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Application of ADDIE Instructional Model to Machine Learning and Assessment of Learner's Outcomes in Higher Institutions in Delta State

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Abstract

The study explored the application of the ADDIE instructional model to machine learning and the assessment of learner's outcomes in higher institutions in Delta State. The study adopted pretest, posttest control group quasi-experimental design. The design comprised of two groups, experimental and control group. In this study, the researcher applied the ADDIE model to the design and implementation of a machine learning course and assess the outcomes of learners using various assessment methods. The population for the study comprised 3,478 300level undergraduate in Delta State University, Abraka and University of Delta, Agbor. The sample of the study comprised 139 300level undergraduates in Delta State University, Abraka and University of Delta, Agbor. Educational Technology Achievement Test (ETAT) and Machine Learning Questionnaire (MLQ) were used for data collection. The two instruments were duly validated. The reliability of ETAT and MLQ were established using Kuder-Richardson 21 and Cronbach Alpha analysis respectively. A reliability coefficient of 0.71 and 0.78, were obtained for ETAT and MLQ respectively. ETAT was administered as pretest and posttest before and after a six weeks treatment using ADDIE and traditional instructional models to students in experimental and control groups respectively. MLQ was only administered at the end of the treatment. Findings showed that ADDIE model provided a structured framework for designing, developing, and evaluating machine learning courses, leading to improved learning outcomes for students. The assessment of learner's outcomes has also been more effective and efficient with the implementation of the ADDIE model. It was recommended that higher institutions in Delta State should provide training and capacity building for educators on how to effectively implement the ADDIE instructional model in machine learning courses. Educators should collaborate and share best practices in the application of the ADDIE model to machine learning to enhance teaching and learning outcomes.

Keywords: ADDIE Instructional Model, Machine Learning, Learner's Outcome, Assessment.

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Introduction

Machine learning is a branch of artificial intelligence that concentrates on creating algorithms and statistical models to enable computers to learn and make predictions or judgements without explicit programming. The field is experiencing significant growth and has diverse applications across several industries, such as healthcare, finance, marketing, and others. Machine learning has gained popularity in recent years because of its capacity to analyse vast quantities of data and derive significant insights. A fundamental characteristic of machine learning is its capacity to enhance performance over time by using data (Jordan & Mitchell, 2015). Through the process of inputting substantial quantities of data into a machine learning algorithm, the system can acquire knowledge from the patterns and trends within the data, enabling it to provide predictions or make informed judgments. The process referred to as training is crucial for the algorithm to achieve optimal performance on unfamiliar data.

LeCun et al. (2015) categorise machine learning algorithms into various kinds, each with distinct advantages and disadvantages. Three prevalent types of machine learning are supervised learning, unsupervised learning, and reinforcement learning. Supervised learning involves training an algorithm with labelled data, where each input is paired with its corresponding accurate output. This enables the algorithm to acquire knowledge about the correlation between inputs and outputs and generate forecasts for novel data. Unsupervised learning, in contrast, entails training the algorithm using unlabeled data, with the objective of identifying patterns or correlations within the data. Reinforcement learning is a form of machine learning in which an agent acquires the ability to make decisions by engaging with an environment and receiving rewards or punishments based on its actions. Machine learning algorithms have the capability to be used to a diverse array of tasks, such as classification, regression, clustering, and other activities. Classification algorithms are employed to classify data into distinct classes or groups, whilst regression techniques are utilised to forecast continuous values. Clustering algorithms are employed to categorise data points that have similarities, whilst anomaly detection methods are utilised to pinpoint atypical patterns or outliers within the data.

Overfitting is a significant obstacle in machine learning, characterised by the algorithm's ability to perform well on the training data but struggle to apply the knowledge to new, unfamiliar data (Goodfellow et al., 2016). In order to tackle this problem, researchers employ several strategies such as cross-validation, regularisation, and ensemble methods to enhance the effectiveness of machine learning algorithms. Machine learning has made great progress in recent years, thanks to the abundance of data and the availability of strong computing resources. Deep learning, a branch of machine learning that use artificial neural networks to represent intricate patterns in data, has gained significant popularity owing to its capacity to acquire knowledge from unprocessed data and identify advanced characteristics (LeCun et al., 2015). Deep learning has been employed in diverse applications, encompassing image and speech recognition, natural language processing, and other domains. In the view of Iroriteraye-Adjekpovu(2012), transfer learning has emerged as a significant advancement in machine learning, involving the utilisation of pre-trained models as a foundation for new tasks. Transfer learning enables researchers to utilise the acquired information from one job to enhance performance on another work, hence diminishing the requirement for extensive amounts of labelled data.

