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Factors Affecting Students' Acceptance of Gamified Learning (SAGL)

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ABSTRACT

Gamification is commonly used for improving student learning experiences. The purpose of this paper is to understand the factors that influence the acceptance of gamification in learning. The paper employs a meta-analysis approach to identify the factors that affect students' acceptance of gamified learning. The benefit of meta-analysis is its ability to synthesize and utilize the results obtained from various primary research papers to discover the critical factors that influence the acceptance of game design elements in online courses. The PRISMA protocol was used to analyze the meta-analysis. While much research has been done on gamified learning, there is a lack of meta-analysis research on the acceptance of gamified learning elements. The results of the meta-analysis indicated that performance expectancy, student satisfaction, and social interaction are the critical factors influencing the acceptance of gamified learning. These results are beneficial because they not only focus on learning but also provide an opportunity for industry experts to be aware of the critical factors that influence the acceptance of gamified learning. This paper's novelty lies in its analysis of statistical heterogeneity, effect size, and publication bias across research that employed various statistical techniques.

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INTRODUCTION

The use of technology to improve student learning is a well-invested aspect in the learning and teaching environment. While technology-assisted learning has been successful, there have been discussions on how to further engage students or learners and improve their learning experience (Randle, 2024). One approach to enhancing learning is through the use of games as a means of making learning fun. This idea is often referred to as gamification. Gamification has improved higher education by motivating students by including leader boards and badges in online learning environments (Andres, 2022; Bordolio, 2018). One critical issue regarding gamification as a tool is the lack of data to identify the factors that influence its acceptance (Andres, 2022).

Gamification refers to the use of game-related objects or tools to enhance the educational experience for students or learners (Andres, 2022). Barna and Fodor (2017) and Bencsik *et al.* (2021) have focused on the significance of gamification in learning and have identified its importance as a tool to improve the learning experience. Gamification has been utilized to support learning through science, technology, engineering, and mathematics (Cao *et al.*, 2022); support physical education (Fernandez-Rio *et al.*, 2020); motivate undergraduates (Gressick *et al.*, 2017; Huang *et al.*, 2013; Jurgelaitis *et al.*, 2018; Redhaei *et al.*, 2022); support distance learning (Sumer *et al.*, 2022); and implement reward systems (Vranesic *et al.*, 2019). This research benefits universities and institutions of higher learning by providing an understanding of the factors that influence the acceptance of gamification in online learning. Additionally, it serves as a guide for universities to manage these factors.

The accessibility of the internet through different platforms has improved student access to various forms of digital games. Africa has shown that a significant number of young people are interested in gaming and are eager to learn through gaming. There are 2.4 billion global game players, of which 600 million are based in Africa (Moerman, 2020; Randle, 2024). Therefore, the question now arises: How do we use gamification as a tool to improve the learning experience in the online learning space? In order to answer that question, we must first ask which game elements are critical to the online learning environment.

The purpose of this research is to:

1. Identify the factors that determine the acceptance of gamification and assist stakeholders and developers in the gamification of learning.
2. Determine the various variations among the major factors influencing the acceptance of gamification as a tool for improving learning experiences.

RESEARCH METHOD

Methodology

The methodology used in this research adheres to the guidelines defined by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Crocetti, 2016; Moher *et al*., 2009; Moher *et al*., 2015). Meta-analysis is a set of procedures used to aggregate and evaluate results obtained from different individual research through a systematic process (Olugbara *et al*., 2021).

The steps required to identify statistical heterogeneity, compute the effect size of each primary research paper, conduct moderator analysis, search for literature, choose primary research, codify primary research, incorporate the polled effect size of all primary research, and investigate publication bias are all influenced by the derived PRISMA procedure (Crocetti, 2016; Olugbara *et al*., 2021). This section of the paper provides a succinct application of these steps.

Defining the Research Questions

Technology acceptance models are useful for discovering the factors that influence student acceptance of game design elements (Olugbara & Letseka, 2020). These models are widely used for research based on the acceptance and adoption of technology. Examples of research in this field include understanding attitudes and beliefs (Bhattacherjee & Premkumar, 2004) and investigating factors that predict e-learning integration by preservice teachers (Olugbara *et al*., 2020).

This paper used a meta-analysis methodology to categorically analyze the results obtained from various diverse research studies and extract the critical factors influencing the adoption of gamification in online learning platforms.

The following research questions were posed to achieve the aim:

1. According to the technological acceptance model, what are the primary important aspects influencing students' adoption of game design elements?
2. Based on the technological acceptance model, what are the sources of difference, if any, among research articles regarding the most relevant factors that affect students' adoption of game design elements?

Specifying Inclusion and Exclusion Criteria

Primary research is defined by specifying exclusion and inclusion criteria. These criteria were used to determine the research eligible for selection in the meta-analysis. Table 1 lists the specific inclusion and exclusion criteria that address the proposed research questions.

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Table 1. Inclusion and exclusion criteria

Included/Excluded	Requirements
Excluded	Repetitive primary research in various journals.
Included	The primary research was conducted in English and included journals from 2013 to 2023 after the development of several MOOCs and online learning platforms. Research with statistically significant results was excluded to enforce the rigor required for the research (Crocetti, 2016; Olugbara *et al*., 2021).
Excluded	Research not using technology was excluded, with the main or primary research focusing on the acceptance of gamification.
Excluded	Primary research that did not provide well-structured detail in its data sets was excluded. The main parameters that were included were factor validity (Crocetti, 2016), average variance (Olugbara & Letseka, 2020; Olugbara *et al*., 2021), and path coefficient (Crocetti, 2016).
Included	Structural equation modelling was used to analyze all relationships among the model factors. All research that did not use structural equation modelling was excluded to promote the validity of the findings.
Included	The sample population included research that used students from universities as well as primary and secondary (high) schools to promote diversity in the research.

Searching the Literature

The South African Department of Education and Training (DHET) recommends a specific list of journals. This list was used as the guide for selecting the primary research for this paper. The list includes platforms such as the Web of Science, which includes Springer, Taylor and Francis, Elsevier, Sage, Scopus, IbSS, and Scielo. This list was used to ensure that only high-quality peer-reviewed papers were included in the research. The parameters included keywords such as 'game design elements', 'gamification', and 'factors of online adoption'. Papers that were extracted from the reference lists of the DHET approved papers were accessed through Google Scholar, which provided a wide range of papers to review.

