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Meta-Analysis on the Effectiveness of Learning Cycle Models and Online Teaching Strategies in Chemistry Education

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The purpose of this meta-analysis was to look at the effects of Learning Cycle Models (LCMs) and Online Teaching Strategies (OTSs) on academic achievement of students in chemistry. The study gathered information from 17 published sources, including dissertations and journal papers, and included a total of 2049 students. The findings revealed high heterogeneity among the included research, necessitating the use of a random-effects model. The overall effect size study found that LCMs and OTSs had a relatively large and beneficial influence on students' academic progress, with an effect size of 1.44. The analysis further examined the impact of different factors on the effect sizes, including grade level, learning modality, duration, and subject matter. Elementary and high school students demonstrated very large effect sizes, while college students had a small effect size. In-person classes showed larger effect sizes than online teaching strategies, although both approaches had positive effects. Longer durations of interventions resulted in larger effect sizes, and specific subject matters, such as matter and acids & bases, showed very large effect sizes. The findings suggest that tailored instructional approaches, incorporating a variety of LCMs and OTSs, can enhance students' academic achievement in chemistry education. Recommendations were provided for educators, curriculum designers, and policymakers to guide the implementation of LCMs and OTSs, considering specific grade levels, learning modalities, durations, and subject matters. Continued research is necessary to refine instructional strategies and improve outcomes in chemistry education.

Keywords: COVID-19, pandemic, effect sizes, heterogeneity, learning modality

INTRODUCTION

In recent years, the field of education has witnessed a significant shift toward online teaching and learning, driven by advancements in technology and the need for flexible and accessible educational opportunities (Alenezi, 2023; Gupta & Yadav, 2023; Mukul,

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E., & Büyüközkan, G., 2023). Within the realm of chemistry education, the integration of online teaching strategies (OTSs) and learning cycle models (LCMs) has gained prominence as a potential solution to enhance students' academic achievement (Simonson, 2023; Boonsuk, Y., & Ambele, E. A., 2021; Suwito et al., 2020; Suardana, I N. et al., 2018). LCMs provide a structured framework that guides educators in designing instructional sequences and assessments, promoting an active and collaborative learning environment (Yoder, 2014; Ajaja, O.P., 2013; De Corte, E. et al., 2004).

However, as online teaching and learning continue to evolve, there is a need for a comprehensive evaluation of the effectiveness of LCMs in chemistry education (Tiemann & Annaggar, 2023; Jack, 2017; Adesoji & Idika, 2015; Opara, F., & Waswa, P., 2013). This meta-analysis investigates the impact of online teaching and learning cycle models on students' chemistry academic attainment. We hope to answer the following research questions by thoroughly reviewing previous studies:

1. What is the frequency distribution of students' grade levels and subject matter in research looking at the impact of Learning Cycle Models (LCMs) and Online Teaching Strategies (OTSs) on students' chemistry achievement?
2. What methods of learning instruction were used in the research included in the meta-analysis?
3. What are the inferences in terms of the effect sizes on students' academic progress as a result of the use of LCMs and OTSs?
4. What does the meta-analysis forest plot show about the effect sizes of LCMs and OTSs on students' academic achievement?
5. What does the Classic Fail-Safe N analysis suggest regarding the robustness of the observed impacts of LCMs and OTSs on students' academic progress in chemistry education, as well as the possible influence of unpublished or missing studies?
6. What is the current state of publication bias in sample studies investigating the effects of LCMs and OTSs on students' academic progress in chemistry education?
7. How does the impact of learning strategy training on student achievement differ according on:
   a. Participants' grade level
   b. Learning modality
   c. Subject matter
   d. Duration

This meta-analysis intends to give educators, researchers, and policymakers with significant insights on the effectiveness of online teaching and learning cycle models in chemistry education by addressing these research issues. The findings will add to the existing body of information and inspire future teaching practices to improve students' chemistry academic progress.

To conduct this meta-analysis, a systematic review of relevant studies will be carried out, focusing on empirical research investigating the impact of LCMs and OTSs on students' academic achievement in chemistry. The selected studies will be critically analyzed and synthesized to identify trends, patterns, and potential areas for further investigation.

