Transforming Physics Education: Harnessing the Potential of Concept Mapping Across Cognitive Domains

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Abstract: This study aimed to investigate how concept mapping affects student performance in physics education across different cognitive areas. It concerns a study conducted at Tribhuvan University-affiliated education campuses in Kathmandu and Bhaktapur districts, employing a quasi-experimental pre-test and post-test design. The investigation delves into the efficacy of concept mapping as an instructional tool to enhance student learning outcomes in physics education. The research design included a Control group with 70 participants and an Experimental group with 95 participants. The study showcased superior posttest performance in the Experimental group compared to the Control group across Knowledge, Understanding, Application, and Higher levels of cognitive domains. These findings underscore the effectiveness of Concept Mapping in enhancing student performance, positioning it as a promising educational strategy in physics instruction. The study employed the Kuder-Richardson 21 test to validate the instrument's reliability (coefficient of 0.78) and utilized SPSS version 20 for data analysis. Concept Mapping proves effective in enhancing physics education, demonstrating notable improvement in student achievement across various cognitive domains. Finding of the study revealed that Concept Mapping effectively improved posttest outcomes, emphasizing its beneficial influence on students' understanding and utilization of physics principles.

Introduction

Modern scientific inquiry is dedicated to unraveling and interpreting natural phenomena within established frameworks, often articulated through scientific theories. These theories comprise interconnected concepts, propositions, and principles, forming the bedrock for precise explanations and predictions of natural occurrences. The comprehension of scientific concepts is pivotal for students, requiring insights into the nature of science and the methodologies employed by scientists (Ben-Ari, 2005).

Physics, as a division of natural science, allows individuals to comprehend the natural world and various phenomena through the application of natural laws and principles. A grasp of physics contributes to the development of numerous innovations that directly or indirectly enhance our daily lives. It aids in executing tasks with the assistance of technologies, elucidating concepts related to natural phenomena, and constructing mental models for the transmission of information (Aragaw et al., 2022).

Several studies have investigated factors that impede students' learning of physics across various school levels (Agbele et al., 2020; Bao & Koenig, 2019; Beyessa, 2014; Burkholder et al., 2020). Some of the identified barriers to students' physics achievement include ineffective teaching methods, students' perception of physics as a challenging subject, low motivation toward learning physics, inadequate facilities and laboratory equipment for facilitating physics education, and teachers' content knowledge in physics, among others (Aragaw et al., 2022).

Many of these studies have pointed out that the use of inappropriate teaching methods stands out as a significant factor hampering students' understanding of physics, leading to lower academic performance. Numerous investigations highlight the prevalence of conventional teaching methods in secondary school physics classrooms, which have been identified as inadequate for enhancing students' learning and achievement in the subject (Gunta & Ousman, 2015; Higueras-Herbada et al., 2019; Hussain et al., 2011; Kunkle & Allen, 2016; Selcuk et al., 2011).

The literature suggests various research-based teaching approaches for science educators, allowing teachers to choose one or a combination of several methods tailored to the requirements of science learners, aiming to foster conceptual understanding (Tufail et al., 2020). These approaches encompass the utilization of analogy, cooperative learning, inquiry-based learning, advanced organizers, and concept mapping instructional techniques. Numerous studies in the literature have advocated for the effectiveness of concept mapping in aiding students to grasp the interconnections between concepts, anticipate, observe, and elucidate scientific topics, thereby enhancing their comprehension of abstract terms (Karakuyu, 2010).

The teaching strategy known as concept mapping was originally developed by Novak and his research group as a method of visually representing frameworks to illustrate the interconnectedness of concepts (Novak & Gowin, 1984). Daley and Torre (2010) asserted that concept mapping incorporates creativity by establishing a framework for thinking that encourages holistic consideration of topics and promotes collaborative learning. Applied as a teaching strategy in secondary schools, the concept map offers precise information about the knowledge domains being studied. Use of concept mapping methods in science empowers students to systematically navigate through a problem or topical issue by visualizing the connections between arguments, concepts, topics, and evidence, thereby enhancing their understanding and problem-solving abilities.

