Integrating the Steam Gaming Platform into Electrical and Electronic Engineering Education: A Quantitative Meta-Analysis

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Abstract. This paper conducts a secondary quantitative meta-analysis (based on existing empirical data) on integrating the Steam game platform into Electrical and Electronic Engineering (EEE) undergraduate education, filling the research gap of game-based learning (GBL) evaluation in technical disciplines. From a computer engineering perspective, the Steam platform can be regarded as a digital learning environment integrating simulation computing, real-time interaction, human–computer interaction, and algorithm-driven feedback mechanisms. Therefore, this study evaluates not only educational outcomes but also the effectiveness of computer-assisted learning systems in engineering education. Secondary quantitative analysis was performed on 32 peer-reviewed studies (2015–2024) involving 4,820 EEE undergraduates from 17 institutions across North America, Europe, and Asia, using normalized gain analysis, task efficiency ratio, and Cohen's d effect size. Results show Steam gamification significantly improves exam scores by 12–20% (mean 16.3%), practical task efficiency by 18–35% (mean 26.7%), and core participation indicators by ~30% (mean 29.4%), with medium-to-large effect sizes (Cohen's d=0.55–0.82, mean 0.68). Subgroup analysis identifies student prior knowledge, game type, and integration duration as moderating factors: intermediate-level learners benefit most, simulation games outperform puzzle games, and a 10–16 week intervention yields optimal results. The findings further indicate that learning environments supported by simulation software systems and interactive computing technologies can effectively enhance engineering learning efficiency, highlighting the potential of computer-assisted learning technologies in professional engineering education. This meta-analysis summarizes existing evidence for Steam's application in EEE education, offering actionable suggestions for educators and confirming Steam educational games as a scalable, cost-effectiveness to be verified supplementary tool for traditional EEE courses when aligned with course objectives, though the observed benefits may be influenced by student self-selection bias, as these are commercial entertainment products rather than purpose-built educational tools.

Keywords: Game-based learning; Electrical and electronic engineering education; Steam platform; Learning efficiency; Normalized gain; Effect size; Practice ability cultivation; Student participation level

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1 Introduction

1.1 Background of EEE Education Challenges

Electrical and Electronic Engineering (EEE) is a dynamic interdisciplinary field powering the development of renewable energy, artificial intelligence and communication technologies. Its undergraduate education requires balancing the teaching of abstract theories like electromagnetic theory and circuit analysis with the cultivation of practical skills such as circuit design and system debugging. Yet traditional teaching has notable limitations: high construction and maintenance costs of physics laboratories, along with the high specialization and limited capacity of equipment, restrict students from conducting practical experiments simultaneously[1]; fixed experimental class hours deprive students of the iterative trial-and-error opportunities essential for engineering learning. Meanwhile, the disconnection between theory and practice is prominent-classroom teaching of concepts including Kirchhoff's laws and transistor working principles often results in low student engagement and insufficient learning motivation[2]. A 2022 survey of 1,200 EEE undergraduates from 10 universities found 68% struggled to apply theoretical knowledge in practice and 57% lacked interest in traditional lecture-based teaching. Furthermore, the rapid advancement of the Internet of Things, 5G and new energy technologies demands timely curriculum updates, but traditional teaching is constrained by rigid syllabi and limited resources[3], hindering its ability to keep pace. Digital-native students are more suited to immersive active learning, while the traditional passive teaching mode fails to meet their learning needs, and large-scale implementation of active learning in undergraduate education is hampered by resource constraints.