METHOD

This meta-analysis integrates primary study findings to investigate the effect of learning strategy training on student accomplishment at various grade levels, including college students. This study's approach includes identifying dependent and independent variables, eliminating publication bias, conducting a comprehensive literature search, applying a rigorous coding process, and establishing inclusion criteria.

Dependent and independent variables: In this meta-analysis, the dependent variable focused on the effect sizes derived from the outcomes of LCMs and OTS on student achievement. Meanwhile, the independent variable examined was the learning strategy instruction.

Publication bias: A traditional fail-safe N test was used to determine the presence of publication bias. This test calculates the number of studies with non-significant effects required to lower the significant findings to a p-value of 0.05. A funnel plot was also used to investigate any potential publishing bias graphically.

Literature Search: A thorough literature search was carried out in order to collect empirical research that investigated the impact of learning strategy instructions on student accomplishment. This search included a broad range of study findings that were especially focused on these methods and their relevance to student progress. A thorough search of published and unpublished graduate theses and dissertations in chemistry teaching was conducted. Furthermore, computerised searches were conducted using educational journals from both domestic (Commission on Higher Education, Department of Science and Technology, National Library of the Philippines, De La Salle University-Manila, and the University of the Philippines) and international sources, such as ERIC (Education Research Information Centre), as well as standard search engines such as Google and Google Scholar, with relevant search terms.

Coding Process: Several processes are involved in the coding process to ensure correctness and reliability. To collect pertinent data from the publications, a coding form developed from Cavanaugh (2001) was initially used. Two raters independently coded all research that matched the selection criteria. Grade level, sample size, year of publication, subject content, contact hours, study design, country, and descriptive data such as mean and standard deviations were all extracted. To preserve consistency, the two independent raters compared their coding results, attaining an inter-rater agreement of 0.90. Any questions or difficulties regarding study eligibility were resolved through one-on-one discussions, guaranteeing agreement. This technique obtained 100% agreement on coding judgements, greatly improving the data extraction procedure's dependability and accuracy.

Inclusion Criteria: A surface-level screening was initially performed on each of the gathered chemistry education publications to select studies for inclusion in the synthesis. If the essential characteristics of the study were not apparent from the title and abstract, the full text was carefully examined. Rigorous inclusion criteria were applied to ensure the quality and relevance of the studies. The following criteria were used: a) The studies focused on students' achievement as a result of using instructional learning strategies; b) The studies were completed between 2010 and 2022; c) The studies were conducted in-person for LCMs, while studies utilizing online distance learning (ODL) were considered for OTS; d) The studies involved students ranging from elementary to college level; e) The studies used experimental or quasi-experimental research designs. By applying these inclusion criteria, the selected studies for synthesis were carefully chosen based on their relevance and adherence to rigorous research design and reporting standards.

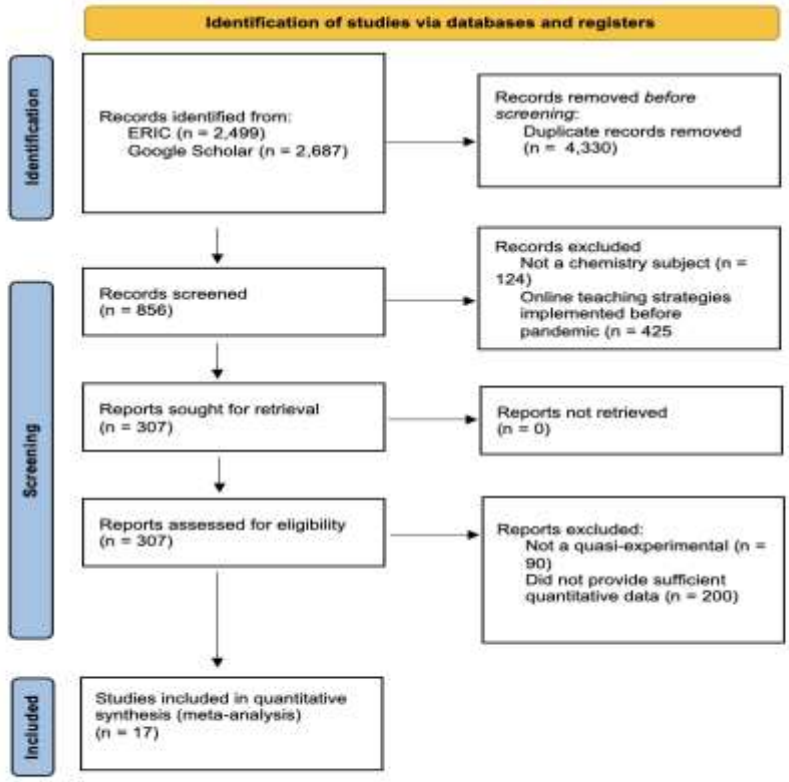


Figure 1
Prisma flow diagram (2020) for the effectiveness of learning instruction strategies