The generation of new knowledge is a constructive procedure that involves leveraging existing knowledge alongside the motivation to create fresh interpretations and novel representations. Concept mapping, as a creative endeavor, requires learners to actively engage in clarifying meaning. This involves the conscious identification of key concepts and their relationships, connecting them to pre-existing knowledge structures and frameworks. Consequently, a well-designed learning activity should yield a concept map that mirrors the organization of students' comprehension and illustrates the interconnectedness of their ideas (Bakouli & Jimoyiannis, 2016). Additionally, concept mapping has been employed for evaluating students' knowledge and comprehension across various fields of knowledge and educational levels (Bramwell-Lalor & Rainford, 2014).

This study addressed the following research question:

How does the implementation of a concept mapping model, targeting specific levels of cognitive domains, influence physics achievement among undergraduate students in the science education stream?

Theoretical Framework

The study utilized Ausubel's Theory of Human Cognitive Learning, commonly referred to as the Theory of Meaningful Learning in scholarly discourse, and Constructivist learning theory as theoretical frameworks.

According to Ausubel (1963), (1968), and (2012), meaningful learning occurs when students connect new information with concepts they already understand, contrasting with rote memorization. Concept maps and advance organizers are suggested as essential tools to facilitate this process, aiding students in applying prior knowledge to new instructional contexts and organizing the learning process logically. Ausubel (1960), (1968), and (2012) advocated for the use of advance organizers, which are abstract and inclusive materials presented before a lesson to help students connect prior knowledge with new concepts.

In constructivist learning environments, advance organizers and concept maps provide flexible scaffolding for learners (Melrose, 2013). Concept mapping, a constructivist method, allows students to demonstrate their understanding of complex ideas (Marchand et al., 2002), fostering self-reflection and enhancing critical thinking (Canas et al., 2003). Concept maps clarify knowledge organization, improve critical thinking, and bridge knowledge gaps by linking old and new understanding (Harpaz et al., 2004).

Methodology

Research Design

The design of this study was a pretest-posttest non-equivalent group quasi-experimental, where two intact groups of Bachelor level's science classes at constituent Education Campuses of Tribhuvan University in Kathmandu and Bhaktapur districts were selected. The control group received conventional teaching methods, while the experimental group underwent teaching sessions using concept mapping methods, with the researcher personally conducting instruction for both groups, enabling direct comparison of the interventions' effectiveness.

Population of the Study

The population of the study constituted the students enrolled in Tribhuvan University at bachelor in education level in with science education as major subject.

Sample and Sampling Techniques

The sample included seventy students from two constituent campuses of Tribhuvan University Faculty of Education in Kathmandu and Bhaktapur districts, divided into a Control group with 70 participants and an Experimental group with 95 participants. The selection of campuses was purposive with respect to the population density of students studying science education so that the researcher could gather more data and, secondly, a comfortable distance so that the researcher could communicate from one to another school daily. The selection of control and experimental campuses was randomized from the available options.

Research Instrument

Concept maps were employed as an intervention tool aligned with the second-year curriculum of Bachelor level of Science Education, employing an advanced organizer approach based on Ausubel's meaningful learning theory. The method involved presenting main concepts in advance, followed by hierarchical differentiation into various sub concepts, accompanied by illustrations. Finally, integration was facilitated to connect sub concepts back to the main concept, covering topics such as Electrostatics and Direct current circuits over the course of 43 teaching episodes.

Validity and Reliability of the Instruments

The questionnaires were evaluated by two Tribhuvan University professors from the departments of science education. They evaluated the instruments, made required revisions by eliminating, adding, and rearranging certain items, and guaranteed that the study questions were acceptable for improving the questionnaires' validity. The instruments' reliability was examined using Kuder Richardson -21 test in SPSS version 20, obtaining a reliability value of 0.78.