Machine learning is an expanding discipline that has the capacity to profoundly transform multiple businesses and sectors (Murphy, 2022; Lawrence &Egbule, 2021). Due to the increasing demand for machine learning skills, it is vital to have effective instructional design models, like the ADDIE model, to ensure that learners acquire the required information and skills. The ADDIE instructional model is a holistic approach to education that emphasises the amalgamation of technology, pedagogy, and content knowledge (Brown et al., 2019). The purpose of this model is to assist educators in developing captivating and efficient learning opportunities for students by utilising the potential of technology to improve teaching methods. The ADDIE model operates under the premise that technology may be a potent instrument for enhancing educational outcomes by employing it in a deliberate and purposeful manner. The ADDIE instructional model consists of four essential components: Analysis, Design, Implementation, and Evaluation. Every individual component has a crucial function in ensuring the overall effectiveness of the instructional process. When combined, these components enable educators to develop vibrant and captivating learning experiences for students (Brown et al., 2019).

The initial element of the ADDIE instructional model is Analysis. This stage entails the collection of data and information pertaining to the educational requirements of students, as well as the aims and objectives of the instructional programme (Smith & Jones, 2020; Egbule, 2020). During this stage, educators may carry out needs assessments, analyse student performance data, and pinpoint areas where technology can be utilised to improve instruction. Through a comprehensive examination of the learning environment, educators can gain a deeper understanding of their students' requirements and devise precise instructional approaches to address those requirements. The Design phase is the second component of the ADDIE instructional model. In this stage, educators utilise the data collected in the analysis phase to formulate a comprehensive instructional plan (Smith & Jones, 2020). This modelincludes the identification of suitable technological tools, the formulation of learning activities and assessments, and the establishment of a timeframe for execution. The design step is crucial for ensuring that instruction is in line with the goals and objectives of the instructional programme, and that technology is utilised purposefully and deliberately to improve learning outcomes.

Implementation is the third element of the ADDIE instructional model. During this stage, the instructional plan is implemented and instruction is provided to students (Garcia, 2020). During this stage, instructors can utilise a range of technological tools and resources to actively include students in educational activities, offer feedback on their advancement, and evaluate their comprehension of essential ideas. The implementation phase provides educators with the chance to monitor students' response to instruction and make necessary modifications to ensure the achievement of learning objectives. The last element of the ADDIE instructional modelis Evaluation. This stage entails evaluating the efficacy of the instructional programme and utilising data-driven strategies to enhance future training (Johnson, 2017; Iroriteraye-Adjekpovu, 2013). During the assessment phase, educators engage in the collection and analysis of student performance data, solicit input from students and other stakeholders, and engage in introspection regarding their own teaching techniques.

Through the assessment of the influence of teaching on student learning outcomes, educators can pinpoint areas that need improvement and make well-informed choices on how to better instruction in the future.

The primary objective of the ADDIE instructional model is to assist educators in developing captivating and efficient learning opportunities for students by utilising technology to improve instruction. By adhering to the four essential elements of the model - Analysis, Design, Implementation, and Evaluation - educators can create specific instructional techniques that address the requirements of their students and enhance learning results. Recent studies have demonstrated that the ADDIE instructional paradigm is a highly successful strategy for teaching and learning. An empirical investigation conducted by Smith and Jones (2020) revealed that instructors who implemented the ADDIE model reported significantly elevated levels of student engagement and academic performance in comparison to their counterparts who did not employ this model. In a further investigation conducted by Brown et al. (2019), it was discovered that the use of the ADDIE model enabled educators to generate more vibrant and engaging learning opportunities for students, resulting in enhanced academic achievements. The ADDIE model is a methodical approach to instructional design that has gained extensive usage in the education sector. The study sought to utilise the ADDIE model in machine learning education to establish a methodical and efficient learning experience for learners. Additionally, it attempts to evaluate the influence of the ADDIEmodel on the outcomes of the learners.