This meta-analysis included 856 research on learning teaching methodologies. As a result, only 17 articles qualified. The research was carried out in Malaysia (n=1), Indonesia (n=2), the United States (n=1), Turkey (n=8), Rwanda (n=1), Nigeria (n=3), and Kenya (n=1). The key reason for the small number of qualifying articles was that some of the papers acquired did not match the inclusion criteria and lacked the essential statistical data.

Data Analysis

Homogeneity: For the collected effect sizes, homogeneity statistics were used to evaluate if the results shared a common effect size in the population or whether the collection of effect sizes differed statistically significantly. Depending on whether the Q statistics are insignificant or significant, either a fixed-effects or a random-effects model would be used to analyse the data. The fixed effects statistical model posits that the distribution of effect sizes around their mean is smaller than or equal to the sampling error inferred from the data. The random effects statistical model, on the other hand, implies population effect heterogeneity, given that the relationships between LCMs and online teaching styles and student achievement vary among studies.

Calculating Effect Sizes: We used Hedge's g, a standardised mean difference that compares the means of two groups, to compute the effect sizes for this meta-analysis. Hedge's g was chosen because it provides a more accurate approximation of population variations, especially with smaller sample numbers. For the meta-analysis, we used the Meta-Essentials programme, which simplifies the integration and synthesis of effect sizes from diverse research. The Meta-Essentials utility is a collection of Microsoft Excel worksheets. By inputting the necessary information, such as effect sizes and sample sizes, the tool automatically generates essential statistics, tables, figures, and more (Suurmond et al., 2017). This allowed us to efficiently analyze and interpret the data collected from the retrieved studies. Once the common effect size was determined, we clustered the studies to explore potential differences in average effects among different groups. For example, studies that provided separate data on various topics were combined to conduct subgroup analyses and evaluate specific areas of interest.

By employing these methodologies and techniques, we aimed to derive meaningful insights from the collective effect sizes and analyze any variations or trends across different study groups.

FINDINGS AND DISCUSSION

To explore the impact of learning with Learning Cycle Models (LCMs) and Online Teaching Strategies (OTS) on students' chemistry achievement, a complete analysis of the gathered studies was undertaken. The synthesis of the impact sizes determined from the selected research provides important insights into the efficacy of different instructional approaches. This section summarises the findings and analyses the consequences for students' chemical achievement.

Table 1
Frequency of students' grade level and subject matter

Level of participants	Frequency	Percentage
Elementary	1	*5.88*
High school	13	*76.47*
College	3	*17.65*
Topics		
Electrolysis	3	*17.65*
Matter	4	*23.53*
Organic compounds	2	*11.76*
Acids and bases	2	*11.76*
Hydrocarbons	3	*17.65*
Non-metals	1	*5.88*
Mole concept	1	*5.88*
Chemical properties	1	*5.88*
TOTAL	17	100

The distribution of topic matter covered in the research included in the meta-analysis is shown in Table 1. The identified subject matters encompassed a range of essential topics in chemistry education, shedding light on the areas that received significant attention within the research.

Upon analyzing Table 1, it is evident that a diverse array of subject matter was investigated in the selected studies. The subjects explored in the studies included electrolysis, matter, organic compounds, acids and bases, hydrocarbons, non-metals, mole concepts, and chemical properties. These topics represent fundamental concepts and principles within the field of chemistry, covering a broad spectrum of content areas.

Among the topics investigated, it is worth mentioning that a greater number of studies focused on matter. The prominence of matter as a subject of investigation highlights its importance in chemistry education and the significance of understanding its properties, behavior, and interactions. This emphasis on matter underscores its foundational role in solidifying understanding of various chemical phenomena and concepts.

