibility was assessed through Mplus software. The fit indices outcomes in Table 8 show an actual value of 1.27 for χ^2/df. This is significantly below the upper threshold of 5, indicating an excellent fit. A lower value suggests that the model discrepancies relative to the degrees of freedom are minimal, highlighting that the hypothesized model is close to the implied covariance matrix derived from the data. The root mean square error of approximation (RMSEA) was 0.013, which is far below the acceptable limit of 0.08, indicating a well-fitting model with little error of approximation. This low RMSEA value suggests that the model effectively captures the patterns in the data without overfitting. The comparative fit index (CFI) and the Tucker-Lewis index (TLI) were both 0.997, which exceeds the minimum standard of 0.90 and closely approaches the ideal value of 1.00. This reflects an almost perfect fit relative to a baseline model. High values for CFI and TLI signify that the model provides a substantially better fit than a null model in which no variables are interrelated. The standardized root mean square residual (SRMR) was 0.014, which is well below the threshold of 0.08, indicating a small residual mean square that suggests that the model's specified correlations closely approximate the actual

Table 9
Structural equation modeling path coefficients and hypothesis evaluation.

Path	Standardized Path coefficients	S.E.	p	Significance	Hypothesis test results
SN→OGLE	0.194	0.028	0.000	Significant	Supported
HA→OGLE	0.162	0.027	0.000	Significant	Supported
IE→OGLE	0.210	0.027	0.000	Significant	Supported
PBC→OGLE	0.238	0.029	0.000	Significant	Supported
PE→HA	0.334	0.027	0.000	Significant	Supported
PF→HA	0.213	0.028	0.000	Significant	Supported
PE→IE	0.340	0.026	0.000	Significant	Supported
PF→IE	0.274	0.027	0.000	Significant	Supported

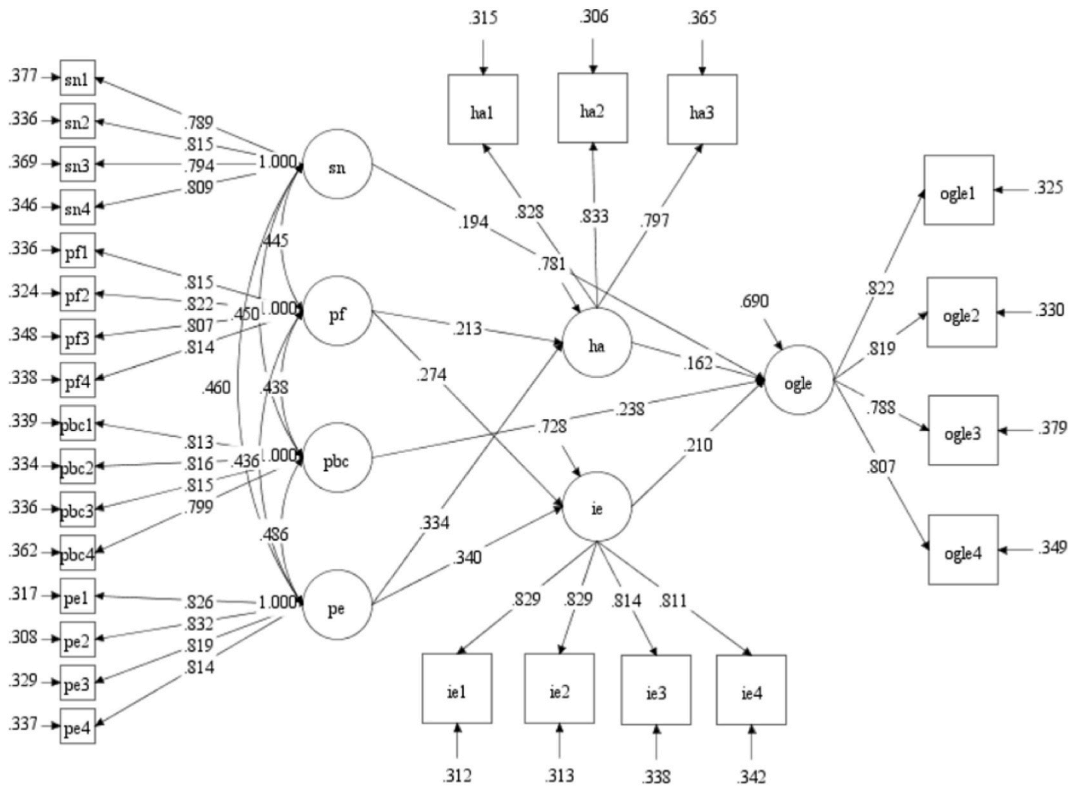

Fig. 4. Structural equation model standardized path analysis visualization.