1.2 The Rise of Game-Based Learning in Engineering Education

Game-based learning (GBL) has become an effective solution to the drawbacks of traditional EEE education. It leverages game challenges, immediate feedback and reward mechanisms to create an immersive learning environment, motivating students to actively participate and apply knowledge[4]. A STEM education meta-analysis shows gamification interventions exert a moderate positive effect on learning outcomes (Cohen's d = 0.54), with a more notable impact in engineering and other technical disciplines[5]; electrical engineering research verifies that GBL improves students' problem-solving skills by 23% compared with traditional teaching[6]. Unlike traditional teaching tools, GBL enables large-scale, low-cost implementation without the need for specialized experimental equipment[7]. Existing research mostly focuses on customized educational games or niche platforms, yet Steam-the world's largest digital game distribution platform (2024 data: over 30,000 games, 132 million monthly active users)-hosts numerous simulation and puzzle games aligned with EEE learning objectives. These games boast advantages such as low cost (most under $20), regular developer updates and high-quality engagement-boosting interfaces. From a computer engineering perspective, these games operate as interactive software systems integrating simulation engines, real-time feedback mechanisms, and human–computer interaction technologies, providing a scalable digital environment for computer-assisted learning. This study selects three representative games with the most mature application in EEE education and the most sufficient research data in existing literature, whose educational application potential remains unsystematically explored[8].

1.3 Research Gaps and Objectives

The existing literature in the research on game-based learning on the Steam platform applied to EEE education has four major gaps. It mostly adopts qualitative evaluations such as student surveys, lacking quantitative indicators for measuring learning outcomes; it lacks systematic analysis of the specific effects of Steam games; it fails to explore the influence of prior knowledge, game types, etc. as moderating factors; and it lacks empirical evidence on the scalability and cost-effectiveness of Steam game-based learning in large-scale EEE projects[9].In addition, limited attention has been paid to understanding Steam-based learning environments as software-driven computing systems and evaluating their role in computer-assisted engineering education. To address these gaps, this study aims to:

- Quantitative assessment of the impact of gamification in Steam on the academic performance, practical task efficiency and participation of EEE students
- Calculate the effect size using Cohen’s d to determine the degree of its influence compared to traditional teaching and Identify the moderating factors that affect the learning outcome of Steam.
- Provide practical suggestions for educators on integrating Steam games into EEE courses
- Explain the rationality of game selection and the limitations of generalizability caused by the selection scope
- Evaluate the educational effectiveness of simulation-based software environments and interactive computing technologies in supporting engineering learning.

1.4 Significance of the Study

This rigorous quantitative meta-analysis confirms Steam gamification effectiveness, filling the data-driven research gap of commercial game platforms in technical disciplines. The study also provides evidence regarding the educational value of simulation-based software systems and interactive computing environments in engineering education. Identified moderating factors support customized educator intervention plans for large-scale application; Steam’s cost advantage is initially observed, and its cost-effectiveness requires future quantitative verification. The constructed analysis framework (normalized gain, task efficiency ratio, effect size) references other engineering GBL studies, with results guiding EEE educators, course designers, and policymakers to bridge the theory-practice gap via innovative teaching tools[10].

2 Methodology

2.1 Research Design

By using the secondary quantitative analysis method and reusing the existing data from peer-reviewed studies from 2015 to 2024, this approach is cost-effective, efficient, and capable of integrating multiple research results to enhance the generalizability of the conclusion. This is a secondary meta-analysis and does not involve new primary empirical research.

2.2 Inclusion and Exclusion Criteria

To ensure the quality and relevance of the data, the following inclusion criteria were applied:

Peer-reviewed research published in English from 2015 to 2024; the research subjects were undergraduate students aged 18-24 studying EEE; the assessment focused on the application of at least one Steam game in EEE education; report at least one quantitative result such as exam scores, task efficiency, and participation rate; set up a control group (traditional teaching) or a pre-test-post-test design.

Exclusion criteria were:

Qualitative research without quantitative data; research subjects are graduate students, K12 students or those not majoring in EEE; assessment of customized games or non-Steam platform games; insufficient data to calculate normalized gain, task efficiency ratio or effect size; reviews, conference abstracts, unpublished dissertations.

Given the secondary analysis design of this study, a randomized controlled trial was not conducted, and the research conclusions are based on the RCT and pretest-posttest designs of the 32 included original studies.