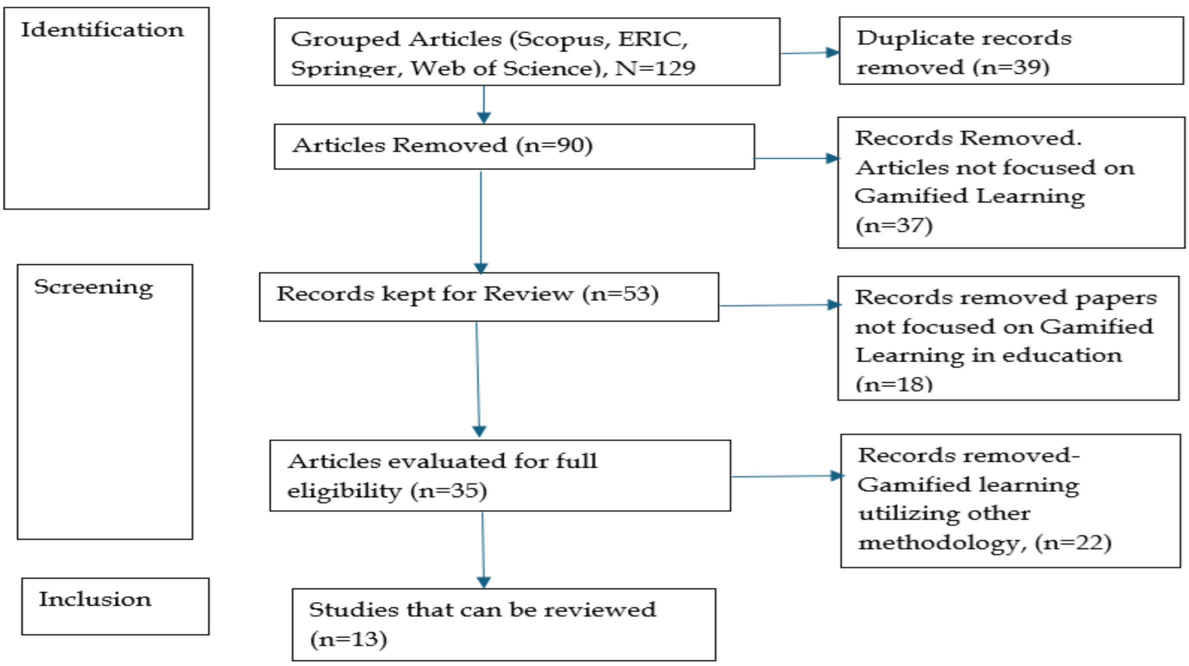


Figure 1. PRISMA protocol for factors affecting students' acceptance of gamified learning

Selecting Primary Research

To ensure that appropriate research was included, inclusion and exclusion criteria were adopted for many of the research papers to determine their eligibility for the meta-analysis. The researcher followed an unblinded approach. This exercise had the benefit of excluding duplicate research that did not meet the requirements for inclusion during the analysis phase.

The papers needed to meet certain requirements, one of which was that they used specific words such as 'adoption', 'use', 'usage', 'critical', and 'intention' as part of the screening process. Only papers that fulfilled this requirement in their abstracts were reviewed with a focus on gathering information about their acceptance criteria, sample size, use of structural equation modelling, research location, and country of origin.

The qualitative synthesis utilized papers that passed the first stage, which required that their abstracts met the preliminary requirements. These approved papers were included in the list for the meta-analysis. Out of the 129 papers that were investigated, 35 primary research papers met the criteria. Thirteen of those 35 papers met all of the requirements and were included in the meta-analysis. The percentage of papers accepted was 16.77%. This approach addresses the conformist rigidity of the PRISMA protocol, as presented in Figure 1.

The selection process used papers that implemented technology acceptance models to investigate the factors that influence students' acceptance of learning gamification (SAGL). Some of the models included self-determination.

Extensions of technology acceptance models include the following: computer self-efficacy and self-regulated learning (Al-Adwan, 2020); knowledge storage, access, and application (Arpaci *et al*., 2020); perceived enjoyment and collaboration (Razami & Ibrahim, 2020); usability, perceived quality, and perceived enjoyment (Tao *et al*., 2019); time perception (Teo & Dai, 2019); and learning and self-efficacy (Zhang *et al*., 2017).

The technology acceptance model serves as the theoretical foundation for the unified theory of acceptance and use of technology (UTAUT). According to Altalhi (2021), Fianu *et al*. (2020), Haron *et al*. (2020), and Mulik *et al*. (2018), service quality, computer self-efficacy, instructional design, and UTAUT have been expanded through perceived value, media, assessment, and motivation.

The research included the authors' names, year of publication, sample size of participating students, country of research, path coefficient, theoretical model underpinning the research, most significant factors, reliability coefficient, and sample description.

Coding Primary Research

The coding procedure is designed to help researchers obtain effect sizes. In order to conduct this research and meet the necessary requirements, a codebook was developed to gather crucial data. The codebook was used to code the data.

The decoded information included variables that affect student acceptance of gamified learning, such as demographic information, research characteristics (author, publication), the size sample of students who participated, path coefficient, country of research, underpinning model used to identify the factors, the most important factor influencing SAGL, and the behavior type involved in accepting technology. This behavior type may take the form of actual MOOC usage (usage), continuous intention to use (continual), willingness and attitude to use.

In the structural model, the exogenous variables are the influencing factors while the endogenous variable represents the type of technological acceptance behavior. Numerous influencing elements have been identified by Olugbara *et al*. (2020) based on previously explained technology adoption models. Nonetheless, the most significant factor with the highest path coefficient statistic was chosen. The acceptance component with the strongest path coefficient per paper was systematically retrieved from each primary research paper and stored in a structured format for further analysis. This was motivated by the intrinsic limitation of a technological acceptance model to yield a low R^2.

Similar codes were grouped into themes and patterns using qualitative synthesis. The emerging themes were investigated to offer a comprehensive picture of the variables affecting student acceptance. Statistical techniques were employed to synthesize quantifiable data, such as effect sizes or frequency counts, whenever possible.

Estimating Effect Size

The effect sizes of each main research paper that was included and the aggregated effect size of all the primary research papers were determined using the data that was gathered during the coding phase. This research used forest plots and random-effects models to calculate effect sizes and offer a comprehensive depiction of the variables affecting students' acceptance of game jams in art-based projects. The effect size indicators used in the meta-analysis were Cohen's d for continuous outcomes and odds ratios for categorical outcomes. These metrics provide uniform measurements that make it easier to compare the outcomes of various investigations (Pigott & Polanin, 2020; Valentine *et al*., 2019).

The main statistical framework for calculating effect sizes is the random-effects model (Pigott & Polanin, 2020). This model is especially appropriate for accounting for potential heterogeneity across research as it takes both within-research and between-research variability into account. The random-effects model offers a more conservative and reliable estimate since it assumes that genuine impact sizes may differ between research (Valentine *et al*., 2019). When conducting individual investigations, effect sizes are calculated for each identified outcome measure. The primary papers are mined for pertinent statistical data, including means, standard deviations, correlation coefficients, and odds ratios. The calculation procedure is accurate and consistent as it follows the accepted formulas for odds ratios and Cohen's d (Mikolajewicz & Komarova, 2019).

Forest plots were created to graphically depict the effect sizes and associated confidence intervals from separate research. These plots are easily understood visual aids that facilitate a prompt evaluation of the variability and distribution of outcomes. Each research paper provided a brief synopsis of the combined data, which was represented as a point on the plot, and the overall impact size was represented as a diamond (Mikolajewicz & Komarova, 2019; Valentine *et al*., 2019). When calculating effect sizes, sample size variations between research were taken into account to promote a fairer representation. This ensured that research with bigger sample sizes did not disproportionately influence the final synthesis.