Statement of the Problem

The sector of education has witnessed a surge in popularity of machine learning, with many educators looking for ways to incorporate this technology into their instructional practices. One potential approach is to apply the Addie instructional model to machine learning, in order to design and implement effective learning experiences for students. By applying this model to machine learning, educators can ensure that their instructional materials are well-designed, engaging, and effective in promoting student learning.Despite the potential benefits of applying the Addie instructional model to machine learning, there is a lack of empirical research on this topic. While there is a growing body of literature on both instructional design and machine learning separately, there is a gap in the research that explores how these two approaches can be integrated to enhance student learning outcomes. Therefore, the problem of the study in question form, is: Will the application ofADDIE instructional model to machine learning enhance learning outcomes?

Purpose of the Study

The purpose of the study is to investigated the application of ADDIE instructional model to machine learning and assessment of learner's outcomes. The study will specifically determine:

1. how the implementation of ADDIE instructional model impacts the effectiveness of machine learning in educational settings;

2. the key factors that influence the successful application of the ADDIE instructional model in the context of machine learning;
3. how learner outcomes differ when using the ADDIE instructional model compared to traditional approach in machine learning.

Research Question

The study was guided by the following research questions:

1. How does the implementation of the ADDIE instructional model impact the effectiveness of machine learning in educational settings?
2. What are the key factors that influence the successful application of the ADDIE instructional model in the context of machine learning?
3. How do learner outcomes differ when using the ADDIE instructional model compared to traditional approach in machine learning?

Hypothesis

The study was guided by one hypothesis:

1. There is no significant difference between learners' outcomes in machine learning when using the ADDIE instructional model and traditional instructional model.

Methodology

Pretest, posttest control group quasi-experimental design was employed in this study. The design comprised of two groups, experimental and control group. The researcher employed quasi-experimental design because students in intact classes were used in this study. Kenneth and Bruce (2014) described quasi-experimental designs as those that resemble pure experimental designs but differ in non-randomization of subjects. In this study, intact classes were used to avoid disruption of normal school lessons. The population for the study comprised 3,478 300level undergraduate offering educational technology course in Delta State University, Abraka and University of Delta, Agbor. The sample of the study comprised 139 300level undergraduates in Delta State University, Abraka and University of Delta, Agbor. Educational Technology Achievement Test (ETAT) and Machine Learning Questionnaire (MLQ) were used for data collection. ETAT comprised of fifty multiple choice items with option A-D, in which one option is the correct answer while the other three options are distracters. The students are expected to pick one option, whereby the right option attracted a score of two marks, while the wrong option attracted a score of zero. MLQ comprised twenty, four points-likert scale items that sought information on the impact of ADDIE instructional model on effective implementation of machine learning and the key factors that promotes the implementation of ADDIE instructional model in the context of machine learning.

The two instruments were duly validated. The face validity of the two instruments were ascertained by the judgment of three experts in the Department of Science Education, Delta State University, Abraka. The content validity of the achievement test was established using a table of specification. The reliability of ETAT and MLQ were ascertained through a pilot test. The instrument was administered to 30 300level undergraduates in Faculty of Education, University of Benin, who were outside the area of study. The responses of the students to ETAT and MLQ were scored and subjected to Kuder-Richardson 21 and Cronbach Alpha analysis respectively. A reliability coefficient of 0.71 and 0.78, were obtained for ETAT and MLQ respectively.

As for the actual treatment, theintact classes were divided into two groups: the experimental group and the control group. The students in the experimental group were exposed to machine learning utilising the ADDIE instructional methodology. In this group, the researcher designed and implemented a machine learning in Educational Technologycourse using the ADDIE instructional model, specifically, the supervised learning algorithm. The course was divided into five phases: Analysis, Design, Development, Implementation, and Evaluation. During the Analysis phase, the researcher identified the learning objectives, target audience, and instructional strategies. In the Design phase, the researcher developed the course content, activities, and assessments. The Development phase involved creating the course materials and resources. The Implementation phase focused on delivering the course to learners, while the Evaluation phase assessed the outcomes of the learners using various assessment methods such as achievement test and surveys. As for the control group, they were exposed to machine learning in Educational Technology course using the traditional instructional model, with a combination of lectures, readings and discussions.The Educational Technology Achievement Test (ETAT) was administered as pretest and posttest before and after a six weeks treatment using ADDIE and traditional instructional models to students in experimental and control groups respectively. The Machine Learning Questionnaire (MLQ) was only administered at the end of the treatment. Thereafter, the pretest and posttest scores of the two groups were compiled and analysed using weighted mean, mean, standard deviation and t-test analysis.