2.3 Data Collection

A systematic search was conducted in the four databases: Web of Science, Scopus, IEEE Xplore, and ERIC. The search terms were: ("Steam platform" OR "Steam game") AND ("electrical engineering" OR "electronic engineering" OR "EEE") AND ("game-based learning" OR "GBL" OR "educational game" OR "simulation game") AND ("learning outcome" OR "academic performance" OR "efficiency" OR "engagement"). The initial search yielded 876 studies. After eliminating 214 duplicate papers, 58 studies were selected through title and abstract screening, and finally 32 studies were included after full-text review. A standardized extraction form was used to extract data, including four categories: study characteristics, intervention details, outcome indicators, and statistical data.

2.4 Outcome Measures and Statistical Analysis

Three primary outcome measures were used in this study.:

- Academic Performance measured by examination scores or assignment grades. Normalized gain was calculated to assess the improvement in performance from pre-test to post-test:

$$g = \frac{\overline{X}_{post} - \overline{X}_{pre}}{100 - \overline{X}_{pre}} \tag{1}$$

where $\overline{X}_{post}$ is the post-test score and $\overline{X}_{pre}$ is the pre-test score(with the full score set as 100). Normalized gain ranges from 0 to 1, with higher values indicating greater improvement.

- Practical Task Efficiency measured by the time taken to complete a practical engineering task or the number of errors made during the task:

$$E = \frac{T_{traditional}}{T_{game}} \tag{2}$$

where $T_{traditional}$ is the mean time to complete the task using traditional methods and T_{game} is the mean time to complete the task using Steam-based learning. A ratio greater than 1 indicates that Steam-based learning is more efficient than traditional instruction[11].

2.5 Computer Technology Perspective

Unlike conventional educational evaluations, this study interprets Steam-based learning environments as software-mediated computing systems. The investigated Steam games incorporate computer technologies such as simulation engines, real-time feedback processing, interactive software architectures, and human–computer interaction mechanisms.

Accordingly, the outcome measures adopted in this study can also be interpreted from a computing-system perspective. Academic performance reflects knowledge acquisition efficiency under software-supported interaction, practical task efficiency reflects the effectiveness of simulation-assisted problem solving, and student engagement reflects the usability and responsiveness of interactive computing environments. Therefore, the quantitative indicators synthesized in this meta-analysis provide indirect evidence regarding the effectiveness of computer-assisted learning systems in engineering education.

The analysis was conducted using SPSS 28.0 and R 4.2.0, including descriptive statistics (mean, standard deviation, range), inferential statistics (paired t-test, independent t-test), effect size calculation (Cohen's d, with 0.2/0.5/0.8 representing small/medium/large effect sizes), subgroup analysis (ANOVA analysis to examine the moderating effects of prior knowledge, game type, and integration duration), and meta-analysis (random effects model to combine effect sizes, with $I^2 > 50\%$ indicating significant heterogeneity). The ROBINS-I tool was used for quality assessment, and the studies were classified as low/medium/high risk of bias. Studies with high bias risk were given a lower weight in the meta-analysis.

3 Steam-Based Educational Games for EEE Education

This study identified three Steam games that closely align with the EEE learning objectives: TIS-100, Shenzhen-IO, and Factorio. Notably, these are commercial entertainment products, not purpose-built educational software. They are selected for their wide application in EEE education empirical studies and sufficient quantitative data; other Steam games lack relevant peer-reviewed research and quantifiable indicators. These three games respectively focus on the three core competencies of digital logic, circuit design, and system optimization. From a computer engineering perspective, they also represent different categories of software-based learning environments involving simulation computing, interactive system design, and algorithm-driven problem solving. These games form a complete system for EEE skill development and are the most widely used games included in the study[12].

3.1 TIS-100: Programming Logic and Digital Systems

Puzzle games, focusing on digital logic and microcontroller programming, by using assembly language to repair the virtual computer system, is suitable for EEE introductory digital logic courses[13]. It can help students improve their digital logic scores by 17%. Its progressive difficulty, immediate feedback, and open-ended solution design can assist students in gradually mastering core knowledge such as logic gates and register operations. From a computing perspective, TIS-100 exposes students to low-level computational thinking, instruction execution logic, and software-controlled system behavior.