Detecting Statistical Heterogeneity

Statistical heterogeneity refers to the variety of effect sizes across research. Random-effects models are used to identify and resolve statistical heterogeneity in the context of calculating effect sizes for the retrieved data (Langan, 2022). The random-effects model considers variability within and across research. This model provides a more adaptable and realistic framework by assuming that true effect sizes may vary between research papers. The random-effects model is well-suited to handle statistical heterogeneity since it introduces an additional degree of variance (Cheung, 2019). The Q-statistic is a commonly used metric to evaluate statistical heterogeneity. It measures the extent of effect size variability beyond what would be predicted by pure chance.

A significant result indicates the presence of heterogeneity, and the Q-statistic follows a chi-squared distribution (Holzmeister *et al*., 2023; Konstantopoulos & Hedges, 2019). The I^2 index enhances the Q-statistic by providing a percentage estimate of the overall variation across research that is due to heterogeneity rather than chance. I^2 values range from 0% to 100%, with higher values indicating increasing heterogeneity (Lin, 2020; Schober *et al*., 2021). I^2 values are interpreted as follows: Low heterogeneity is defined as 0% to 25%; moderate heterogeneity as 26% to 50%; substantial heterogeneity as 51% to 75%; and significant heterogeneity as 76% to 100% (Borenstein, 2020; Schober *et al*., 2021). It has the advantage of determining consistency over other heterogeneity metrics, and it is not influenced by the number of trials.

Conducting moderator analysis

Moderator analysis provides insightful information about the possible sources of diversity in effect sizes among primary research by emphasizing the factors taken into consideration and the methodology used to investigate their impact on the observed outcomes (Hansen *et al.*, 2022). The variables, or factors known as moderators, have the potential to affect how the independent and dependent variables are related. In order to comprehend how particular traits or circumstances may moderate the impact sizes connected to student acceptance of game jams in art-based projects, moderators were investigated in the context of this meta-analysis.

A comprehensive analysis of the literature, theoretical frameworks, and empirical data was conducted to identify potential moderators. Moderators that are frequently considered include previous experience with game jams, differences in instructional techniques, and demographic traits such as age and academic level (Borenstein, 2020).

The influence of modifiers on effect sizes was examined using quantitative methods such as meta-regression (Borenstein, 2020; Nakagawa *et al.*, 2023). This entailed doing a statistical test to determine whether any particular moderator variables could account for the variation in effect sizes. To determine the importance of variations between subgroups, statistical tests (such as ANOVA and regression analysis) were performed and effect sizes were stratified based on moderator categories. To identify patterns, trends, and connections between moderator variables and effect sizes, the moderator analysis results were interpreted. It was thus necessary to find the modifiers that significantly contributed to the observed variability. Subgroup analyses were carried out to investigate the differences in effect sizes within particular moderator categories.

The overall interpretation of the results incorporated the learnings from the moderator analysis. In order to present a comprehensive grasp of how different elements may limit the relationship between game jams and student acceptance in art-based projects, this knowledge had to be synthesized. We looked for statistically significant differences in the analysis outcomes. As moderators in the meta-regression model, the year of publication, the acceptance model used, the kind of technology accepted, the research nation, and the sample size were examined.

Analyzing Publication Prejudice

Publication bias describes the tendency for research with statistically significant or favorable results to be published more frequently than research with non-significant or unfavorable outcomes (Ropovik *et al.*, 2021). As a result, the actual effect magnitude may be overestimated (Nakagawa *et al.*, 2023). Several methods are used to identify potential publishing bias, including statistical techniques that are intended to identify the existence of selective reporting, visual examination of funnel plots, and asymmetry tests (such as Egger's test) (Doleman *et al.*, 2020; Dowdy *et al.*, 2022; Page *et al.*, 2022). Funnel plots are created by plotting effect sizes versus a research precision metric, such as standard error (Doleman *et al.*, 2020). An asymmetrical funnel plot could indicate publishing bias, while symmetry shows little to no prejudice.

To identify possible outliers, funnel charts are inspected visually. A quantitative technique for evaluating funnel plot asymmetry is the Egger's test, which is based on regression analysis (Nakagawa *et al.*, 2023). The degree of asymmetry is shown by the regression line's intercept, and statistical significance points to the possibility of publishing bias. This meta-analysis attempted to improve the validity and dependability of its results by methodically investigating publication bias, offering a more realistic portrayal of the actual relationship between gamified learning and SAGL.

RESULTS AND DISCUSSION

The findings of this work were presented in line with the work of Olugbara *et al*. (2021). These were presented and discussed under the three dimensions of factors influencing SAGL, sources of variations in research addressing SAGL, and the significant biases in research.

Factors Influencing SAGL

Out of the 35 papers that made it to the final stage of the inclusion check, only 13 were eventually adopted for the meta-analysis. The remaining 22 did not meet the requirements of the author. Although the excluded papers discussed topics related to gamification, they failed to conduct any in-depth statistical analysis or structural equation modelling. Some merely used descriptive statistics. A few were systematic literature reviews or qualitative research. One was rejected for failing to provide the values of the path coefficients, despite claiming that the process was carried out.

A list of the most significant exogenous factors (MSEFs) that affect SAGL was drawn up from the selected papers and is presented in Table 2. The table includes the names, codes, and definitions for each of these factors. In order to avoid conflicting definitions, the definitions were drawn from the authors whose research was selected for this work. As such, the definitions are directly related to gamified learning. The codes and definitions are referenced thereafter. Eleven factors were identified from the research papers.

Table 2. The MSEFs influencing SAGL from the included papers

Factor	Factor Code	Definition
Entertainment	Ent	Perceived entertainment of the users of a gamified learning platform regarding the functions it offers them (Su, 2019).
Knowledge improvement	KnwImp	Perception of whether there has been an improvement in knowledge while using gamified learning (Filippou *et al*., 2018).
Learning goal orientation	LGO	An orientation towards growth by learning new skill sets and mastering new situations while using gamified learning (Soepriyatna & Pangaribuan, 2022).
Monetary rewardability	MonRwd	When gamified learning includes virtual financial rewards for completing game tasks, students perceive that the rewards allow them to pay for what they need to further immerse themselves in the game (Xu *et al*., 2023).
Perceived enjoyment	PerEnj	Users' perception of the level of enjoyment they derive from gamified learning (Yan *et al*., 2022).
Performance expectancy	PerExt	The degree to which it is believed that gamified learning will help improve performance (López *et al*., 2021).
Perceived usefulness	PerUse	The degree to which gamified learning is perceived to be useful (Yan *et al*., 2022).
Satisfaction	Satis	The sense of contentment that students feel when they engage with the gaming elements of the course (Baah *et al*., 2023).
Social interaction	SocInt	The sense of relatedness that provides a platform to encourage and motivate towards using gamified learning among peers, thereby enhancing the confidence, comfort, and success in their use (Ssekibaamu, 2015). Chung and Pan (2023) also referred to it as peer interaction.
Student engagement	StuEng	The keen enhancement or deep involvement with gamified lessons in order to enhance better understanding by students (Murillo-Zamorano *et al*., 2021).