Results

Research Question One: How does the implementation of the ADDIE instructional model impact the effectiveness of machine learning in educational settings?

Table 1
Mean Responses on how the Implementation of the ADDIE Instructional Model Impact the Effectiveness of Machine Learning in Educational Settings

S/n	Items	Mean	Decision
1	The ADDIE instructional model helps in the customization of machine learning content for different learners.	3.80	SA
2	The ADDIE instructional model supports the assessment and evaluation of machine learning outcomes in educational settings.	3.73	SA
3	The ADDIE instructional model facilitates the planning and organization of machine learning activities.	3.85	SA
4	The ADDIE instructional model promotes collaboration among educators and students in implementing machine learning.	3.86	SA

5	The ADDIE instructional model helps in the identification of learning needs and gaps in machine learning implementation.	3.64	SA
6	The ADDIE instructional model assists in the development of instructional materials for machine learning.	3.70	SA
7	The ADDIE instructional model encourages continuous improvement and iteration in machine learning practices.	3.82	SA
8	The ADDIE instructional model supports the integration of technology in machine learning activities.	3.73	SA
9	The ADDIE instructional model enhances the adaptability of machine learning strategies to different educational settings.	3.77	SA
10	The ADDIE instructional model promotes the use of evidence-based practices in machine learning instruction.	3.77	SA
	Grand mean	**3.77**	**SA**

Table 1 displays a mean score of 3.77, which surpasses the criterion mean of 2.50. Furthermore, every item had a mean score that surpassed the criterion mean. The respondents' agreement indicates that items 1 to 10 reflect the impacts of implementing the ADDIE instructional paradigm on the effectiveness of machine learning in educational contexts. Hence, it can be concluded that the implementation of ADDIE instructional model impact the effectiveness of machine learning in educational settings as follows; it helps in the customization of machine learning content for different learners, support assessment and evaluation of machine learning outcomes, facilitates the planning and organization of machine learning activities, promotes collaboration among educators and students, helps in the identification of learning needs and gaps in machine learning implementation, assists in the development of instructional materials, encourages continuous improvement and iteration in machine learning activities, enhances the adaptability of machine learning strategies to different educational settings, and promotes the use of evidence-based practices in machine learning instruction.

Research Question 2: What are the key factors that influence the successful application of the ADDIE instructional model in the context of machine learning?

Table 2

Mean Responses on the key Factors that Influence the Successful Application of the ADDIE Instructional Model in the Context of Machine Learning

S/n	Items	Mean	Decision
1	Clarity of learning objectives in relation to machine learning concepts.	3.87	SA
2	Availability of resources for designing and developing machine learning content.	3.76	SA
3	Alignment of assessment methods with machine learning skills and knowledge.	3.73	SA
4	Support from stakeholders for implementing machine learning	3.75	SA

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	training programmes.		
5	Flexibility of the ADDIE model to accommodate changes in machine learning technology.	3.79	SA
6	Integration of real-world machine learning examples in instructional materials.	3.77	SA
7	Use of interactive technology to enhance machine learning experiences.	3.60	SA
8	Collaboration between instructional designers and machine learning experts.	3.74	SA
9	Feedback mechanisms for continuous improvement of machine learning training programmes	3.61	SA
10	Adaptability of the ADDIE model to different machine learning styles.	3.59	SA
	Grand mean	**3.72**	**SA**

Table 2 displays a mean score of 3.72, which surpasses the criterion mean of 2.50. Furthermore, all the items obtained a mean score higher than the criterion mean. This indicates that the respondents agreed that items 1 to 10 are the key factors influencing the successful implementation of the ADDIE instructional model in the context of machine learning. Therefore, it can be inferred that several key elements that impact the effective implementation of the ADDIE instructional model in the machine learning environment are;clarity of learning objectives in relation to machine learning concepts, availability of resources for designing and developing machine learning content, alignment of assessment methods with machine learning skills and knowledge, support from stakeholders for implementing machine learning training programmes, flexibility of the ADDIE model to accommodate changes in machine learning technology, Integration of real-world machine learning examples in instructional materials, use of interactive technology to enhance machine learning experiences, collaboration between instructional designers and machine learning experts, feedback mechanisms for continuous improvement of machine learning training programmes, and adaptability of the ADDIE model to different machine learning, learning styles.

Research Question 3: How do learner outcomes differ when using the Addie instructional model compared to traditional approach in machine learning?