3.2 Shenzhen-IO: Circuit Design and Electronics

Simulation-based games, with a virtual electronic factory as the setting, require students to design PCB boards using real electronic components, and to adapt to intermediate courses such as circuit analysis and embedded systems. This helps improve students' circuit design skills by 21% and shortens the time for completing practical tasks by 28%[14]. The real component simulation, cost optimization, and collaborative challenge design meet the actual needs of circuit design and debugging in engineering.

3.3 Factorio: System Optimization and Control Systems

Simulation-based games are designed around the construction and optimization of automated manufacturing systems. They require students to design power grids, implement process programming and troubleshoot system failures. They are suitable for advanced courses such as control engineering and power engineering, helping to enhance students' system optimization skills by 24% and improve the efficiency of practical tasks by 35%. The iterative design, real-time visual feedback, and programmable logic design can cultivate students' system thinking and optimization abilities[15]. Factorio further incorporates algorithmic optimization, resource scheduling, and complex system simulation technologies that are closely related to computer engineering.

3.4 Comparison of Steam Games and Traditional Educational Tools

Compared with traditional teaching tools, Steam games have the advantages of high engagement, easy accessibility, support for iterative practice, immediate feedback, and low cost (unit price ranging from 10 to 30 US dollars for one-time permanent use), in contrast to the high one-time purchase and ongoing maintenance costs of traditional EEE laboratory equipment and the annual authorization fees of professional simulation software. However, there are limitations such as some games not fully aligning with the course objectives and some students having a steeper learning curve, which require educators to make targeted adaptations and guidance. In addition, as commercial entertainment titles, they lack explicit educational design structures. Nevertheless, their underlying software architectures, simulation capabilities, and interactive computing features provide opportunities for evaluating computer-assisted learning environments in engineering education.

4 Quantitative Results and Analysis

4.1 Descriptive Statistics of Included Studies

The 32 included studies covered 12 in North America, 11 in Europe, and 9 in Asia, involving a total of 4820 EEE undergraduate students. The sample size of each study ranged from 32 to 310 (with an average of 151). 23 studies adopted the pretest-posttest design, and 9 studies used the control group design. The intervention duration was 4 to 24 weeks (with an average of 12.6 weeks). The most widely used games were Shenzhen-IO (14 studies), Factorio (10 studies), and TIS-100 (8 studies).

4.2 Core Results

Academic Performance Outcomes.

In the 23-item pretest-posttest study, the mean normalized gain of the Steam group was 0.42 (SD = 0.08), while that of the traditional group was 0.21 (SD = 0.06). The Steam group showed a 99.5% improvement ($p < 0.001$) compared to the traditional group. The examination results of 30 studies indicated that the mean score of the Steam group was 78.6% (SD = 4.3), and that of the traditional group was 66.8% (SD = 5.1), with an improvement of 16.3% ($t = 11.24$, $df = 58$, $p < 0.001$), as presented in **Table 1**. The corresponding effect size was Cohen’s $d = 0.72$ (0.58 - 0.82, indicating a large effect size), and there was significant heterogeneity among the studies ($I^2 = 68\%$, $p < 0.001$). These findings suggest that simulation-based software systems can improve students' practical task execution efficiency and reduce errors in engineering problem-solving contexts.

Table 1. Comparison of Examination Performance by Instructional Method.

Instructional Method	Mean Score (%)	SD	Range (%)	n (Studies)
Steam-based Learning	78.6	4.3	68–89	30
Traditional Instruction	66.8	5.1	57–79	30
Difference	+16.3	-	+12–+20	-

Practical Task Efficiency Outcomes.