Factor	Factor Code	Definition
Teaching design	TeachDes	Crafting the gamified learning experience to include some minimal criteria that will make the learning successful (Santos-Villalba *et al*., 2020).

Table 2 presents a list of factors obtained from literature. The table further explains how these factors are relevant to gamification and their roles in the process. Having defined and coded the most significant factors, Table 3 presents the key characteristics of the 13 research papers included in the meta-analysis. The table provides information about the authors, the year of publication, sample size, model adopted, path coefficient, reliability, validity, model factors, and type of factor for each research study.

The papers listed in Table 3 were published between 2015 and 2023, with the majority being published in 2023 (38.5%), followed by 2022 (23.1%). One paper (7.7%) was published in each of the years 2021, 2020, 2019, 2018, and 2015, respectively. This indicates that the research was conducted recently and can be used to measure the factors affecting SAGL accurately.

The majority of research listed in Table 3 was carried out in Spain (23.1%), followed by Taiwan (15.4%), and China (15.4%), while Ghana, Tunisia, Malaysia, Australia, Indonesia and the USA had the lowest publication rate (7.7%). This suggests that more studies have been conducted on gamified learning in Spain, Taiwan, and China compared to other countries. These details are captured in Figure 2.

Table 3. Characteristics of the included primary papers

Research ID	Author(s)	Year	Country	Sample size	Model Adopted	MSEF	Path Coefficient (PCoeff)	Reliability (Rel)	Validity (Val)	Endogenous Model Factor	Factor Type
S1	Baah *et al.*	2023	Ghana	60	(ARCS; SDT)[b]	Satis	0.939	0.680	0.530	Mot	AA – Intention
S2	Chung and Pan	2023	Taiwan	250	FSIEM[a]	SocInt	0.355	0.916	0.844	Eng	BB – Continual
S3	Denden *et al.*	2022	Tunisia	83	(TAM; FFMPT)[b]	PerUse	0.546	0.850	0.750	BInt	AA – Intention
S4	Filippou *et al.*	2018	Australia	84	FLM[d]	KnwImp	0.410	0.900	0.692	PerUse	CC – Usage
S5	López *et al.*	2021	Spain	339	CAN[a]	PerExt	0.810	0.920	0.750	BInt	AA – Intention
S6	Murillo-Zamoranoa *et al.*	2023	Spain	90	EKS[d]	StuEng	0.540	0.945	0.895	SSat	CC – Usage
S7	Roslan *et al.*	2023	Malaysia	269	(ECM, UTAUT2)[b]	PerUse	0.314	0.895	0.631	ContUse	BB – Continual
S8	Santos-Villalba *et al.*	2020	Spain	187	ECM[a]	TeachDes	0.459	0.870	0.769	IntAdt	BB – Continual
S9	Soepriyatna and Pangaribuan	2022	Indonesia	46	TAM[a]	LGO	0.617	0.894	0.680	Eng	BB – Continual
S10	Ssekibaamu	2015	United States	160	UTAUT[a]	SocInt	0.681	0.870	N/A	BInt	AA – Intention
S11	Su	2019	Taiwan	177	(GAR-STEM, MRT, TAM)[b]	Ent	0.379	0.940	0.750	BInt	AA – Intention

Research ID	Author(s)	Year	Country	Sample size	Model Adopted	MSEF	Path Coefficient (PCoeff)	Reliability (Rel)	Validity (Val)	Endogenous Model Factor	Factor Type
S12	Xu *et al.*	2023	China	212	AT[a]	MonRwd	0.437	N/A	N/A	ImExp	BB – Continual
S13	Yan *et al.*	2022	China	616	(TAM)[c]	PerEnj	0.324	0.933	0.828	Bint	AA – Intention

[a] One single existing model.
[b] Combination of two or more models blended/modified.
[c] Single modified model.
[d] Model developed by author(s).

ARCS – Attention, relevance, confidence, and satisfaction
AT – Affordance theory
CAN – Cognitive-affective-normative
ECM – Expectation-confirmation model
EKS – Engagement-knowledge-satisfaction
FFMPT – Five-factor model of personality traits
FLM – Fun and learning model
FSIEM – Flow-social interaction-engagement model
GAR-STEM – Gamification augmented reality
MRT – Media richness theory
SDT – Self-determination theory
TAM – Technology acceptance model
UTAUT and UTAUT2 – Unified theory of acceptance and use of technology

Bint – Behavioral intention to use
ContUse – Continuous use intention
Eng – Engagement
Ent – Entertainment
ImExp – Immersive experience
IntAdt – Intention to adopt sustainable practices
KnwImp – Knowledge improvement
LGO – Learning goal orientation
MonRwd – Monetary rewardability
Mot – Motivation
PerEnj – Perceived enjoyment
PerExt – Performance expectancy
PerUse – Perceived usefulness
Satis – Satisfaction
SocInt – Social interaction
SSat – Students' satisfaction
StuEng – Student engagement
TeachDes – Teaching design

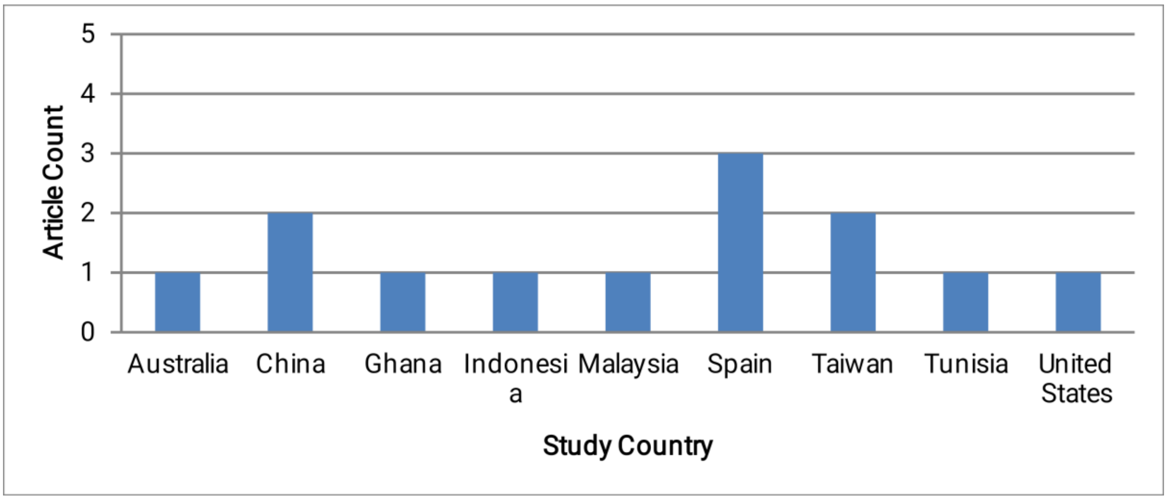
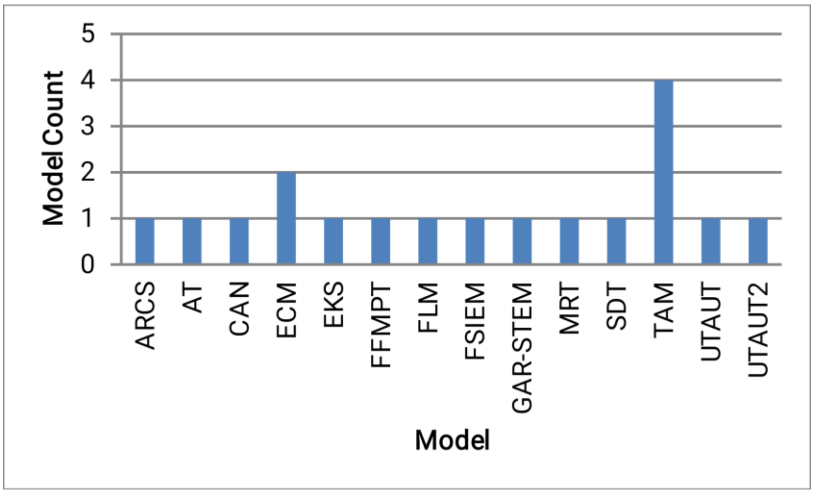