Method of Data Collection

Before revealing the reason for the visit, the researcher presented to the administrators, classroom teachers, and students at the selected campuses. Following the introductions, the researcher told both the participants and the school administration of the reason for their visit.

Achievement tests, observations, diary keeping (reflection), and interviews were employed as research tools. Two parallel forms of achievement test items, each comprising 40 science-related questions on electrostatics and Direct current circuits and covering four cognitive domains (Knowledge, Comprehension, Application, and Higher order - Analysis, Synthesis, and Evaluation), were created. Separate forms with the same cognitive domain were used for the pre-test and post-test to assess students' achievement results. Additionally, observation checklists for students' reflective behavior and classroom observations were developed. To ensure discreet observations, field notes were used, concealing the recording of participants' activities.

Analysis and Interpretation

SPSS version 20 was employed to analyze the student data. The student's responses to each item were calculated, collated, and presented using Analysis of Variance (ANOVA) to address the research question.

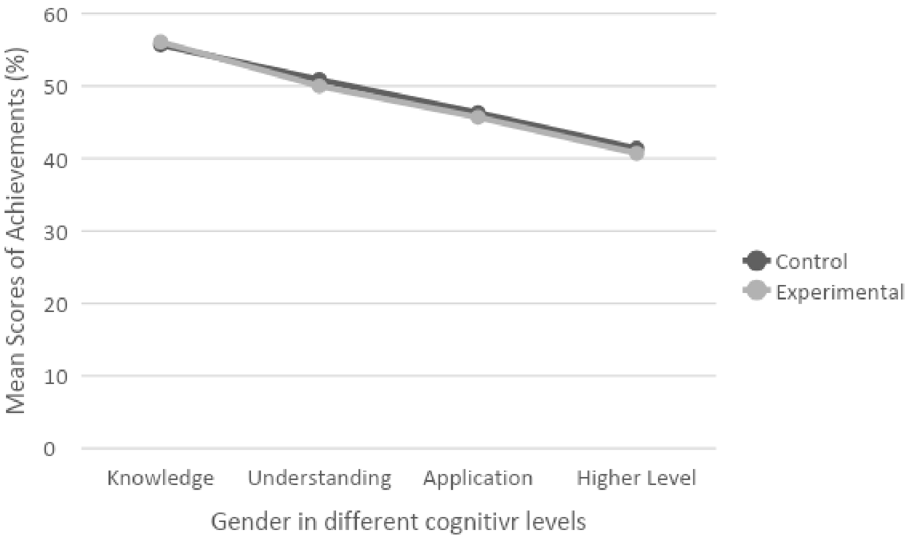
Table 1: *Level-wise comparison of experimental and control group mean achievement in physics by use of concept mapping method*

Level of Cognitive Domain	Control and Experimental	N	Mean	Std. Deviation
Knowledge	Control	70	5.57	1.314
	Experimental	95	5.61	1.299
Understanding	Control	70	5.09	1.189
	Experimental	95	5.00	1.042
Application	Control	70	4.63	1.364
	Experimental	95	4.57	1.318
Higher level	Control	70	4.14	1.133
	Experimental	95	4.07	1.240

Table 1 presented a comparison of descriptive statistics between the Control and Experimental groups across various cognitive domains. In the Knowledge domain, the Experimental group (N=95) demonstrated a slightly higher mean score (5.61) compared to the Control group (N=70), which had a mean score of 5.57. Standard deviations for both groups were similar (1.299 and 1.314, respectively). Similarly, in the Understanding domain, the Control group (N=70) exhibited a slightly higher mean score (5.09) than the Experimental group (N=95), with mean scores of 5.00. Standard deviations remained comparable (1.189 and 1.042, respectively). In the Application level of domain, the Control group (N=70) had a marginally higher mean score (4.63) compared to the Experimental group (N=95), which scored 4.57. Their standard deviations were also similar (1.364 and 1.318, respectively). Lastly, in the Higher-level domain, the Control group (N=70) and the Experimental group (N=95) displayed mean scores of 4.14 and 4.07, respectively, with comparable standard deviations (1.133 and 1.240, respectively). Overall, the differences in mean scores between the two groups across all cognitive domains were relatively minor, and both groups exhibited similar performance variability.

