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Research article

Effects of game-based learning on academic outcomes: A study of technology acceptance and self-regulation in college students

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ABSTRACT

Objective: This study investigates the interplay between the Technology Acceptance Model (TAM), self-regulation strategies, and academic self-efficacy, and their collective impact on academic performance and perceived learning among college students engaged in remote education.
Methods: A sample of 872 university students from Southern China participated in this study. Structural Equation Modeling (SEM) was employed to analyze the theoretical relationships among the variables. The research focused on two primary areas: the connection between academic self-efficacy and gameful self-regulation strategies within the framework of TAM, and the influence of TAM's three dimensions on students' perceived learning and academic performance.
Results: Findings highlight self-efficacy and gameful self-regulation strategies, in enhancing technology acceptance. Improved acceptance of technology is shown to positively affect academic performance and the perceived learning experience of students in classes using game-based online resources.
Conclusion: The study emphasizes the significance of self-efficacy and gameful self-regulation strategies in shaping students' perceptions and attitudes towards technology. These factors are found to be key determinants of both perceived learning and academic achievement in the context of game-based online resource classes.

1. Introduction

The COVID-19 pandemic necessitated a rapid transition to online learning in universities across China from 2020 to 2022 [1–4] This abrupt shift raised concerns among students about the quality and adequacy of their education, likely stemming from challenges in effectively developing online teaching skills despite some instructor training [5–7]. Online learning requires access to technology, tools, and educational resources that proved difficult in developing regions like China due to issues such as poor internet connectivity and limited ICT knowledge [8,9].

Transitioning to remote education presented unique obstacles in Asia, including inadequate broadband, varying institutional capacities, reduced oversight potentially impacting outcomes, and lower student self-regulation skills crucial for distance learning success[10–12]. Concerns exist around academic performance given low digital literacy among students and the greater autonomy online classes demand compared to traditional settings(X. [13–17]). Consequently, research exploring factors influencing perceived learning and achievement in online education is warranted[18–20].

Prior studies highlight psychological, individual, instructional, familial, economic, and technological variables impacting academic outcomes, emphasizing self-efficacy, self-regulation strategies, and technology acceptance as key factors[21–24]. The Technology

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Acceptance Model (TAM) suggests perceived usefulness and perceived ease of use determine system usage intentions[25]. In higher education, these factors directly influence technology acceptance, with gameful self-regulation strategies also associated with usefulness and ease of use perceptions as students adapt to online classes[24,25]. In Asia, studies report that these factors are associated with e-learning technology acceptance among university students. Moreover, the relationship between gameful self-regulation strategies, PU, and PEOU is emphasized as students adapt to online learning.

The current study extends previous research by introducing the novel concept of gameful self-regulation strategies into classroom gamification design within the TAM framework. Specifically, it investigates whether gameful self-regulation can improve student acceptance of classroom technology and games[26]. Exploring this relationship is vital for optimizing future classroom design to enhance the online educational experience and academic achievement in the context of remote learning in China.

Therefore, based on the research hypothesis and the relationship between variables, the theoretical model of this study is shown in Fig. 1.

2. Methods and data

2.1. Measurement

Data Sheet: A data sheet collected sociodemographic information including age, gender, university affiliation, and grade point average from the last semester.

Academic Self-Efficacy: The study utilized the Perceived Self-Efficacy Scale Specific for Academic Situations[27], adapted to the Chinese university context. This scale assesses students' self-perceived academic competence through a unidimensional, 9-item format (e.g., "I consider myself qualified enough to successfully handle any academic assignment"). Responses are measured on a Likert scale ranging from 1 (Never) to 4 (Always)[28–30].

Gameful Self-Regulation Strategies: The Gameful Self-Regulation Strategies was adapted to the Chinese context[31]. This dimension, composed of 7 items (For example, "Guided: Feelings of being guided as to how, through what, and when can the goals of the gamified service be attained "; "Playfulness: Feelings of voluntary engagement with imaginative or exploratory activities that have clearly defined rules"), evaluates students' ability to regulate their cognitive processes during learning, including planning, monitoring, and regulation strategies. The response format is a Likert scale from 1 (Totally false) to 7 (Totally true).