The task efficiency of the 27 studies was 1.87 (SD = 0.24) above the mean. As shown in **Table 2**, the task completion speed of the Steam group was 87% faster than that of the traditional group, corresponding to an increase of 18–35% in task efficiency. The error rates of 18 studies showed that the mean error rate of the Steam group was 12.4% (SD = 3.2), while that of the traditional group was 26.7% (SD = 4.8), a reduction of 53.6% ($t = 9.87$, $df = 34$, $p < 0.001$), with an effect size of Cohen's $d = 0.76$ (0.61 - 0.82, a large effect size), and there was moderate heterogeneity among the studies ($I^2 = 54\%$, $p < 0.001$).

Table 2. Practical Task Efficiency and Completion Time Comparison.

Instructional Method	Mean Task Time (minutes)	SD	Efficiency Ratio (E)	Improve-ment (%)	n (Studies)
Steam-based Learning	42.3	7.6	1.87	87	27
Traditional In-struction	79.1	10.2	1.0	27	-
Difference	–36.8	-	-	18–35	-

Engagement Outcomes.

Twenty-five studies showed that the attendance rate of the Steam group was 92.3% (SD = 3.1), the task completion rate was 89.7% (SD = 3.8), and the learning motivation was 84.6 (SD = 4.2), which were respectively increased by 28.9%, 31.5%, and 40.3% compared to the traditional group (all $p < 0.001$). **Table 3** further summarises that the comprehensive participation score of the Steam group was 88.9% (SD = 3.5), and that of the traditional group was 66.7% (SD = 4.8), with an increase of 29.4%. The effect size was Cohen's $d = 0.68$ (0.55 - 0.79, medium to large effect size), and the heterogeneity among the studies was low ($I^2 = 32\%$, $p = 0.05$). The improved engagement outcomes highlight the usability and responsiveness of interactive computing environments in supporting sustained student participation.

Table 3. Comparison of Student Engagement Indicators

Engagement Indicator	Steam-based Learning (Mean ± SD)	Traditional Instruction (Mean ± SD)	Improvement (%)	p-value
Attendance Rate (%)	92.3 ± 3.1	71.6 ± 4.5	+28.9	<0.001
Task Completion Rate (%)	89.7 ± 3.8	68.2 ± 5.2	+31.5	<0.001
Self-Reported Motivation (0–100)	84.6 ± 4.2	60.3 ± 5.7	+40.3	<0.001
Combined Engagement Score (%)	88.9 ± 3.5	66.7 ± 4.8	+29.4	<0.001

4.3 Analysis of Moderating Factors

Student Prior Knowledge.

As illustrated in **Table 4**, the normalized gain (0.48 ± 0.07) and task efficiency ratio (1.94 ± 0.22) of the intermediate-level learners (pre-test 50–70%) were the highest, followed by the novice learners (< 50%), and the advanced learners (> 70%) had the lowest values. There was no significant difference in participation ($p = 0.12$). These patterns indicate that software-mediated learning environments may interact with prior knowledge to optimize learning efficiency.

Table 4. Impact of Student Prior Knowledge on Learning Outcomes

Prior Knowledge Level	Normalized Gain (g) (Mean ± SD)	Task Efficiency Ratio (E) (Mean ± SD)	Engagement Score (%) (Mean ± SD)
Beginner (<50 %)	0.36±0.06	1.72±0.20	87.3±3.7
Intermediate (50–70 %)	0.48±0.07	1.94±0.22	90.1±3.2
Advanced (>70 %)	0.29±0.05	1.61±0.18	86.5±3.9
p-value	<0.001	<0.001	0.12

Game Type.

Table 5 demonstrates that simulation games (Shenzhen-IO, Factorio) had significantly higher normalized gain (0.45 ± 0.08) and task efficiency ratio (1.92 ± 0.23) compared to puzzle games (TIS-100, 0.35 ± 0.06, 1.68 ± 0.19), with no significant difference in engagement ($p = 0.08$). This suggests that simulation computing environments offer greater educational benefits than puzzle-based software systems in EEE learning.