Figure 2. Distribution of included papers according to country

The sample sizes of the 13 papers varied from 46 to 616, with the majority having between 150 and 300 participants. In total, 2 573 participants were involved in the research. Several theoretical models were used, with the technology acceptance model being the most common with four authors using this model. Almost half of the authors (46.2%) used a single theoretical model without modification, while one author (7.7%) adopted a single modified model. Furthermore, 30.8% of the authors used two or more theoretical models, while 15.4% developed their own models. In all, 14 models were adopted.

A complete distribution of the model adoption is presented in Figure 3. The technology acceptance model had four occurrences (22.2%), while the expectation-confirmation model and UTAUT (including UTAUT2) had two occurrences each (11.1%). This indicates that these models are important for understanding SAGL. The other 12 models only had one occurrence (5.6%) of adoption.

The path coefficients were also stated for the MSEFs. Perceived usefulness, which was rated by 269 students, recorded the lowest path coefficient of 0.314. On the other hand, satisfaction, as rated by a sample of 60 students, recorded the highest path coefficient of 0.939. The reliability values of the identified exogenous factors ranged from 0.680 to 0.945, while the validity values ranged between 0.530 and 0.895. These are all deemed to be within a satisfactory range (Daud *et al.*, 2018; Hair *et al.*, 2021; Raharjanti *et al.*, 2022). Student engagement recorded the highest reliability value of 0.945, while satisfaction recorded the lowest value of 0.68. These factors also corresponded to the validity of the research, with the highest validity being 0.895 and the lowest being 0.530, respectively.



ARCS – Attention, relevance, confidence, and satisfaction
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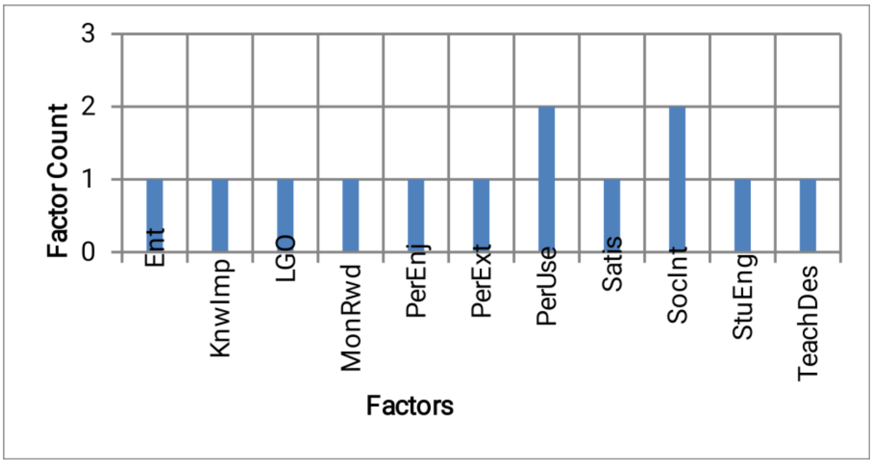
SDT – Self-determination theory
TAM – Technology acceptance model
UTAUT and UTAUT2 – Unified theory of acceptance and use of technology

Figure 3. Distribution of the technology acceptance models in the included papers

Figure 4 presents the distribution of the MSEFs across the 13 included papers. These factors are the key drivers of SAGL and should be considered on gamified learning platforms. With the exception of perceived usefulness and social interaction that occurred twice (15.4%), each of the other factors occurred only once (7.7%). This suggests that the factors driving SAGL are broad and must be captured entirely on gamified learning platforms.



Ent – Entertainment
KnwImp – Knowledge improvement
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MonRwd – Monetary rewardability
PerEnj – Perceived enjoyment
PerExt – Performance expectancy
PerUse – Perceived usefulness
Satis – Satisfaction
SocInt – Social interaction
StuEng – Student engagement
TeachDes – Teaching design

Figure 4. Distribution of the MSEF in the included papers

The endogenous factors listed in Table 2 describe what the exogenous factors are investigating in the papers included in this research. Based on these factors, the research papers were categorized into three subgroups: AA: intention to use SAGL (46.2%); BB: continuous use of SAGL (38.5%); and CC: usage of SAGL (15.4%). The MSEFs predicting 'Intention to use SAGL' (Subgroup AA) are satisfaction, performance expectancy, perceived usefulness, social interaction, entertainment, and perceived enjoyment. The MSEFs predicting 'Continuous use of SAGL' (Subgroup BB) are social interactions, perceived usefulness, teaching design, learning goal orientation, and monetary rewardability. The MSEFs predicting 'Usage of SAGL' (Subgroup CC) are knowledge improvement and student engagement.

Sources of Variations in the Research Addressing SAGL

The sources of variation in the included research were examined using the meta-analysis tool of Suurmond *et al*. (2017). The results in Table 4 show the distribution of the effect sizes of each of the included research papers.