Acceptance of Technologies: An adapted version of the Technology Acceptance Model (TAM) scale was employed[32,33]. This version, tailored to the Chinese context, consists of 12 items across three dimensions: Perceived Usefulness, (e.g., "The use of technology increases efficiency") Ease of Use (e.g., "I am easily trained in the use of technology"), and Attitudes towards Use (e.g., "I am comfortable using technology"). Responses are recorded on a Likert scale from 1 (Strongly disagree) to 7 (Strongly agree).

Perceived Learning: The Cognitive Perceived Learning in Virtuality Questionnaire, based on the conceptual frameworks of Rovai (M. [34,35]), was utilized. This unidimensional questionnaire includes 6 items (e.g., "I have understood the main concepts of the game/online resources I have participated in"), with responses ranging from 1 (Strongly disagree) to 5 (Totally agree).

All the questionnaire used in the study have been calculated the Cronbach's alpha, and performed well that ranged from 0.78 to 0.92 (detailed in Table 1).

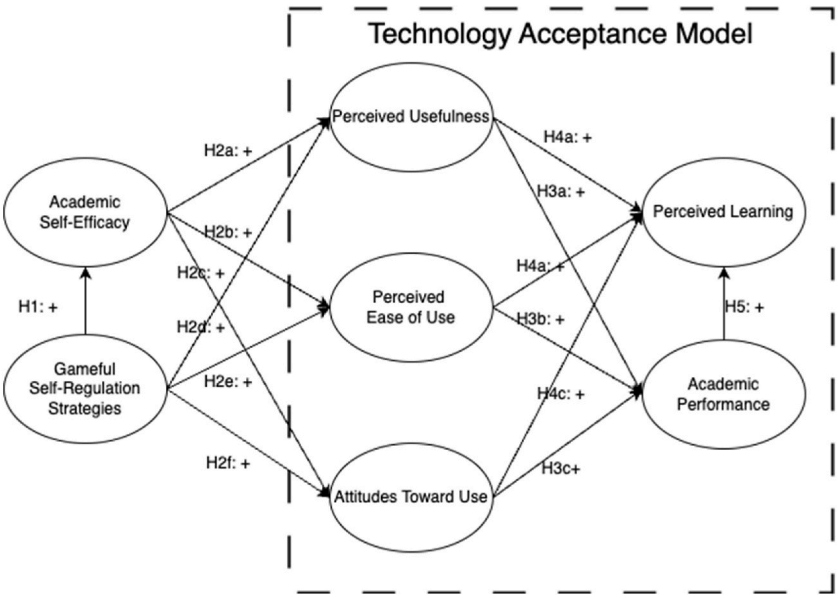

Fig. 1. Hypothesis model.

2.2. Procedure

The study employed a cluster randomized experiment involving 22 classes from four universities with similar academic standings, each offering a Liberal Course on Innovation and Innovation Management in Mar 2022.

The gamification was implemented through a series of interactive activities and assignments. Each student was assigned a simulated business, which they were responsible for managing according to Liberal principles learned in the course. This hands-on approach allowed students to apply theoretical knowledge in a practical, engaging context. The gamification elements included point scoring based on ESG compliance, leaderboards to encourage healthy competition, and badges for achieving specific milestones. These elements were designed to enhance student engagement, motivation, and understanding of ESG concepts (detailed in Fig. 2).

The instruments were administered virtually through a course evaluation survey after the class score was evaluated at the end of August 2022. Participants first encountered an informed consent form outlining the study's purpose and the nature of their participation. This was followed by the sociodemographic data sheet and the various questionnaires. The study adhered to ethical guidelines and ensured confidentiality and voluntary participation throughout the process.

2.3. Analysis schema

The collected data were processed and analyzed using the R 4.3.2 and lavaan 0.6.16. The initial stage involved scrutinizing the dataset for missing values and outliers. Descriptive statistics were subsequently calculated to provide a foundational understanding of the data's general characteristics.

The core of the analysis entailed the application of a structural equation modeling approach. This method was chosen due to its robustness and flexibility in examining complex relationships between multiple variables. The robust maximum likelihood estimation (MLM) method was utilized, which is particularly advantageous for datasets that may deviate from multivariate normality. This method corrects for potential non-normality, ensuring the reliability and validity of the model's estimates.