Regarding the study's characteristics, the effect size values analyzed were derived from 17 published sources, comprising 15 effect sizes from dissertations and two from journal articles. The research included 2049 students, including 1037 in the experimental group and 1012 in the control group. One of the studies, which lasted from 2010 to 2022, focused on primary pupils and had a sample size of 65 people. Thirteen studies centered on high school students, encompassing a larger sample of 1698 students. Additionally, three studies specifically targeted college-level students, with a total sample size of 148 participants.

Table 2
Learning instruction strategies utilized by obtained studies

Learning Cycle Model	Frequency	Percentage
5E	4	*57.14*
7E	2	*28.57*
Piagetian	1	*14.29*
Total	7	*100.00*
Online teaching strategies		
Computer simulation	4	*40.00*
Animation video	1	*10.00*
Android-based game	2	*20.00*
Web-based discussion	2	*20.00*
Project-based e-learning	1	*10.00*
Total	10	*100.00*

In the literature, studies conducted by Uyanik (2016), Santyasa et al. (2021) on Matter, Ercan (2014) on hydrocarbons, Uzezi & Deya (2020) on acid-base reactions, Jack (2017) on non-metals, and Oladejo et al. (2021) on electrolysis have demonstrated very large and positive effect sizes of 7.812, 5.322, 2.817, 2.425, 1.984, and 1.544, respectively. These findings indicate that the meta-analysis results align with the subject matter investigated in these studies, suggesting a consistency of effects based on the specific topic under investigation.

Table 2 provides insights into the most commonly used learning cycle models (LCMs) and online teaching strategies employed in the included studies. Among the LCMs, the 5E model was the most frequently utilized, followed by the 7E model and then the Piagetian model. The most commonly employed approaches for online teaching strategies were computer simulation, android-based games, and web-based discussion, followed by animation video and project-based e-learning. These findings shed light on the diverse instructional strategies employed in the studies, highlighting the range of innovative approaches utilized to enhance students' academic achievement in chemistry education.

Table 3
Finding students' academic achievement effect sizes

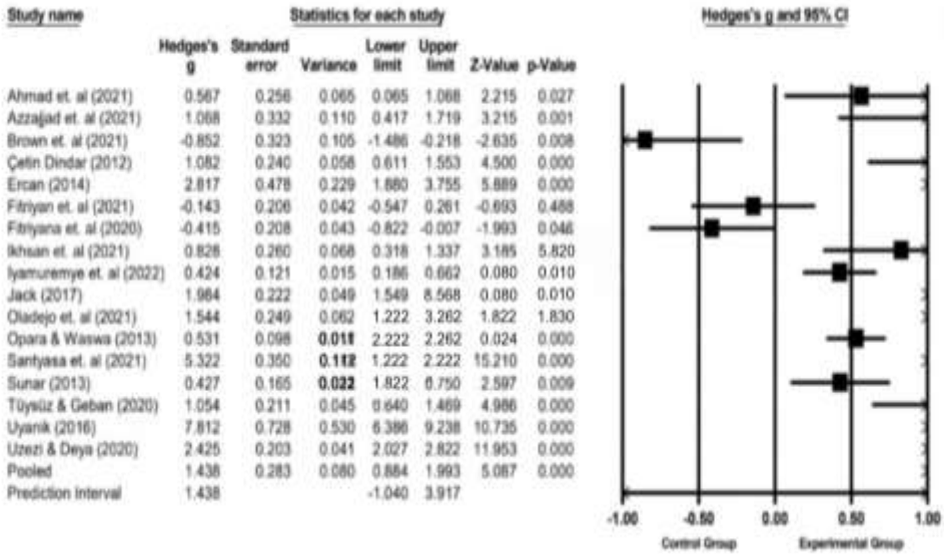
					95% CI				Heterogeneity			
Mod.	k	ES	SE	Var.	Low.	Up.	Z	pa	Q	Df (Q)	p	I^2
FEM	17	0.83	0.05	0.002	0.731	0.992	16.92	0.00	486.57	16	0.00	96.71
REM	17	1.44	0.49	0.080	0.884	1.993	5.09	0.00	486.57		0.00	96.71

Table 3 offers important findings on the effect sizes of LCMs and OTSs on students' academic progress in chemistry instruction. The table includes detailed information such as the overall effect size (ES), the number of studies (k), standard error (SE), variance, confidence intervals (CI), Z-value, p-value, and heterogeneity indicators.