Table 4. Distribution of effect sizes for the included research papers on SAGL

Research Paper No.	Research Paper ID	Effect Size	Confidence Interval Lower Limit	Confidence Interval Upper Limit	Weight
1	S1	0.94	0.73	1.14	6.86%
2	S2	0.36	0.20	0.51	7.65%
3	S3	0.55	0.39	0.70	7.72%
4	S4	0.41	0.26	0.56	7.82%
5	S5	0.81	0.72	0.90	8.60%
6	S6	0.54	0.41	0.67	8.17%
7	S7	0.31	0.20	0.43	8.35%
8	S8	0.46	0.36	0.56	8.52%
9	S9	0.62	0.42	0.81	7.00%
10	S10	0.68	0.62	0.74	9.01%
11	S11	0.38	0.16	0.59	6.61%
12	S12	0.44	0.24	0.63	6.96%
13	S13	0.32	0.12	0.53	6.72%
	Overall	0.53	0.41	0.64	100.00%

The forest plot is presented in Figure 5 for clarity. With a 95% confidence interval, the overall effect size of 0.53 was within a positive range (the upper and lower limits were 0.64 and 0.41, respectively). This indicates that the MSEF contributed approximately between 0.41 and 0.64 to SAGL.

Table 5 provides additional details on the results. It indicates that the results are statistically significant at a 5% level of significance ($p = 0.00$). The heterogeneity results show that the overall variation (or heterogeneity) across the included research is significant with Cochran's Q of 100.32 ($p = 0.00$; degrees of freedom, $k = 12$).

Considering that Cochran's Q power of testing heterogeneity may have been influenced by the small number of included papers (Gavaghan *et al*., 2000). The Higgin's and Thompson's I^2 value was also used as a further test of heterogeneity. The value is satisfactorily high ($I^2 = 88.04\%$), indicating the presence of high statistical heterogeneity (Borenstein *et al*., 2017; Kavvoura & Ioannidis, 2008). Furthermore, the homogeneity measure of $\tau 2 = 0.03$ supports the results. These imply that the total variance in the included papers is attributed to the heterogeneity of the effect sizes.

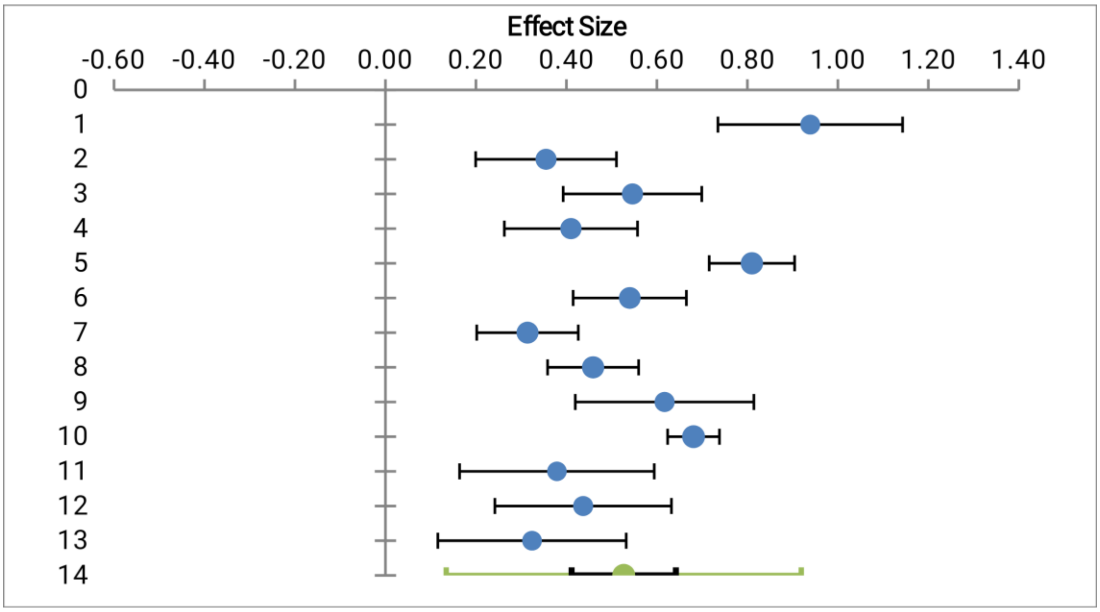

Figure 5. Forest plot for the distribution of effect sizes of included papers on SAGL

Table 5. Details of the meta-analysis

Detail of research	
Number of incl. papers	13
Number of incl. observations	2 573
Combined effect size	
Effect size	0.53
Standard error	0.05
Confidence interval lower limit	0.41
Confidence interval upper limit	0.64
Prediction interval lower limit	0.13
Prediction interval upper limit	0.92
Z-value	9.96
One-tailed p-value	0.000
Two-tailed p-value	0.000
Confidence level	95%
Heterogeneity	
Q	100.32
p_q	0.000
I^2	88.04%
T^2	0.03
T	0.17

Subgroup Analysis of Factors Influencing SAGL

For the purpose of subgroup analysis, three subgroups of the endogenous factors were adopted, namely AA (Intention to use SAGL); BB (Continuous use of SAGL); and CC (Usage of SAGL). Refer to Table 3 for the factors under each of the subgroups. The meta-analysis tool of Suurmond *et al*. (2017) was adopted.

The results presented in Table 6 indicate that there is significant intra-group heterogeneity for the 'Intention to use SAGL' subgroup. The heterogeneity is very high with an I^2 of 0.86 (or 86%) and effect size of 0.63 within a 95% confidence interval. These are found to be significant ($p = 0.000$). The other two subgroups did not show significant intra-group heterogeneity. Although their heterogeneity measure was still moderate (I^2 values were 0.54 and 0.44 for the 'Continuous use of SAGL' and 'Usage of SAGL' subgroups, respectively), they were insignificant with $p > 0.05$ for both subgroups. This was confirmed with the extremely low Cochran's Q of 8.76 and 1.79 for the subgroups, respectively.

Table 6. Subgroup analysis result

Subgroup Name	Effect Size	Confidence Interval (Lower Limit)	Confidence Interval (Upper Limit)	Weight	Q	p	I^2	T^2	T
AA	0.63	0.38	0.87	0.22	35.71	0.0000	0.86	0.02	0.16
BB	0.42	0.29	0.56	0.44	8.76	0.0674	0.54	0.01	0.08
CC	0.48	−0.34	1.30	0.34	1.79	0.1810	0.44	0.00	0.06
Combined effect size	0.54	0.37	0.61	1.00	100.32	0.0000	0.88	0.03	0.17

The results of the subgroup analysis are explained by the fact that the exogenous factors in the AA subgroup (Intention to use SAGL) had the most influence on SAGL. The AA subgroup had the highest number of exogenous factors among the 13 included papers, and they also had the highest path coefficients among the subgroups (Table 6). However, the majority of the factors in the papers belonging to the BB subgroup (Continuous use of SAGL) and CC subgroup (Usage of SAGL) had average to low path coefficients.

The effect sizes of the subgroups were compared to further explain the results. According to Table 5, the overall effect size from the subgroup analysis was 0.54. However, the effect size of the AA subgroup was 0.63, which was higher than the overall effect size. This indicates that the MSEF of the AA subgroup had a stronger influence. On the other hand, the BB and CC subgroups had weaker effect sizes (0.42 and 0.48, respectively). Therefore, the MSEFs for the BB and CC subgroups only contributed weakly to the overall impact on SAGL, whereas the MSEFs of AA contributed strongly. As expected, a corresponding trend was observed with the path coefficients (see Table 7).