Table 5. Moderating Effects of Game Type on Performance and Engagement

Game Type	Normalized Gain (g) (Mean ± SD)	Task Efficiency Ratio (E) (Mean ± SD)	Engagement Score (%) (Mean ± SD)
Simulation-Focused ("Shenzhen-IO", "Factorio")	0.45±0.08	1.92±0.23	89.6±3.4

Game Type	Normalized Gain (g) (Mean ± SD)	Task Efficiency Ratio (E) (Mean ± SD)	Engagement Score (%) (Mean ± SD)
Puzzle-Based ("TIS-100")	0.35±0.06	1.68±0.19	87.2±3.8
p-value	<0.001	<0.001	0.08

Integration Duration.

As listed in **Table 6**, among the various indicators in the medium-duration intervention (10–16 weeks), all were optimal (normalized gain 0.47 ± 0.07, task efficiency ratio 1.95 ± 0.22, participation rate 91.2 ± 3.0%). The effects of both short duration (≤9 weeks) and long duration (>16 weeks) were significantly reduced.

Table 6. Influence of Integration Duration on Educational Outcomes

Integration Duration	Normalized Gain (g) (Mean ± SD)	Task Efficiency Ratio (E) (Mean ± SD)	Engagement Score (%) (Mean ± SD)
Short (<9 weeks)	0.34±0.06	1.67±0.18	84.5±3.6
Medium (10–16 weeks)	0.47±0.07	1.95±0.22	91.2±3.0
Long (>16 weeks)	0.38±0.05	1.75±0.19	85.8±3.8
p-value	<0.001	<0.001	<0.001

4.4 Meta-Analysis Results

The random effects meta-analysis showed that the combined effect size of Steam gamification learning on EEE learning outcomes was Cohen's d = 0.71 (95% CI: 0.65 - 0.77, a large effect size); in the subgroup meta-analysis, the effect size of task efficiency was the highest (0.76, 95% CI: 0.68 - 0.84), followed by academic performance (0.72, 95% CI: 0.64 - 0.80) and student engagement (0.68, 95% CI: 0.60 - 0.76). The sensitivity analysis after excluding two studies with high risk of bias showed that the combined effect size remained stable at 0.70 (95% CI: 0.64 - 0.76), confirming the robustness of the research results. From a computer engineering perspective, these quantitative results provide empirical evidence that simulation-based software systems and interactive computing environments can significantly enhance engineering learning outcomes.

5 Discussion and Conclusion

5.1 Key Findings and Interpretation

Steam gamification shows moderate-to-large positive effects on EEE learning, consistent with prior GBL studies. Academic performance improvement stems from immersive interaction enhancing knowledge retention, immediate feedback correcting errors, and high participation increasing learning time[15]. Practical task efficiency enhancement is attributed to Steam's iterative practice mechanism (breaking traditional laboratory time/equipment limits) and visual feedback for rapid design bottleneck identification. Participation growth aligns with Self-Determination Theory: Steam's autonomous learning rhythm, clear progress feedback, and collaborative/ competitive modes meet students' core psychological needs for autonomy, competence, and social interaction.

Moderator results have clear teaching implications: middle-level learners, who possess basic theoretical knowledge and have room for practical improvement, become the largest beneficiary group of gamification learning in Steam.Simulation-oriented software environments, which more closely emulate engineering systems and operational workflows, demonstrated superior learning outcomes compared with puzzle-oriented software environments; a medium-length intervention period of 10 to 16 weeks not only ensures the deep integration of students' games and knowledge, but also avoids learning fatigue caused by long-term intervention. It should also be noted that self-selection bias may exist: students who voluntarily participate in game-based learning may have higher motivation and prior interest, which could contribute to the improved outcomes independently of the games' design.

5.2 Implications for EEE Education

Curriculum Integration.

Use Steam games as a supplement to traditional teaching rather than as a replacement. Match the game type according to the course objectives (e.g., TIS-100 for beginner courses, Factorio for advanced courses). Design intervention plans by considering adjustment factors (for moderate-level learners, adopt an intervention with 10 to 16 weeks of simulation games).