Table 3's estimated Q statistic and p-value show significant heterogeneity among the gathered studies (Q > df, p 0.05). This shows that the effect sizes in the studies included in this meta-analysis are not comparable. Because of the presence of significant heterogeneity, the random-effects technique was used to synthesise the research (Borenstein et al., 2009). The random-effects model accounts for study variability and allows for the assessment of potential causes of heterogeneity.

Furthermore, with an effect size of 1.44, the overall weighted random effect size estimated by the meta-analysis reveals a significantly very large and favourable effect of using LCMs and online teaching methodologies on students' academic progress. This suggests that the implementation of LCMs and OTSs in chemistry education has a substantial impact on enhancing students' academic achievement.

In addition, the I^2 statistic received a high score of 96.71, indicating significant heterogeneity among the trials. This implies that there may be considerable discrepancies in impact sizes between studies, necessitating further examination via moderator or subgroup analysis (Borenstein et al., 2009). Conducting such analyses can help identify potential factors contributing to the observed heterogeneity and provide insights into the variations in the effects of LCMs and OTSs on students' academic achievement across different contexts.



Study name	Statistics for each study						
	Hedges's g	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value
Ahmad et. al (2021)	0.567	0.256	0.065	0.065	1.068	2.215	0.027
Azzajad et. al (2021)	1.068	0.332	0.110	0.417	1.719	3.215	0.001
Brown et. al (2021)	-0.852	0.323	0.105	-1.486	-0.218	-2.635	0.008
Çetin Dindar (2012)	1.082	0.240	0.058	0.611	1.553	4.500	0.000
Ercan (2014)	2.817	0.478	0.229	1.880	3.755	5.889	0.000
Fitriyan et. al (2021)	-0.143	0.206	0.042	-0.547	0.261	-0.693	0.488
Fitriyana et. al (2020)	-0.415	0.208	0.043	-0.822	-0.007	-1.993	0.046
Ikhsan et. al (2021)	0.828	0.260	0.068	0.318	1.337	3.185	5.820
Iyamuremye et. al (2022)	0.424	0.121	0.015	0.186	0.662	0.080	0.010
Jack (2017)	1.984	0.222	0.049	1.549	8.568	0.080	0.010
Oladejo et. al (2021)	1.544	0.249	0.062	1.222	3.262	1.822	1.830
Opara & Waswa (2013)	0.531	0.098	**0.011**	2.222	2.262	0.024	0.000
Santyasa et. al (2021)	5.322	0.350	**0.112**	1.222	2.222	15.210	0.000
Sunar (2013)	0.427	0.165	**0.022**	1.822	6.750	2.597	0.009
Tüysüz & Geban (2020)	1.054	0.211	0.045	0.640	1.469	4.986	0.000
Uyanik (2016)	7.812	0.728	0.530	6.386	9.238	10.735	0.000
Uzezi & Deya (2020)	2.425	0.203	0.041	2.027	2.822	11.953	0.000
Pooled	1.438	0.283	0.080	0.884	1.993	5.087	0.000
Prediction Interval	1.438			-1.040	3.917		

Figure 2
The forest plot

Figure 2 depicts a forest plot to graphically depict the distribution of effect sizes and provide a detailed examination of each meta-analyzed study. The forest plot shows the effect sizes, their confidence intervals, and the weights allocated to each research in the meta-analysis. This visualization helps contextualize the analysis and allows for a better understanding of the individual study contributions to the overall findings.

The forest plot of the meta-analysis reveals essential insights into the effect sizes of students' academic achievement resulting from using Learning Cycle Models (LCMs) and Online Teaching Strategies (OTSs) in chemistry education. As seen in the forest plot, the overall distribution of effect sizes favours the experimental group, which got instruction with LCMs and online teaching methodologies, over the control group, which did not receive these interventions.

The forest plot demonstrates that several studies significantly contribute to the overall findings. Notably, the studies conducted by Opara & Waswa (2013) regarding LCMs and Iyamuremye et al. (2022) concerning online teaching strategies played a substantial role in shaping the outcomes, as evidenced by their shorter confidence intervals. These studies provide strong evidence supporting the effectiveness of LCMs and OTSs in enhancing students' academic achievement in chemistry.