Note: SN represents Subjective Norm, HA represents Habit, IE represents Immersive Experience, PBC represents Perceived Behavioral Control, PE represents Performance Expectancy, PF represents Perceived Fun, LS represents Learning Style, and OGLE represents Online Gamified Learning Engagement.

Table 10

Analysis of mediation effects and associated impact measures.

Effect	Path	Effect values	S.E.	p	99 % confidence intervals
Mediated effect	PE→HA→OGLE	0.054	0.010	0.000	[0.029, 0.084]
	PE→IE→OGLE	0.072	0.011	0.000	[0.044, 0.101]
Total mediated effect	PE→OGLE	0.126	0.014	0.000	[0.088, 0.163]
Mediated effect	PF→HA→OGLE	0.035	0.007	0.000	[0.017, 0.060]
	PF→IE→OGLE	0.057	0.009	0.000	[0.034, 0.088]
Total mediated effect	PF→OGLE	0.092	0.011	0.000	[0.063, 0.128]

data correlations.

These indices collectively suggest a robust fit of the model, confirming that the model is well-suited to explain the phenomena under study.

6.4. Path analysis and hypothesis test

Analyzing the standardized path coefficients, we meticulously evaluated the variables' impact, detailing these coefficients and hypothesis test results in Table 9. Fig. 4 displays the structural equation model's path analysis outcomes, demonstrating significant variable relationships at a 95 % confidence level ($P < 0.05$). This confirms the validity of all the hypotheses proposed in the study.

6.5. Mediation effect test

The detailed findings of our mediation model are outlined in Table 10. To enhance the model's validity, we utilized a bias-corrected percentile bootstrap test, conducting 5000 resampling iterations to establish a 99 % confidence interval. The findings reveal that all path coefficients hold statistical significance, with the 99 % confidence intervals excluding zero. This underscores the critical influence of these pathways within the mediation framework, affirming the validity of the hypotheses proposed in this investigation.