Table 7. Path coefficients of the MSEFs arranged in order of strengths

Research ID	MSEF	Path Coefficient (PCoeff)	Subgroup
S1	Satis	0.939	AA
S5	PerExt	0.81	AA
S10	SocInt	0.681	AA
S9	LGO	0.617	BB
S3	PerUse	0.546	AA
S6	StuEng	0.54	CC
S8	TeachDes	0.459	BB
S12	MonRwd	0.437	BB
S4	KnwImp	0.41	CC
S11	Ent	0.379	AA
S2	SocInt	0.355	BB
S13	PerEnj	0.324	AA
S7	PerUse	0.314	BB

Research ID	MSEF	Path Coefficient (PCoeff)	Subgroup
	Average overall path coeff	0.523923077	
	Average path coeff for AA subgroup	0.671	
	Average path coeff for BB subgroup	0.4364	
	Average path coeff for CC subgroup	0.475	

Ent – Entertainment; ImExp – Immersive experience; KnwImp – Knowledge improvement; LGO – Learning goal orientation; MonRwd – Monetary rewardability; PerEnj – Perceived enjoyment; PerExt – Performance expectancy; PerUse – Perceived usefulness; Satis – Satisfaction; SocInt – Social interaction; StuEng – Student engagement; TeachDes – Teaching design

The high overall level of statistical heterogeneity in the results can be attributed to several factors, including the variability in the sample size, the number of papers included, and the research design adopted in each research study (Borenstein *et al*., 2017). The overall subgroup analysis results indicate high heterogeneity with a statistically significant overall subgroup effect with a p-value of less than 0.05. This affirms that MSEFs can significantly influence SAGL.

Publication Bias in Research Addressing SAGL

A visual examination of the funnel plot (Figure 6) suggests that the included research is asymmetrical and randomly distributed. The funnel plot displays the individual research studies based on their precision, which is measured by their standard errors on the vertical axis and the effect size on the horizontal axis. To avoid publication bias, the plots should be contained inside the funnel's boundaries, which indicate the 95% confidence interval. The presence of outlier plots may indicate publication bias and variation. Moreover, the plots should be symmetrical about a center point that passes through the combined effect size. The research conducted by Crocetti (2016), Lin and Chu (2018), and Olugbara *et al*. (2021) highlighted that a symmetrical arrangement of study plots around the center of the funnel plots suggests the absence of publication bias. The results of this current research indicate a somewhat asymmetrical funnel plot, which includes outlier plots (Figure 6). Research papers 1, 5, 9, and 10 are on the right of the funnel plot while the others are on the left, resulting in an asymmetrical outlook with approximately six research studies outlying the 95% confidence interval boundary.

However, the research by Sterne and Harbord (2004) on funnel plots suggests that an asymmetrical arrangement of research studies in a meta-analysis may not necessarily indicate publication bias, especially in cases where the number of research studies is low. The fact that the plots are randomly positioned suggests the absence of bias. This highlights the necessity to determine heterogeneity further, particularly given the limited number of research studies.

The publication bias was further assessed by Egger regression analysis. Nakagawa *et al*. (2017) and Olugbara *et al*. (2021) suggested the use of this analysis as a complementary tool in explaining publication bias. Regression analysis is used to determine if the linear relationship between effect sizes and standard errors has an intercept that is significantly different from zero. In other words, it measures whether the regression line describing this relationship deviates from the origin of the graph and how significant this deviation is.

The t-test was conducted with a significance level of $p < 0.05$. The regression results presented in Table 8 indicate that the deviation of the Egger regression line from the origin of the graph is quite insignificant at $p = 0.139$ ($p > 0.05$). This suggests that there is no publication bias in this research, which confirms that the inclusion and exclusion process used in the research has been effective in eliminating any potential bias towards certain publications.

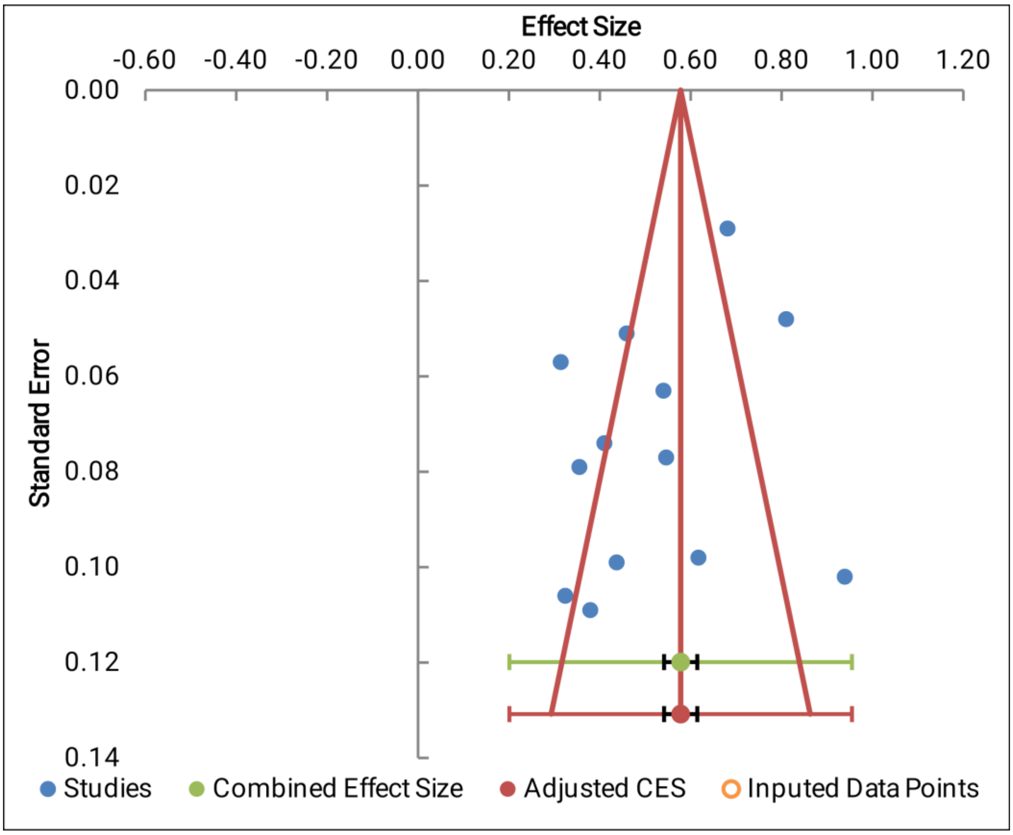

Figure 6. Funnel plot showing publication bias

Table 8. Egger test for examining publication bias

	Estimate	Standard Error (SE)	Confidence Interval (Lower limit)	Confidence Interval (Upper limit)
Intercept	−2.95	1.85	−6.98	1.08
Slope	0.74	0.11	0.50	0.98
t-test	−1.59			
p-value	0.139			

Discussion

This research executed a meta-analysis of research on SAGL. Research papers that were published within the past 20 years were examined. Thirteen papers were eventually included for meta-analysis with a total sample size of 2 573 participants. The research's uniqueness stems from being the first meta-analysis focused on SAGL. Other research studies have explored related areas, such as the meta-analysis of the influence of gamified learning on learning outcomes (Puspitasari & Arifin, 2023; Sailer & Homner, 2020; Wang, 2021; Zhan *et al.*, 2022), academic achievement (Dikmen, 2021), and academic performance (Zeng *et al.* 2024). These research studies primarily examined the impact of gamified learning based on student progression in their learning outcomes. The research was entirely independent of the students' perception and acceptance of gamified learning as addressed in this work. Any argument supporting the use of gamified learning to enhance student performance will be undermined if the students as end users do not find gamified learning acceptable. Addressing this aspect brings out this research's uniqueness. Although a similar approach was adopted in the work of Olugbara *et al.* (2021), they focused on investigating online education systems and not necessarily gamified learning.