To validate the observed effects of LCMs and OTSs, a Classic Fail-Safe N analysis was used. This approach is a robust way for assessing the impact of any unpublished or missing research that may have an impact on the findings. Table 4 presents the analytical results, which provide additional insight into the strength and reproducibility of the effects reported in the meta-analysis.

Table 4
Classic fail-safe N

Z-value for observed studies	20.18531
P-value for observed studies	0.00000
Alpha	0.05000
Tails	2.00000
Z for alpha	1.95996
Number of observed studies	17.00000
Number of missing studies that would bring p-value to > alpha	1787

The Classic Fail-Safe N analysis results provide insights into the robustness and potential impact of unpublished or missing research on the observed impacts of Learning Cycle Models (LCMs) and Online Teaching Strategies (OTSs) on students' academic progress in chemistry education.

The Classic Fail-Safe N analysis results in the conclusion that the meta-analysis, based on 17 empirical research, is valid and resistant to publication bias ($p < 0.05$). According to the Classic Fail-Safe N analysis, an additional 1787 studies would be required to invalidate the obtained conclusion. This finding shows that the observed effects of LCMs and OTSs on students' academic progress in chemistry, as established in the meta-analysis, are robust and are not unduly influenced by unpublished or missing research.

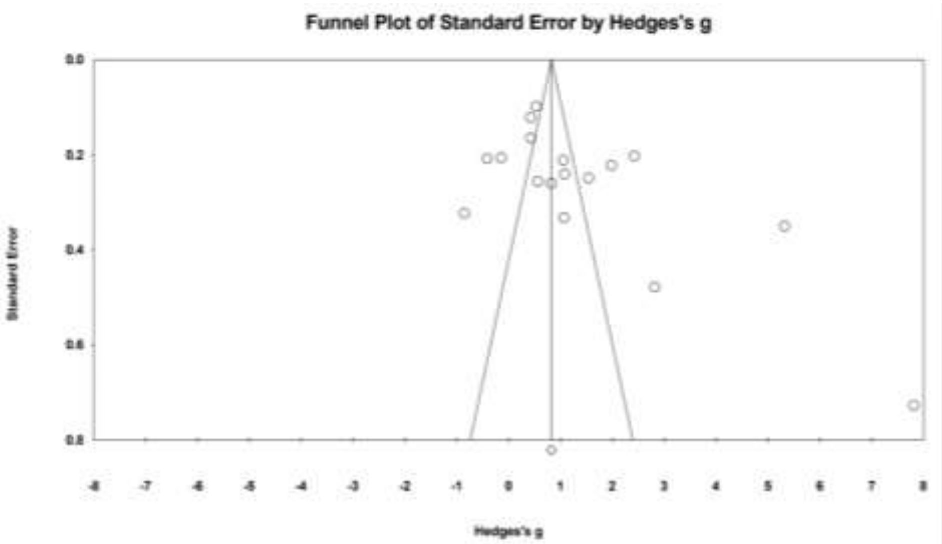


Figure 3
Funnel plot

A funnel plot and the Begg-Mazumdar test were used to visually confirm the meta-analysis's validity and detect publication bias. The funnel plot, shown in Figure 3, is a graphical representation of the effect sizes placed against their respective standard errors. The funnel plot shows that the distribution of research is symmetrical, demonstrating that there is no publishing bias. Furthermore, as demonstrated in Table 5, the Begg-Mazumdar test supports this conclusion, indicating that publication bias has no effect on meta-analysis results.

Table 5
Publication bias status of sample studies

Publication bias	
Kendall's S (P-Q)	42.00000
Kendall's tau	0.30882
Tau for z-value	1.73009
P	0.08361

Figure 3 depicts the examination of publication bias in the included meta-analysis literature, which shows that no substantial publication bias was identified. When the funnel plot exhibits significant asymmetry, particularly around the line showing the mean effect size, publication bias is often observed (Çoğaltay et al., 2014). However, the Begg-Mazumdar test results show a p-value of 0.08361 ($p > 0.05$), indicating the absence of publication bias, particularly in smaller research (Harbord et al., 2009). It should be noted that this test is a generic method for evaluating minor study effects in meta-analyses.