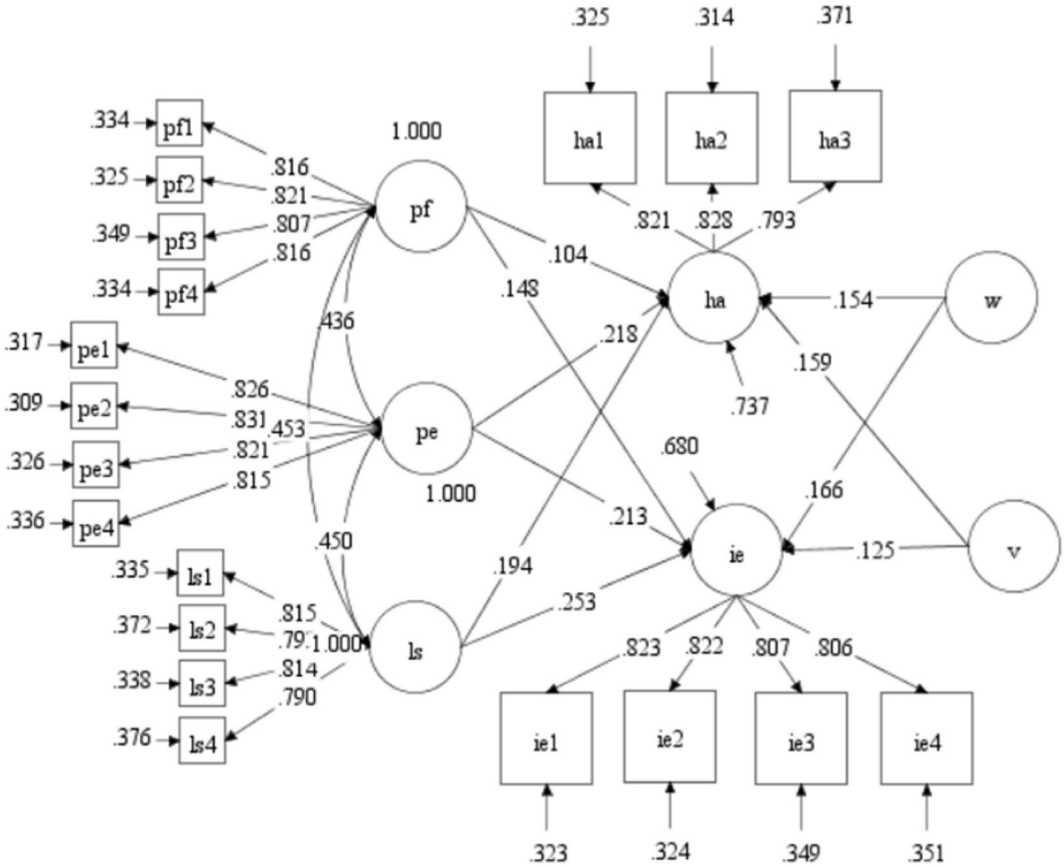

Fig. 5. Moderating effects path analysis illustration.

Table 11
Analysis of moderation effects and impact magnitude.

Path	Effect values	S.E.	p
LS x PE - > HA	0.154	0.032	0.000
LS x PF- > HA	0.159	0.032	0.000
LS x PE - > IE	0.166	0.031	0.000
LS x PF- > IE	0.125	0.030	0.000

6.6. *Moderation effect testing*

We integrated LS as a moderating variable to examine its effect on the model's integrity. The outcomes, including standardized path coefficients, standard errors, critical ratios, and p-values, are detailed in Fig. 5 and Table 11. The analytical results reveal that LS plays a significant moderating role in the relationships between PE and HA, PF and HA, PE and IE, and PF and IE. Specifically, when the level of LS is higher, the impact of PE on HA, PF on HA, PE on IE, and PF on IE is enhanced.

7. Discussion and contribution

7.1. *From awareness to normalization: the core mediator of college students' online gamified learning engagement*

The results from the QCA reveal that both IE and HA emerge as core conditions in the configurations leading to high OGLE and the absence of IE tends to low OGLE results. SEM analysis further confirms the significant mediating effects of IE and HA, unveiling their crucial roles as bridges connecting learning motivation and behavior. These findings align with Bandura's self-efficacy theory and Csikszentmihalyi's flow theory [58,87], emphasizing the impact of individuals' beliefs in their abilities and their experience of complete engagement in OGLE activities. Despite attempts to extend the TAM by introducing new external variables to enhance the model's explanatory power, these models often fall short of delving into potential mediating relationships among variables [88], particularly how IE and HA mediate the relationship between perceptual factors and usage behavior.

OGLE unfolds as an intricate operational continuum. Online learning is inherently associated with reduced efficacy and attention [2,3], for which gamification can be a potent remedy [8]. However, the assimilation of novel concepts or technological behaviors necessitates a gestation period, characterized by a fusion of perceptual and rational cognitions. It is only when cognition transmutes from the ephemeral to the enduring that individuals can transfigure it into a sustained impetus for acceptance [89]. Gamified learning is both a technical and a learning behavior. For technical behaviors, PE and PF do not necessarily need to be mediated by IE and HA to have an impact on OGLE but stimulating self-discipline and continuity is very important for online learning behaviors. This highlights the role and importance of IE and HA as mediators [90,91] with HA embodying the automatic and constant nature of learning behaviors that reinforce the influence of PE and PF on OGLE. IE shows its impact on OGLE in terms of mental perception. Amalgamating QCA and SEM presents a meticulous scrutiny of the determinants of OGLE and also clarifies its essential mediating role in this process. Moreover, it prescribes a pathway for pedagogical praxis to bolster IE through the augmentation of PE and PF, fostering the cultivation of active learning HA as a viable means to enhance learning engagement and efficacy.