To evaluate the fit of the structural equation model, a range of fit indices were considered. These indices included the Bentler-Bonett Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). A good model fit was determined based on established criteria: CFI and TLI values exceeding 0.90, RMSEA values below 0.06, and SRMR values under 0.08. These thresholds, recommended by various scholars in the field, ensure that the model adequately represents the data and captures the underlying relationships between variables[36].

3. Result

3.1. Descriptive analysis

In the descriptive analysis of the study's sample, a total of 872 participants were reported, with an average age of 21 years. Gender distribution among the participants was fairly balanced, with a slight female predominance: 58 % of the participants were female (n = 507), while 42 % were male (n = 365), detailed in Table 2

The distribution of majors among the participants was diverse, with several fields of study represented. The most common majors were Accounting and Meteorological Sciences, each constituting 19 % of the sample (n = 153 and n = 168, respectively). This was followed by Language and Psychology, both at 16 % (n = 140 and n = 164, respectively). Other fields of study represented in smaller numbers included Economics (3 %, n = 27), History and Politics (3 % and 2 % respectively), and Art (2 %, n = 15). Some majors had very few representatives, such as Electronic, which had only two participants, and Medicine, Math, and International Relationship, each with fewer than ten students represented in the sample. Computer Science had a noticeable representation at 18 % (n = 153).

The diversity of academic disciplines among the participants indicates a broad representation across different fields of study, providing a comprehensive view of the student body's academic orientation during the period of remote education necessitated by the Covid-19 pandemic.

3.2. Confirmatory factor analysis

In the confirmatory factor analysis (CFA), the standardized factor loadings for each latent factor and their respective indicators were examined. Table 3 displays the results of the CFA, including the standardized factor loadings, 95 % confidence intervals (CIs), significance levels, standard errors (SE), z-values, and p-values.

For the latent factor of Academic Performance (AP), all indicators exhibited strong factor loadings ranging from 0.721 to 0.873, all with p-values less than 0.001, indicating a significant relationship between the indicators and the latent factor. Similarly, for Academic

Table 1
Cronbach's alpha for each latent variable.

AP	GSR	ASE	PU	PEU	ATU
0.91	0.9	0.92	0.85	0.78	0.78

Notes: AP: Academic Performace, GSR: Gameful Self-regulation, ASE: Academic Self-efficacy, PU: Perceived Usefulness, PEU: Perceived Ease of Use, ATU: Attitudes towards Use.

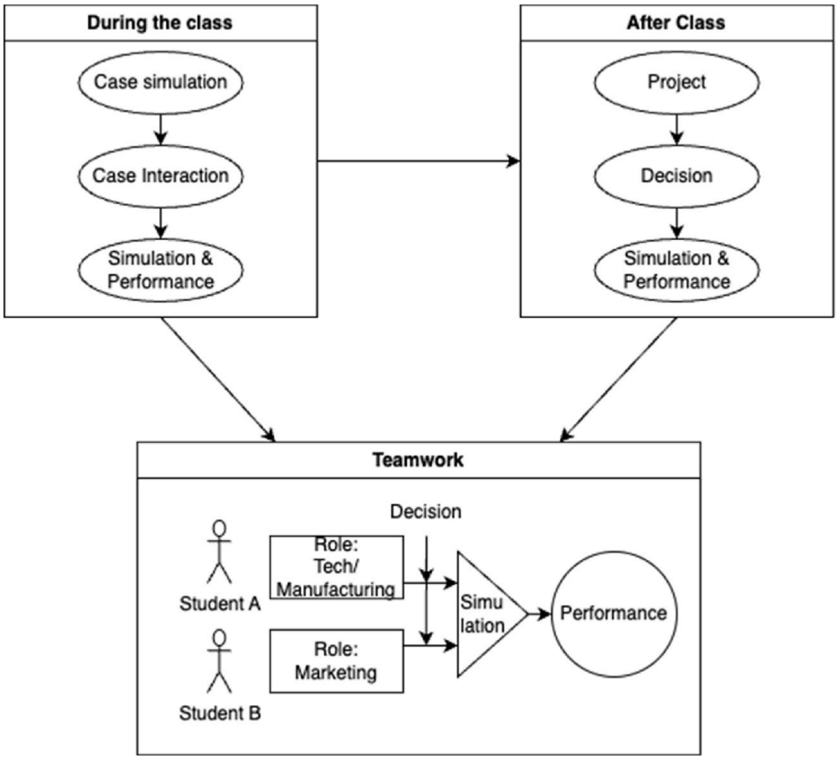

Fig. 2. Gamification setting.