Similarly, Graph 1 below depicted the percentage mean achievement scores in a Pre-test for both the Experimental and Control groups across four categories. Regarding Knowledge, the Control group attained a mean score of 55.7%, whereas the Experimental group achieved slightly higher, with an average of 56.1%. In terms of Understanding, the Control group achieved an average score of 50.9%, while the Experimental group scored 50%. In the Application category, the Control group averaged 46.3%, and the Experimental group achieved a slightly lower average of 45.7%. Furthermore, in the Higher-Level domain, the Control group scored 41.4%, whereas the Experimental group obtained a mean score of 40.7%.

Figure 1: *Percentage mean scores of achievements of experimental and control groups in pretest*



In summary, the table compared the descriptive statistics of the Control and Experimental groups across various cognitive domains. The findings revealed that in the Knowledge domain, the Experimental group had a slightly higher mean score than the Control group, accompanied by similar standard deviations. Conversely, in the Understanding, Application, and Higher-level domains, the Control group exhibited marginally higher mean scores compared to the Experimental group, with comparable standard deviations. Overall, both groups demonstrated similar performance across the different cognitive domains, with only minor discrepancies observed. Additionally, an analysis of the pre-test results from the graph indicated minimal differences in mean scores between the Experimental and Control groups across all four achievement categories. The Experimental group held a slight advantage in Knowledge and Understanding but lagged slightly in Application and Higher-Level skills.

Now the following Table 2 were tested the difference that existed in pretest was found significant or not?

Table 2 : *Analysis of variance (ANOVA) for experimental and control groups in pretest*

Level of Cognitive Domain		Sum of Squares	df	Mean Square	F	Sig.
Knowledge	Between Groups	3.744	1	3.744	2.227	.138**
	Within Groups	274.050	163	1.681		
	Total	277.794	164			
Understanding	Between Groups	1.390	1	1.390	1.142	.287**
	Within Groups	198.392	163	1.217		
	Total	199.782	164			
Application	Between Groups	.681	1	.681	.381	.538**
	Within Groups	291.113	163	1.786		
	Total	291.794	164			

Higher level	Between Groups	.000	1	.000	.000	.990**
	Within Groups	233.248	163	1.431		
	Total	233.248	164			

Note. Analyzed by SPSS 20, * Significant, ** Not significant at 0.05 level of Significant

Table 2 displays the outcomes of Analysis of Variance (ANOVA) conducted on the pretest scores of the Experimental and Control groups across various cognitive domains. Regarding the Pretest of Knowledge, the ANOVA revealed no noteworthy difference between the two groups, as indicated by the non-significant F-statistic (F=2.227, p=0.138). Similarly, for the Pretest of Understanding and Pretest of Application, the ANOVA findings demonstrated no significant distinctions between the Experimental and Control groups, with p-values of 0.287 and 0.538, respectively. Additionally, in the Pretest of Higher level, the F-statistic was exceptionally low (F=0.000, p=0.990), confirming the absence of a significant difference between the two groups. In summary, the ANOVA analysis conducted on the Experimental and Control groups' pretest scores across various cognitive domains revealed no significant differences between the groups, as indicated by non-significant F-statistics ($p > 0.05$) for all domains. The subsequent Table 3 illustrates the comparison between the experimental and control groups of students in the post-test across four levels of cognitive domains. The descriptive and statistical tests conducted for significance depict the status of students in the posttest.