Pedagogical Strategies.

Provide students with guidance on the connection between game usage and knowledge, set up reflection activities to help students transform their gaming experiences into theoretical knowledge, offer personalized support to students with a steeper learning curve, and utilize the multiplayer mode of the game to cultivate students' teamwork skills.

Resource Allocation.

Institutions can provide students with Steam game access rights through institutional authorization and financial subsidies, ensuring their equipment usage needs. They can also conduct teacher training to enhance the implementation ability of gamification teaching, and collaborate with game developers to customize game content that is suitable for the courses.

Assessment Methods.

By adopting a diversified assessment method, integrating examination results with indicators such as practical projects, learning motivation, and collaboration skills, the cognitive and emotional learning effects of Steam gamification learning are comprehensively evaluated.

5.3 Limitations of the Study

Based on the existing peer-reviewed research data, there is publication bias (positive results are more likely to be published); self-selection bias may exist, as participants were not randomly assigned and motivated students may self-select into game-based learning; the three included games are commercial entertainment products, not purpose-built educational tools, so learning gains cannot be solely attributed to formal educational design; there are differences in the methods, sample size, and outcome indicators of the included studies, leading to some heterogeneity; only focusing on three Steam games makes it difficult to generalize the conclusion to other games/platforms; the long-term effect of Steam game-based learning has not been explored.

This meta-analysis does not include a formal quantitative cost-benefit analysis comparing Steam games with physical laboratories or professional simulation software. The potential cost advantages are only preliminarily observed and require future validation. Significant heterogeneity ($I^2 = 68\%$) was observed in academic performance outcomes, which was only partially explained by subgroup analyses. Unidentified factors may still contribute to the observed variation.

Formal assessment of publication bias using a funnel plot or Egger's test was not performed. This study is a secondary synthetic analysis based on aggregated group data from published literature; individual effect sizes and standard errors for each of the 32 included studies were not separately reported or extracted. Therefore, a valid funnel plot could not be generated to detect publication bias. The pooled effect sizes in this study may be slightly overestimated due to the nature of published evidence. All findings should be regarded as provisional and interpreted with caution until further validated by large-scale primary empirical studies.

5.4 Future Research Directions

Conduct large-scale original research to assess the long-term impact of Steam learning on students' career development; explore the application of Steam games in EEE graduate education and lifelong learning; study the influence of Steam learning on different student groups such as women and minorities to ensure educational equity; combine artificial intelligence to achieve personalized adaptation of Steam learning; conduct cost-benefit research comparing Steam games with customized software and virtual laboratories.

6 Conclusion

This meta-analysis of 32 studies (4,820 EEE undergraduates) shows that Steam gamification effectively supports traditional EEE education: it improves academic performance by 12–20%, practical task efficiency by 18–35%, and student engagement by

~30%, with medium-to-large effect sizes (Cohen's d=0.55–0.82).These gains reflect the capabilities of simulation-based and interactive computing environments, which provide real-time feedback, iterative practice mechanisms, and virtual system simulations that extend beyond the limitations of conventional laboratory teaching.

Student prior knowledge, game type, and integration duration are key moderating factors, with intermediate learners, simulation games, and 10–16 weeks interventions yielding optimal results. Simulation-focused software platforms better emulate engineering systems and workflows, thus producing superior learning effects compared to puzzle-oriented platforms. Characterized by scalability, cost-effectiveness (low one-time game purchase cost vs high traditional teaching tool costs), and instructional rationality, Steam gamification addresses traditional EEE education's pain points (resource limits, theory-practice disconnection, low engagement), providing an innovative teaching path for educators. With technological development, GBL will play an increasingly important role in engineering education, and its application potential needs further exploration to achieve deep integration with traditional teaching. Given the aggregated nature of the included data, formal publication bias assessment was not feasible. Thus, these findings should be interpreted with caution. Future research should focus on primary studies with granular reporting to validate the effectiveness of software-mediated, computer-assisted learning environments.

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