Table 2
Summary statistics.

Variable		N	Mean
Gender		872	
	Female	507	58 %
	Male	365	42 %
Major		872	
	sociology	18	2 %
	history	3	0 %
	politics	23	3 %
	Art	15	2 %
	computer	153	18 %
	electronic	2	0 %
	Accounting	3	0 %
	meteorological	168	19 %
	design	43	5 %
	economy	27	3 %
	educate	15	2 %
	finance	6	1 %
	physics	5	1 %
	manage	24	3 %
	hospitality	9	1 %
	language	140	16 %
	literature	17	2 %
	Medicine	9	1 %
	Math	7	1 %
	Psychology	164	19 %
	International Relationship	21	2 %
Age		872	21

Self-efficacy (ASE), Attitudes towards Use (ATU), and Gameful Self-regulation (GSR), all indicators demonstrated substantial factor loadings ranging from 0.628 to 0.885, with all p-values less than 0.001.

Regarding Perceived Usefulness (PU) and Perceived Ease of Use (PEU), the indicators also displayed notable factor loadings,

Table 3
CFA and Factor loading.

Latent Factor	Indicator	Standardized Loading	95 % CI	sig	SE	z	p
AP	AP1	0.721	0.687–0.756	***	0.018	40.766	0.000
AP	AP2	0.821	0.797–0.846	***	0.013	64.885	0.000
AP	AP3	0.834	0.811–0.858	***	0.012	69.718	0.000
AP	AP4	0.796	0.769–0.824	***	0.014	57.073	0.000
AP	AP5	0.788	0.760–0.816	***	0.014	54.690	0.000
AP	AP6	0.873	0.854–0.893	***	0.01	87.943	0.000
ASE	ASE1	0.764	0.733–0.794	***	0.016	48.803	0.000
ASE	ASE2	0.688	0.650–0.726	***	0.019	35.650	0.000
ASE	ASE3	0.791	0.763–0.819	***	0.014	55.425	0.000
ASE	ASE4	0.818	0.793–0.843	***	0.013	63.702	0.000
ASE	ASE5	0.678	0.639–0.717	***	0.02	34.334	0.000
ASE	ASE6	0.808	0.782–0.834	***	0.013	60.357	0.000
ASE	ASE7	0.628	0.586–0.671	***	0.022	28.695	0.000
ASE	ASE8	0.699	0.663–0.736	***	0.019	37.288	0.000
ASE	ASE9	0.808	0.782–0.834	***	0.013	60.363	0.000
ATU	ATU1	0.666	0.620–0.712	***	0.024	28.189	0.000
ATU	ATU2	0.791	0.753–0.829	***	0.019	40.922	0.000
ATU	ATU3	0.660	0.614–0.707	***	0.024	27.717	0.000
ATU	ATU4	0.633	0.585–0.682	***	0.025	25.517	0.000
GSR	GSR1	0.793	0.766–0.821	***	0.014	56.652	0.000
GSR	GSR2	0.867	0.847–0.887	***	0.01	85.628	0.000
GSR	GSR3	0.828	0.804–0.852	***	0.012	68.043	0.000
GSR	GSR4	0.885	0.867–0.903	***	0.009	96.396	0.000
GSR	GSR5	0.644	0.603–0.685	***	0.021	30.494	0.000
GSR	GSR6	0.666	0.626–0.705	***	0.02	33.000	0.000
GSR	GSR7	0.467	0.412–0.521	***	0.028	16.815	0.000
PEU	PEU1	0.714	0.670–0.758	***	0.023	31.658	0.000
PEU	PEU2	0.744	0.702–0.787	***	0.022	34.331	0.000
PEU	PEU3	0.757	0.715–0.798	***	0.021	35.452	0.000
PEU	PEU4	0.230	0.160–0.301	***	0.036	6.395	<0.001
PU	PU1	0.120	0.046–0.193	**	0.037	3.202	0.001
PU	PU2	0.566	0.512–0.621	***	0.028	20.365	0.000
PU	PU3	0.612	0.561–0.664	***	0.026	23.294	0.000
PU	PU4	0.574	0.519–0.628	***	0.028	20.813	0.000