7.2. Subject cognition and external influence: two-way interaction between structural factors and online gamification behavior

Extended TAM introduced two additional constructs, SN and PBC, which serve as core conditions for two configurations. Notably, the absence of these two core conditions is more likely to lead to non-high OGLE, underscoring their significance. The theory of planned behavior posits that these factors collectively shape students' behavioral intentions, subsequently influencing their actual participation [55]. In this framework, SN and PBC, as structural factors, reflect the dual constraints of external social environment and intrinsic capabilities on learning behavior. From a macrostructural perspective, Giddens' structuration theory is in agreement. From this perspective, individuals are not only products of social structures but also producers thereof [92]. Applied to online gamified learning, this implies that while students' learning behavior is influenced by existing educational structures and norms, it also has the potential to alter this structure through their participation and practices. Learning in the context of gamified elements implies a change in traditional educational models and the adoption of new educational approaches. The emergence of something new is more likely to bring about the constraining effect of external norms, such as the influence of traditional thoughts. However, the subjectivity of the student is very important, and self-efficacy, the degree of control over the e-learning system, and the game technologies are also important factors influencing learning engagement [93]. For instance, SN not only constrain students' learning behavior, but their active engagement might also change societal perceptions and acceptance of gamified learning, consequently influencing the structure of educational practices.

SN and PBC not only exert constraints on students' learning behavior from external influences but also undergo continuous reciprocal influences from students' cognition and behavior through their participation in gamified learning activities, creating a dynamic interactive process [94]. This perspective aligns with Giddens' core discourse on "agency and structure" interaction in his structuration theory, asserting that individuals, in their daily lives, are not only influenced by social structures but also contribute to the reproduction and transformation of these structures through their own actions [92]. Additionally, Bandura [95], in discussing social cognitive theory, emphasized that individuals' beliefs and behaviors can influence the social environment and structure. Similarly, educational technology and practices are shaped not solely by external societal norms and structures but also by students' active engagement and behavior, which can reciprocally shape and improve the application of these educational practices and technologies [96]. This bidirectional interaction unveils the complex interplay between individuals and societal structures within the field of educational technology, underscoring the need, in designing and implementing gamified learning strategies, to recognize students not only as recipients of the learning process but also as agents capable of influencing and changing the educational environment. By recognizing the dynamic interplay between subjective cognition and external influences, this study advances the understanding of how structural factors and online gamification behaviors interact, offering a nuanced perspective on the factors that drive and constrain OGLE.

7.3. Learning styles: a moderator between perceptibility and normalization

LS influences how individuals perceive and respond to educational activities, including activities within online gamified learning environments. When learning activities align with an individual's learning style, it may enhance their perceived performance and enjoyment [97], thereby fostering a more positive formation of HA and deeper levels of IE. Social-cultural theory emphasizes the role of social interaction and cultural tools in learning development. Online gamified learning environments, as cultural contexts, necessitate designs and interactive approaches that consider learner diversity and individual differences [98]. Research indicates that diverse LSs are closely associated with learners' experiences in online and gamified learning environments [99,100]. For instance, learners with a graphical LS may experience higher levels of PF and IE in visually rich gamified learning environments [101]. This experience, in turn, enhances their positive learning HA and reinforces their OGLE. The variation between perception and normality is strong or weak mainly because it is related to the characteristics of the learning subject, and differences between people are the main reason for the eventual formation of different habits and deep experiences. In learning, this difference is expressed as learning styles [102]. This suggests that LS indirectly impacts learning behavior and outcomes by modulating the relationship between perceptual and habitual factors. This finding underscores the importance of considering individual differences, particularly the diversity in LSs, when designing and implementing online gamified learning activities. Educational interventions and the design of learning activities should be adjusted to fit the individualized needs of learners [103]. By identifying LS as a critical moderating factor, this study enriches the existing theoretical models and provides practical insights for the design of gamified learning environments, ensuring that they cater to the diverse needs of learners and thereby enhance their engagement and learning outcomes.

7.4. Theoretical and practical implications

This study validates the extended TAM at a theoretical level and verifies and improves the relationships of the extended TAM from the perspective of the combined QCA and SEM, emphasizing the theoretical implications of HA and IE as mediating effects. The study identified the effects of different configurations of core conditions on learning engagement in terms of the dimensions of QCA's perceptual, normative and structured condition variables, refining the theoretical assumptions derived from the literature. This research finding can undoubtedly be applied to other educational disciplines related to behavioral engagement.