This study investigates six different subgroups to gain a better understanding of the effects of Learning Cycle Models (LCMs) and Online Teaching Strategies (OTSs) on student achievement: participant level, number of participants, learning environment, pedagogical approaches, duration, and subject matter. Table 6 provides a comprehensive overview of these subgroups and their respective analyses, allowing for a more nuanced exploration of the impact of LCMs and OTSs on student achievement.

Table 6
Sub-group analysis statistics

Sub-group	(Q_B)	p	N	ES	%95 CI	
Level of Participants	97.88	0.000			Lower	Upper
Elementary			1	7.81	6.36	9.27
High School			13	2.42	2.02	2.83
College			3	0.41	0.07	0.75
Total			17	2.57	1.07	4.07
Learning Modality	2.26	0.133				
In-person			6	1.96	0.24	3.68
Online distance learning			11	1.07	-0.02	2.15
Total			17	1.32	-0.80	3.44
Duration	0.34	0.561				
Long (≥20 hours)			7	1.67	-0.31	3.65
Short (<20 hours)			10	1.31	0.32	2.30
Total			17	1.38	-0.74	3.50
Subject Matter	168.77	0.000				
Electrolysis			3	0.99	0.70	1.28
Matter			4	1.49	1.23	1.76
Organic compounds			2	0.27	0.04	0.49
Acids and Bases			2	1.87	1.56	2.17
Hydrocarbons			3	-0.01	-0.29	0.26
Non-metals			1	1.98	1.54	2.42
Mole concept			1	0.53	0.34	0.72
Chemical properties			1	1.05	0.63	1.47
Total			17	1.01	0.21	1.81

We discovered that one study focused on elementary kids, 13 studies on high school students, and three studies on college students when we grouped the impact sizes by participant level. The between-group comparison produced a significant result for this grouping (QB (2) = 97.88, $p < 0.05$), showing that effect sizes vary significantly across participant levels. Elementary and high school students, in particular, had very large and positive impact sizes of 7.81 and 2.42, respectively, whereas college students had a small and positive effect size of 0.41.

When the studies were examined and evaluated based on the grade level of the study groups, it was discovered that the maximum effect size values were very large for elementary (ES=7.81) and high school (ES=2.42) students. Notably, Uyanik (2016) conducted a study among elementary students, which obtained a very large effect size of 7.812. Among the studies implemented among high school students, the study by

Santyasa et al. (2021) had the highest effect size of 5.322, followed by studies conducted by Ercan (2014) (ES=2.817), Uzezi & Deya (2020) (ES=2.425), Jack (2017) (ES=1.984), and Oladejo et al. (2021) (ES=1.544). Moreover, among the studies implemented among college students, the study by Azzajjad et al. (2021) had the highest effect size of 1.068, followed by Ikhsan et al. (2021) (ES=0.828). These findings indicate that the effect sizes obtained in the studies conducted by Uyanik (2016), Santyasa et al. (2021), Ercan (2014), Uzezi & Deya (2020), Jack (2017), Oladejo et al. (2021), Azzajjad et al. (2021), and Ikhsan et al. (2021) do not overlap according to the level of participants.

In terms of learning mode, in-person and online distance learning (ODL) approaches produced extremely large and positive impact sizes of 1.96 and 1.07, respectively. LCMs conducted in-person classes, on the other hand, had a bigger effect size than online teaching techniques conducted in ODL. The heterogeneity results (QB (1) = 2.26, $p > 0.05$) did not demonstrate a significant difference, indicating that the effect sizes of the in-person and ODL techniques are similar. This research demonstrates that the impact of LCMs and online teaching tactics on students' academic progress is not affected by learning modality when compared to traditional approaches.

When examining and evaluating the studies according to the implementation of LCMs, it was found that among the very large effect size values, the study by Uyanik (2016) had the highest effect size of 7.812, followed by studies conducted by Ercan (2014) (ES=2.817) and Jack (2017) (ES=1.984). Furthermore, in studies implementing online teaching strategies, the study by Santyasa et al. (2021) had the highest effect size of 5.322, followed by studies conducted by Uzezi & Deya (2020) (ES=2.425) and Oladejo (2021) (ES=1.544). These findings show that the effect sizes found by Uyanik (2016), Ercan (2014), Jack (2017), Santyasa et al. (2021), Uzezi & Deya (2020), and Oladejo (2021) do not overlap according to learning modality.