Notes: AP: Academic Performace, GSR: Gameful Self-regulation, ASE: Academic Self-efficacy, PU: Perceived Usefulness, PEU: Perceived Ease of Use, ATU: Attitudes towards Use.

ranging from 0.120 to 0.612 for PU and from 0.230 to 0.757 for PEU, all with p-values less than 0.001.

Overall, the confirmatory factor analysis results indicate that the selected indicators adequately represent their respective latent constructs, supporting the validity of the measurement model used in this study.

3.3. Path analysis

The path analysis (detailed in Fig. 3 and Table 4) meticulously examined the interrelations among gameful self-regulation

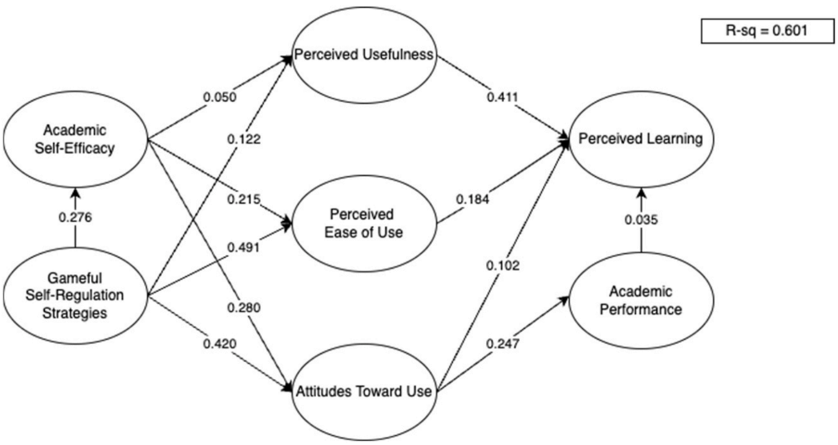

Fig. 3. Structural equation model.

strategies, academic self-efficacy, and the components of the TAM—perceived usefulness and ease of use—and their subsequent effects on academic outcomes, namely perceived learning and academic performance.

The findings affirm Hypothesis 1 (H1), which predicted a positive influence of gameful self-regulation strategies on academic self-efficacy. The analysis revealed a robust and significant relationship (Estimate = 0.276, SE = 0.022, z-value = 12.746, $p < 0.001$), reinforcing the notion that gameful self-regulation can bolster students' confidence in their academic capabilities.

Investigating Hypothesis 2 (H2) yielded nuanced results. Gameful self-regulation strategies were significantly associated with an increased perceived ease of use of technology (Estimate = 0.491, SE = 0.047, $p < 0.001$), as was academic self-efficacy (Estimate = 0.215, SE = 0.074, $p = 0.004$), suggesting that both intrinsic motivation and confidence play vital roles in the technological engagement. Nevertheless, academic self-efficacy's impact on perceived usefulness was positive but modest (Estimate = 0.050, SE = 0.019, $p = 0.010$).

Hypothesis 3 (H3) posited that TAM positively influences academic performance. This hypothesis was partially substantiated through the significant effect of attitudes towards technology use on performance (Estimate = 0.247, SE = 0.092, $p = 0.007$). However, perceived usefulness did not exhibit a significant impact on academic performance.

Hypothesis 4 (H4) suggested that TAM components enhance perceived learning. This was confirmed with a strong positive effect from perceived usefulness to perceived learning (Estimate = 0.411, SE = 1.320, $p = 0.002$).

Finally, Hypothesis 5 (H5), which assumed that academic performance would positively influence perceived learning, was validated by the data, indicating a meaningful relationship (Estimate = 0.035, SE = 0.017, $p = 0.036$).