Educators and developers of gamification systems need to strengthen the PE and PF of students' gamified learning, so that the design and practice of gamified teaching is more relevant, operational and effective so it can fully engage students and shape good learning habits. To understand and facilitate online gamified learning behaviors, educators need to focus not only on students' subjective perceptions and the influence of external social norms, but also recognize the potentially transformative effects of the behavior of students on educational practices and social structures. Gamified learning environments should include more hands-on and teamwork elements for learners who prefer to learn through practice and interaction, and more complex problem solving and personal challenges for learners who prefer logical thinking and independent learning. Reflections on the LS moderation function reveal the need to consider these individual differences when designing and implementing gamified learning environments.

8. Limitation and further research

Firstly, the QCA-SEM hybrid design employed in this study provides a robust tool for understanding the intricate mechanisms of OGLE. However, the diverse methodological foundations and interdisciplinary nature of the research design constrain the inferential capacity of causal relationships [104]. QCA is based on set theory, while SEM remains linear in nature for latent variable modelling. This study seeks to discover the variables that affect the core configurations of the multiple conditional variables through the analysis of set theory, thus supporting the setting of mediating variables. This research design is methodologically Innovative because it relies on the threshold effectivity of the core variables appearing in multiple configurations being low to judge their direct influence on the outcome variables. However, the study is not able to directly judge the direct influence that the perceptual factors, PE and PF, have on these variables. Therefore, assuming these core variables to be mediating variables in structural equation modelling also references their own nature as normalizing factors. However, the QCA results cannot be the sole basis for the mediating assumption. Its generalizability needs to be supported by more similar hybrid study designs and empirical results.

Secondly, the study sample is composed mainly of university students from specific regions or schools in China, potentially limiting the universal applicability of the research findings. Learners with a Chinese background and learners from other countries with different cultural backgrounds and education systems may exhibit different learning styles and motivations. There may also be differences in PF and IM towards gamified learning across different cultural contexts [105]. Although this study explores the moderating role of LS in the relationship between perceptual and habitual factors, there might be other unconsidered moderating or mediating variables, such as individual emotional states that are characteristics of the technological environment. Furthermore, the classification and measurement of learning styles exhibit diversity [106], and different classification and measurement tools may lead to divergent research outcomes.

Future studies may consider a two-stage QCA design mode with the addition of corresponding perceptualization factors. Such a design could treat the perceptualization factors separately from the normality factors to simultaneously discover the direct effect of the perceptualization factors on the normality factors, and to make up for the methodological limitations mentioned above. If the design can be well validated, the formulation of structural equation modelling assumptions will go beyond the framework of merely relying on theoretical and literature support and will be well developed at the technical level of the methodology. Additional research could investigate other variables that might influence the relationship between perceptual and habitual factors, including individual emotions, features of learning environment design, and social support. The introduction of these variables would contribute to a more comprehensive understanding of the intricate mechanisms of OGLE. Furthermore, future research could broaden the scope of the sample, embracing learners from different cultures and academic disciplines. This expansion would aid in assessing the universality and applicability of the findings of this study and exploring how cultural and disciplinary differences might impact the effectiveness of gamified learning. Finally, future research could consider the use of longitudinal studies to deepen the understanding of how learners' behaviors and attitudes change over time in gamified learning environments and how these changes affect learning engagement. This approach would contribute to revealing the dynamic processes underlying the formation of HA and IE, elucidating how they are influenced by continuously changing individual and environmental factors.

9. Conclusion

This study employs a methodological framework that integrates QCA and SEM to conduct an in-depth exploration of the mediating roles of IE and HA in the relationship between PE and PF and the OGLE among university students within the context of online gamified learning environments. The research findings show that IE and HA play pivotal roles as core conditions promoting high levels of OGLE among learners, with a particular emphasis on how IE absence leads to non-high OGLE outcomes. Furthermore, this study investigates the moderating effect of LS on the relationship between perceptual and habitual factors, and underscores the significance of structural factors such as PBC and SN in online gamified learning behavior [80]. In summary, This study not only contributes important insights to the theoretical development and educational practice of gamified learning, but also suggests new directions and recommendations for future research in this field. By gaining a deeper understanding of learners' perceptions, habitual behaviors, and structural factors within gamified learning environments, we can design engaging and effective learning experiences tailored to the preferences and needs of college students.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Hongfeng Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition. **Fanbo Li:** Writing – review & editing, Visualization, Validation, Software, Resources, Methodology, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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