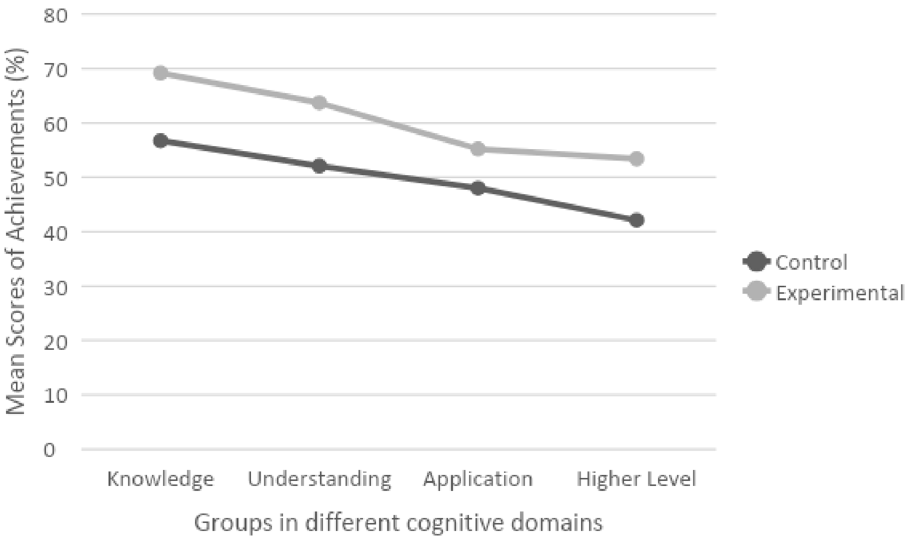
Table 3**:** *Descriptive statistics of experimental and control groups in posttest*

Level of Cognitive Domain	Control and Experimental	N	Mean	Std. Deviation
Knowledge	Control	70	5.67	1.327
	Experimental	95	6.92	1.318
Understanding	Control	70	5.21	1.203
	Experimental	95	6.37	1.321
Application	Control	70	4.80	1.281
	Experimental	95	5.52	1.320
Higher level	Control	70	4.21	1.102
	Experimental	95	5.34	1.268

Table 3 presents the descriptive statistics of the Experimental and Control groups in posttest scores across various levels of cognitive domains. In the Posttest of Knowledge, the Experimental group (N=95) exhibited a significantly higher mean score (6.92) compared to the Control group (N=70), which had a mean score of 5.67. This difference was supported by considerable disparities and small standard deviations (1.318 and 1.327, respectively). Similarly, in the Posttest of Understanding and Posttest of Application, the Experimental group (N=95) surpassed the Control group (N=70) with higher mean scores (6.37 > 5.21, 5.52 > 4.80, respectively). The results remained consistent across these domains, as the standard deviations for both groups were comparable. Additionally, in the Posttest of Higher level, the Experimental group (N=95) achieved a significantly higher mean score (5.34) than the Control group (N=70), which scored 4.21, indicating a notable difference and relatively small standard deviations (1.268 and 1.102, respectively).

Similarly, Graph 2 in the Post-test illustrated the percentage mean achievement scores for both the Experimental and Control groups across four categories. Notably, the Experimental group showed significant improvement in all areas compared to the Control group. In the Knowledge category, the Control group attained a mean score of 56.7%, while the Experimental group demonstrated a considerable increase to 69.2%. Likewise, in Understanding, the Control group scored 52.1%, whereas the Experimental group exhibited notable improvement with a mean score of 63.7%. For Application, the Control group had an average score of 48%, whereas the Experimental group displayed enhanced performance with a mean score of 55.2%. In the Higher Level category, the Control group achieved a mean score of 42.1%, while the Experimental group made substantial progress, reaching a mean score of 53.4%.