In essence, the SEM analysis underscores the pivotal role of gameful self-regulation strategies and academic self-efficacy as precursors to the effective adoption of technology in learning environments, as conceptualized by the TAM. The study's outcomes highlight the imperative of embedding gameful and self-regulatory elements within educational strategies to invigorate student engagement and optimize academic performance. These insights contribute valuable guidance for designing educational interventions and digital learning platforms that align with contemporary pedagogical goals.

The model demonstrated a reasonable fit to the data (detailed in Table 5), with a chi-square statistic ($\chi 2$) of 1372.97 with 547 degrees of freedom (df), resulting in a $\chi 2/df$ ratio of 2.51. While the chi-square statistic was significant due to the large sample size, the $\chi 2/df$ ratio fell within acceptable limits, indicating a reasonable fit between the model and the observed data.

Furthermore, the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) both exceeded the recommended threshold of 0.95, with values of 0.97 and 0.96 respectively. These indices suggest a good fit of the model to the data, indicating that the proposed relationships among the variables are adequately supported by the observed data. Additionally, the Root Mean Square Error of Approximation (RMSEA) was found to be 0.03, which is below the threshold of 0.05, further supporting the model's adequacy. The Standardized Root Mean Square Residual (SRMR) was also within the acceptable range, with a value of 0.07.Overall, the fit indices suggest that the proposed structural equation model provides a satisfactory representation of the relationships among the variables under investigation.

4. Discussion

This study delved into the intricate relationships among psychological factors (academic self-efficacy and gameful self-regulation strategies), technological aspects (perceived usefulness and ease of use of technologies, and attitudes towards technology use), and educational outcomes (perceived learning and academic performance) in the backdrop of the Covid-19 pandemic's unforeseen shift from traditional to distance education.

Table 4
Structural equation model result.

		Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Academic Self-efficacy	~						
	Gameful Self-regulation	0.276	0.022	12.746	0.000	0.479	0.479
Perceived Usefulness	~						
	Academic Self-efficacy	0.050	0.019	2.565	0.010	0.160	0.160
	Gameful Self-regulation						
Perceived Ease of Use	~						
	Academic Self-efficacy	0.215	0.074	2.909	0.004	0.120	0.120
	Gameful Self-regulation	0.491	0.047	10.408	0.000	0.475	0.475
Attitudes towards Use	~						
	Academic Self-efficacy	0.280	0.059	4.704	0.000	0.190	0.190
	Gameful Self-regulation	0.420	0.039	10.659	0.000	0.494	0.494
Perceived Learning	~						
	Perceived Usefulness	0.411	0.132	3.116	0.002	0.781	0.781
	Perceived Ease of Use	0.184	0.035	5.201	0.000	0.202	0.202
	Attitudes towards Use	0.102	0.044	2.325	0.020	0.093	0.093
	Academic Performance	0.035	0.017	2.092	0.036	0.040	0.063
Academic Performance	~						
	Perceived Usefulness	0.812	0.558	1.454	0.146	0.135	0.086
	Perceived Ease of Use	0.041	0.073	0.563	0.574	0.039	0.025
	Attitudes towards Use	0.247	0.092	2.675	0.007	0.195	0.125

Table 5
Fit measures to assess SEM Model.

Model	χ2	*df*	χ2/*df*	CFI	TLI	RMSEA	SRMR
	1372.97	547	2.51	0.97	0.96	0.03	0.07
Common guidelines[a]	—	—	**< 2 or 3**	≥ **.95**	≥ **.95**	**< .05**	≤ **.08**

[a] Based on Schreiber (2017), Table 3.

Central to our findings is the interplay between gameful self-regulation strategies and academic self-efficacy. Consistent with established educational theories, we observed that as students engage in self-monitoring and progress evaluation, they experience enhanced feelings of efficacy([37,38]; X. [39,40]). This in turn motivates them to set and pursue more challenging academic goals. Such dynamic is pivotal in remote learning environments, where students' ability to adapt and self-regulate directly influences their academic success and satisfaction(Y. [41,42]).