From the 13 papers, meta-analysis identified 11 MSEFs whose influence on SAGL was significant. The random-effect analysis places the overall effect size as significant and positive, indicating that these MSEFs influenced SAGL meaningfully. These MSEFs were further categorized into three subgroups for the meta-analysis based on the respective endogenous factors they measure. Subgroup AA is the biggest, accounting for 46.2% of the 13 research studies. Subgroup BB addresses continuous use of SAGL (38.5%), and subgroup CC addresses the usage of SAGL (15.4%). The MSEFs predicting 'Intention to use SAGL' (Subgroup AA) are satisfaction, performance expectancy, perceived usefulness, social interaction, entertainment, and perceived enjoyment. The MSEFs predicting 'Continuous use of SAGL' (Subgroup BB) include social interactions, perceived usefulness, teaching design, learning goal orientation, and monetary rewardability. The MSEFs predicting 'Usage of SAGL' (Subgroup CC) are knowledge improvement and student engagement.

At the subgroup level, the MSEFs measuring the intention to use SAGL have the strongest direct influence. Of these factors, satisfaction has the best effect on SAGL with an effect size of 0.94. One of the MSEFs in the CC subgroup is knowledge improvement, which addresses the improvement of progress in knowledge acquisition during learning. This research shows that it has a moderate effect size and does not depict a strong indicator for SAGL. This shows that the works of authors who emphasized learning improvements-gamified learning relationships may not entirely suffice in investigating SAGL. Entirely new research should be conducted, such as the current research that examines other factors as necessary.

The result of this research on satisfaction as the most significant MSEF is in alignment with recent research on the impact of satisfaction on acceptance of technology-facilitated learning (e.g. Daneji *et al*., 2019; Joo *et al*., 2018; Olugbara *et al*., 2021; Pozón-López *et al*., 2020). While investigating the influence of student satisfaction on continual intention to adopt technology-facilitated learning, Joo *et al*. (2018) found a path coefficient of 0.861. Olugbara *et al*. (2021) also found student satisfaction to be the most significant factor influencing the acceptance of technology-facilitated learning with a statistically significant effect size of 0.61. The factor with the second-best influence was performance expectancy, followed by social interaction. Performance expectancy had an effect size of 0.81 (López *et al*., 2021), while social interaction had an effect size of 0.68 (Ssekibaamu, 2015).

The pooled effect size was 54%. The Cochran's Q of 100.32 and I^2 value of 88.04% were statistically significant ($p = 0.000$), indicating statistical heterogeneity in effect sizes of the included papers, despite the small number of papers included. The heterogeneity may possibly be attributed to variations in the sample sizes, the research model, locality of research study, and research design.

In addition, the view of the funnel plot indicates a possible publication bias, but a detailed statistical test (Egger regression) indicates no significant bias. This disparity has been attributed to the small number of research studies that were included. This argument applies even in cases with a large number of included research studies (e.g. Olugbara *et al*., 2021).

Theoretical and Practical Implication

Theoretically, this paper contributes to existing meta-analysis research on the acceptance of technology-facilitated learning. Specifically, it is the first paper addressing gamified learning. This research found that satisfaction, performance expectancy, and social interaction are the factors with the strongest and most significant influence on SAGL. This finding aligns with literature.

Olugbara *et al*. (2021) and Wan *et al*. (2020) specifically highlighted that greater satisfaction with technology-facilitated learning leads to greater acceptance of the system. This assertion is quite logical and transcends the sphere of technology-facilitated learning. The acceptance of new systems into different spheres of human endeavor is premised on user satisfaction; without satisfaction, acceptance becomes difficult. This explains the prime influence of students' satisfaction on acceptance of technology-facilitated learning systems.

Moreover, the research found that performance expectancy was a significant factor in the acceptance of SAGL. Specifically, Tamrin *et al*. (2022) established a significant path coefficient of 0.826 between performance expectancy and gamified learning. Ofosu-Ampong *et al*. (2019) also revealed that performance expectancy was the second-best predictor of acceptance of gamified learning as established in this research. This is because gamified learning systems are directly related to enhancing academic performance. The gamified learning system is expected to enhance student performance. The stronger students feel about this, the higher their level of acceptance will be.

The importance of peer influence among students is likely to explain why social interaction is also a strong factor that can influence SAGL. Incidentally, peer influence and performance expectancy are the two factors that Tamrin *et al*. (2022) examined in their work (their exclusion in the meta-analysis arises from the bias of narrowing on just two factors). However, their decision to narrow down on these two factors purportedly stems from the understanding of their relevance to influencing SAGL.

Therefore, this research presents a reference for policymakers and education software developers in the field of education and other relevant fields. It provides insight into the key areas that gamified learning systems development should focus on to be acceptable to students. The outcomes provide useful information that will make gamified learning acceptable to the end users. The designers and developers of the gamified learning systems will be able to convert the specific requirements of the learners into the components of the gamified learning systems.

Limitation

A limitation of this research is that research papers were excluded because they did not engage structural equation modelling, hypothesis testing, and similar methods. Some research with rich and applicable results was disqualified due to the absence of information such as sample sizes and reliability coefficients. The meta-analysis excluded research with useful information that did not meet certain inclusion criteria. The meta-analysis further excluded contributions from other stakeholders, such as policymakers, administrators, teachers, and parents. It only focused on students' acceptance and ignored the significance of learning support and contributions of other groups of people.

However, these limitations do not underemphasize the significance of this research. Rather, it calls for possible areas that further research should address.

CONCLUSION

This paper presented meta-analysis research to identify the significant factors that influence SAGL. Effect sizes, statistical heterogeneity, subgroup analysis, and publication bias were examined for the included research. The results indicate that student satisfaction, performance expectancy, and social interaction are the most influential factors. These factors, therefore, need to be considered in the development of gamified learning systems. The significance of this paper is its contribution to the body of knowledge by identifying the factors that influence the acceptance of gamified learning. It is therefore crucial for stakeholders to study these factors and determine the best strategies for mitigating them. Further research will focus on the adoption of gamified learning in African universities.

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