Figure 2: *Percentage mean scores of achievements of experimental and control group in the Post-test*



In summary, the experimental group exhibited better performance than the control group across all cognitive domains in the posttest evaluation, with significantly higher mean scores observed in Knowledge (6.92 > 5.67), Understanding (6.37 > 5.21), Application (5.52 > 4.80), and Higher level (5.34 > 4.21). Overall, the posttest outcomes highlighted a notable positive influence of the intervention on the experimental group's performance, as they consistently surpassed the control group across all four achievement categories.

Table 4**:** *Analysis of variance for experimental and control groups in post-test*

Level of Cognitive Domain		Sum of Squares	df	Mean Square	F	Sig.
Knowledge	Between Groups	62.407	1	62.407	35.721	.000*
	Within Groups	284.769	163	1.747		
	Total	347.176	164			
Understanding	Between Groups	53.685	1	53.685	33.160	.000*
	Within Groups	263.891	163	1.619		
	Total	317.576	164			
Application	Between Groups	20.649	1	20.649	12.154	.001*
	Within Groups	276.926	163	1.699		
	Total	297.576	164			
Higher level	Between Groups	50.787	1	50.787	35.226	.000*
	Within Groups	235.007	163	1.442		
	Total	285.794	164			

Note. Analyzed by SPSS 20, * Significant, ** Not significant at 0.05 level of Significant

Table 4 illustrates the outcomes of an Analysis of Variance (ANOVA) conducted on the posttest scores of the Experimental and Control groups across various cognitive domains, utilizing concept mapping as the intervention. The ANOVA reveals significant differences between the groups in all cognitive domains ($p<0.001$ for Knowledge, Understanding, and Higher level; $p=0.001$ for Application). Regarding the Posttest of Knowledge, the between-groups variability (Sum of Squares = 62.407) far exceeded the within-groups variability (Sum of Squares = 284.769), indicating a substantial impact of the concept mapping intervention. This trend is consistent across the Posttest of Understanding (Between Groups: 53.685, Within Groups: 263.891), Posttest of Application (Between Groups: 20.649, Within Groups: 276.926), and Posttest of Higher level (Between Groups: 50.787, Within Groups: 235.007). In conclusion, the concept mapping intervention significantly contributed to the improved performance of the experimental group compared to the control group in all cognitive domains, highlighting its effectiveness as an instructional strategy.

Discussion

The study confirms Concept Mapping as an effective educational strategy for physics instruction, aligning with Ausubel's meaningful learning theory and constructivism. It enhances students' comprehension and application of physics concepts across cognitive domains, fostering active engagement and knowledge construction. Concept Mapping addresses barriers to learning physics and promotes meaningful learning experiences, resonating with both theoretical frameworks. Its incorporation in science education empowers students to navigate complex topics and construct their understanding, reflecting the principles of meaningful reception learning and active, student-centered learning processes advocated by Ausubel and constructivism.

Furthermore, the study underscores the importance of innovative teaching methods, like Concept Mapping, in reshaping physics education and enhancing student achievements. These findings align with the research conducted by Canas et al. (2017), Nesbit and Adesope (2006), and Malekzadeh et al. (2020), which explored students' understanding and utilization of physics principles across various cognitive domains using concept mapping instruction.

As a result, the study confirmed that Concept Mapping effectively improved posttest outcomes, emphasizing its beneficial influence on students' understanding and utilization of physics principles. The research emphasized the significance of innovative teaching techniques, such as Concept Mapping, in revolutionizing physics education and enhancing student performance.

Conclusion

Upon comparing the descriptive statistics and pretest results, minor differences were noted between the Experimental and Control groups across cognitive domains initially. However, the posttest assessment revealed a substantial improvement in the Experimental group's performance, surpassing the Control group in all domains. The ANOVA analysis confirmed the significance of these differences, emphasizing the positive impact of Concept Mapping intervention on student achievement. This study underscores Concept Mapping as an effective instructional strategy in enhancing performance across diverse cognitive domains in physics education, particularly demonstrating its effectiveness in fostering higher-order thinking skills and application of knowledge.

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