In terms of intervention time, both long and short-term treatments had very substantial and favourable impact sizes of 1.67 and 1.31, respectively. However, LCMs and online teaching techniques that were applied for a longer period of time had bigger effect sizes than those that were deployed for a shorter period of time. The heterogeneity results (QB (1) = 0.34, $p > 0.05$) did not show a significant difference, implying that the effect sizes of the short and long-term interventions are similar. This study implies that, when compared to traditional approaches, the effect of LCMs and online teaching tactics on students' academic achievement does not differ with intervention duration.

When examining and evaluating the studies according to the duration, it was found that among studies with long durations, the study by Uyanik (2016) had the highest effect size of 7.812, followed by studies conducted by Ercan (2014) (ES=2.817) and Jack (2017) (ES=1.984). Moreover, among studies with short durations, the study by Santyasa et al. (2021) had the highest effect size of 5.322, followed by studies conducted by Uzezi & Deya (2020) (ES=2.425) and Oladejo et al. (2021) (ES=1.544). These findings suggest that the effect sizes found by Uyanik (2016), Ercan (2014), Jack (2017), Santyasa et al. (2021), Uzezi & Deya (2020), and Oladejo (2021) do not overlap in terms of time.

Non-metals, acids and bases, matter, and chemical characteristics all had very significant and positive effect sizes of 1.98, 1.87, 1.49, and 1.05, respectively. The mole idea produced a medium and positive effect size of 0.53, whereas electrolysis had a big and positive effect size of 0.99. Organic chemicals exhibited a minor and positive effect size of 0.27, whereas hydrocarbons had a little and negative effect size of -0.01. The heterogeneity results ($QB (7) = 168.77$, $p < 0.05$) revealed a significant difference, indicating that the influence of LCMs and online teaching tactics on students' academic outcomes differs depending on the topic matter when compared to traditional approaches.

IMPLICATIONS

These data help us understand the impact of Learning Cycle Models (LCMs) and Online Teaching Strategies (OTSs) on students' academic progress in chemistry education. By synthesizing the results from multiple studies, this meta-analysis provides robust evidence of the positive effects of LCMs and OTSs on students' academic outcomes.

The findings underscore the importance of implementing tailored instructional approaches specifically designed to address the unique requirements of different chemistry education subjects. The analysis reveals that subject matters such as electrolysis, matter, organic compounds, acids and bases, hydrocarbons, non-metals, mole concepts, and chemical properties significantly influence students' academic achievement. This highlights the need for educators and curriculum designers to develop targeted strategies that effectively address the content and concepts of these subject matters.

Moreover, the analysis showcases the diversity of instructional strategies employed in the field, including the utilization of various models such as the 5E and 7E models and innovative approaches like computer simulation, project-based e-learning, and more. These findings emphasize the importance of employing various instructional strategies to engage students and enhance their academic achievement in chemistry education.

This meta-analysis provides valuable insights for educators, curriculum developers, and policymakers. The findings emphasize the significance of tailoring instructional approaches to specific subject matters while employing diverse instructional strategies. By implementing such strategies, educators can effectively promote students' academic achievement and foster meaningful learning experiences in chemistry education.

RECOMMENDATION

Based on the conclusion of this meta-analysis, a recommendation for educators, curriculum designers, and policymakers in chemistry education should be incorporated into Learning Cycle Models (LCMs) and Online Teaching Strategies (OTSs) to enhance students' academic achievement. To achieve this, tailored instructional approaches should be developed, focusing on significant subject matters such as matter, acids and bases, and non-metals. Utilizing diverse instructional strategies, including the 5E and 7E models, computer simulations, games, discussions, videos, and project-based learning, can promote student engagement and meaningful learning experiences. Furthermore, considering the specific needs and abilities of students at different grade levels, adapting to different learning modalities, extending intervention durations, and addressing areas of improvement, such as hydrocarbons, are crucial. Continuous research should be supported to refine the implementation of LCMs and OTSs, considering contextual factors. By following these recommendations, educators can enhance their practices, curriculum designers can develop effective materials, and policymakers can shape policies that foster the adoption of LCMs and OTSs, ultimately leading to improved academic achievement and a deeper understanding of chemistry concepts among students.

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