Furthermore, the study underscored a direct correlation between academic self-efficacy, perceived usefulness (PU), and perceived ease of use (PEOU) of technologies[43,44]. Students with higher self-efficacy demonstrated more active participation in remote education, embracing technology as a facilitator of learning. Conversely, students with lower confidence in their technological capabilities tended to be more reticent in engaging with digital learning tools[45,46]. This phenomenon highlights the necessity for interventions aimed at boosting students' self-efficacy, particularly in the context of remote learning.

Significantly, our model suggests that PU mediates the relationship between self-efficacy and perceived learning. Students with a robust belief in their abilities tend to perceive higher levels of learning in virtual settings, emphasizing the importance of self-confidence in navigating online courses. This insight underscores the need for educational strategies that not only foster technological familiarity but also build student confidence in managing and excelling in virtual learning environments[47,48]

The study also revealed that gameful self-regulation strategies have a direct relationship with PU, PEOU, and attitudes towards technology use, which subsequently influence perceived learning and academic performance. The ability to self-regulate in an online learning environment is crucial, not only for academic success but also for student satisfaction and intrinsic motivation for learning.

This study highlights the pivotal role of self-regulated learning in the context of remote education. It has been observed that students' capacity for self-regulated learning is a strong indicator of their willingness to enroll and succeed in online courses[49,50]. Those with adept self-regulation skills adapt more effectively to virtual learning environments compared to their peers with lower self-regulatory abilities[51]. Furthermore, a key finding is that students' recognition of the value and functionality of online courses is closely linked to their level of self-regulation. These insights underscore the importance of promoting self-regulated learning processes among students to enhance their interaction with and confidence in utilizing new technologies in online education[52].

In conclusion, this study introduces a novel dimension to the TAM by investigating the impact of gameful self-regulated strategies, a concept not previously explored within this framework. The findings of this research reveal a significant positive association between gameful self-regulated strategies and the acceptance factors outlined in TAM, while also highlighting their role in enhancing self-efficacy. As the importance of gamification in course design continues to grow, encompassing online games, classroom activities, flipped classrooms, and more, it becomes increasingly crucial to explore avenues for achieving success in future information-based learning environments and further refining gameful self-regulated strategies.

This pioneering study, which establishes the link between gameful self-regulated strategies and TAM, opens doors to exciting opportunities for future research. One promising avenue is the development of a Gameful-TAM framework, which could provide a valuable theoretical foundation for advancing our understanding of how gamification and self-regulation can synergistically influence technology acceptance and educational outcomes. This avenue holds promise for educators, researchers, and policymakers seeking to harness the power of gamification to enhance the learning experiences of students in modern classrooms.

Moreover, the effectiveness of online learning appears to hinge more on students' autonomous learning capabilities than merely on their technical proficiency[53,54]. Effective learning strategies are crucial for adapting to the demands and challenges of emergency remote education.

The study also reveals a direct influence of perceived usefulness and ease of use of technologies on educational outcomes, specifically perceived learning and academic performance. The direct impact of technology's perceived usefulness on learning can be attributed to students recognizing and utilizing the technologies' educational benefits, leading to a deeper understanding of course content. Similarly, the ease of use of technologies directly affects academic performance, as students proficiently utilize these tools for assessments and assignments, thereby achieving better grades.

The structural equation model analysis suggests that gameful self-regulation strategies are predictive of academic self-efficacy, and both these factors influence the perceived usefulness and ease of use of technologies. Attitudes towards technology use are primarily influenced by gameful self-regulation strategies. Perceived learning outcomes are largely shaped by the perceived usefulness of technologies, whereas academic performance is influenced by their ease of use.

At the forefront is the need for educational institutions to develop programs that bolster students' self-confidence, particularly in their ability to use online learning technologies effectively. Initiatives such as workshops, tutorials, and peer mentoring systems could play a pivotal role in this enhancement. Additionally, the integration of activities and exercises by teachers and educators to foster gameful skills, including goal-setting, progress monitoring, and reflection, is crucial. These skills can be nurtured through guided learning journals, discussion forums, and reflective assignments, thereby enriching the learning experience.

The role of technology another online education cannot be overstated, and as such, comprehensive training and support for both students and teachers in navigating and effectively utilizing digital learning platforms are imperative. This training should not only cover technical aspects but also include strategies for effective online teaching and fostering student engagement and motivation.

The design of curricula another critical area. Curricula that embed elements of self-regulated learning and self-efficacy into the course structure can significantly enhance the learning experience. This approach involves providing clear learning objectives, robust feedback mechanisms, and ample opportunities for self-assessment and reflection.

Continuous research and improvement are vital to keep pace with the evolving dynamics of remote education and its impact on student learning and engagement. Institutions should be committed to regularly assessing and refining their online education strategies, drawing on empirical findings and student feedback. Such research should also consider expanding into additional educational variables, such as student-content interaction, motivation, course structure, and instructor expertise, to name a few. The impact of variables like virtual instructional support, class size in online courses, and the extent and quality of teacher training are also worthy of exploration.

5. Limitation

While this study provides valuable insights into the relationships between gameful self-regulation strategies, academic self-efficacy, technology acceptance, and educational outcomes in game-based online learning, several limitations should be acknowledged. Firstly, the cross-sectional design limits our ability to establish causal relationships between variables. Although structural equation modeling allows us to test hypothesized relationships, longitudinal research would be necessary to confirm the directionality and stability of these relationships over time. Additionally, the reliance on self-reported measures for all variables, including academic performance, may introduce common method bias.

The study's sample, drawn from university students in Southern China, may limit the generalizability of findings to other geographic regions or cultural contexts. The predominance of specific majors in the sample may not fully represent the diversity of academic disciplines in higher education. Furthermore, the study was conducted during the COVID-19 pandemic, which necessitated a rapid shift to online learning. The unique circumstances of this period may have influenced students' perceptions and behaviors, potentially limiting the applicability of findings to more traditional or post-pandemic educational contexts.

Lastly, while the study provides valuable insights into game-based online resources, it may not fully capture the complexities of other forms of online learning or blended learning approaches. The specific gamification elements used in this study may also limit the generalizability to other game-based learning designs. Despite these limitations, the study contributes significantly to understanding the interplay between psychological factors, technology acceptance, and educational outcomes in game-based online learning environments. Future research should address these limitations to further validate and extend the findings across diverse contexts and populations.

To address the limitations highlighted in this study, future research should focus on enhancing the robustness of the study design, improving sampling methods, and expanding the generalizability of results. Longitudinal studies could be conducted to establish causal relationships between gameful self-regulation strategies, academic self-efficacy, technology acceptance, and learning outcomes over time. This approach would provide stronger evidence for the directionality of effects and allow researchers to examine how these relationships may evolve throughout a student's academic journey.

To improve sampling and generalizability, future studies should aim to include a more diverse range of participants across different geographic regions, cultural contexts, and academic disciplines. This could involve multi-institutional collaborations or cross-cultural studies to examine how the findings may vary in different educational settings. Additionally, researchers should consider employing mixed-methods approaches, combining quantitative data with qualitative insights from interviews or focus groups, to provide a more comprehensive understanding of students' experiences with game-based learning technologies. These enhancements to the research design and sampling strategy would address the constraints identified in the current study and contribute to a more thorough and generalizable body of knowledge in the field of technological acceptance and self-regulation in game-based learning.

6. Conclusion

The research findings underscore the pivotal role of gameful self-regulation strategies and academic self-efficacy in shaping students' perceptions and attitudes towards technology acceptance. These factors emerged as critical determinants of both perceived learning and academic achievement in the context of game-based online resource classes. The study emphasizes the significance of integrating gameful elements and fostering self-regulatory skills within educational interventions to enhance student engagement, motivation, and overall learning outcomes.

The introduction of the novel concept of gameful self-regulation strategies into the Technology Acceptance Model (TAM) framework opens up exciting avenues for future research. This innovative approach holds promise for the development of a unified Gameful-TAM theory, providing a robust theoretical foundation for advancing our understanding of how gamification and self-regulation can synergistically influence technology acceptance and academic performance. Such a framework could prove invaluable for educators, researchers, and policymakers seeking to leverage the power of gamification to enhance the learning experiences of students in modern classrooms.

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CRediT authorship contribution statement

Fang Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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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