Table 3

Mean and Standard Deviation of Learner's Outcome Scores in Machine Learning When Using ADDIE and Traditional Instructional Models

Models	N	Mean ($\bar{x}$)	SD	Mean Difference
ADDIE	61	71.20	7.69	8.86
Traditional	78	62.34	6.44	

Table 3 displays the mean outcome score of 71.20 with a standard deviation of 7.69 for students who were taught machine learning using the ADDIE instructional model. In contrast, students who were taught machine learning using the traditional instructional model had anmean outcome score of 62.34 with a standard deviation of 6.44. The difference between the mean outcome scores of both groups is 8.86, in favour of students in ADDIE instructional model.

Hypothesis One: There is no significant difference between learners' outcomes in machine learning when using the ADDIE instructional model and traditional instructional model.

Table 4
t-test Comparison of Mean Learner's Outcome Scores of Students Exposed to Machine Learning Using ADDIE and Traditional Instructional Model

Models	N	$\bar{x}$	SD	df	t-cal.	Sig. (2-tailed)	Decision
ADDIE	61	71.20	7.69	57	4.784	0.000	Significant
Traditional	78	62.34	6.44				

Table 4 shows a calculated t = 4.784, P(0.000 < 0.05), that indicates is a significant difference between learners' outcomes in machine learning when using the ADDIE instructional model and traditional instructional model. Thus, the null hypothesis is rejected. Therefore, there is a significant difference between learners' outcomes in machine learning when using the ADDIE instructional model and traditional instructional model, in favour of students exposed to ADDIE instructional model.

Discussion

The study revealed that the implementation of ADDIE instructional model impact the effectiveness of machine learning in educational settings as follows; it helps in the customization of machine learning content for different learners, support assessment and evaluation of machine learning outcomes, facilitates the planning and organization of machine learning activities, promotes collaboration among educators and students, helps in the identification of learning needs and gaps in machine learning implementation, assists in the development of instructional materials, encourages continuous improvement and iteration in machine learning activities, enhances the adaptability of machine learning strategies to different educational settings, and promotes the use of evidence-based practices in machine learning instruction. This finding support that of Smith et al. (2020) who reported that incorporating machine learning algorithms into the design phase of the ADDIE model can help educators create more personalized learning experiences for students.

Another finding of the study further revealed that some of the key factors that influence the successful application of the ADDIE instructional model in the context of machine learning include; clarity of learning objectives in relation to machine learning concepts, availability of resources for designing and developing machine learning content, alignment of assessment methods with machine learning skills and knowledge, support from stakeholders for implementing machine learning training programmes, flexibility of the ADDIE model to accommodate changes in machine learning technology, Integration of real-world machine learning examples in instructional materials, use of interactive technology to enhance machine learning experiences, collaboration between instructional designers and machine learning experts, feedback mechanisms for continuous improvement of machine learning training programmes, and adaptability of the ADDIE model to different machine learning, learning styles. This finding corroborates with that of past findings. For instance, Smith (2018) and Iroriteraye-Adjekpovu(2022) reported that ensuring that the learning objectives are clearly defined and aligned with the overall goals of the instructional program is essential for effective implementation of the ADDIE model. Jones and Brown (2019) reported that involving all relevant stakeholders, including teachers, students, and administrators, in the design and implementation of the instructional program can help ensure its success. Again, Lee and Kim, (2021) reported that regularly evaluating the effectiveness of the instructional programme and soliciting feedback from stakeholders can help identify areas for improvement and make necessary adjustments.

The study revealed that there is a significant difference between learners' outcomes in machine learning when using the ADDIE instructional model and traditional instructional model, in favour of students exposed to ADDIE instructional model. This observation could be based on personalized learning experiences and interactive learning offered by ADDIE instructional model. The ADDIE instructional model allows for a more personalized learning experience for students, as it involves analyzing the needs of the learners and designing instruction accordingly. The ADDIE instructional model often incorporates interactive and hands-on learning activities, which have been found to be more effective in promoting understanding and retention of complex concepts. This finding lends credence to that of Pane et al. (2015) and Mayer (2014) who reported that personalized and interactive learning leads to higher engagement and better learning outcomes.

Conclusion

The study on the application of the ADDIE instructional model to machine learning and assessment of learner's outcomes in higher institutions in Delta State has shown promising results. The ADDIE model provides a structured framework for designing, developing, and evaluating machine learning courses, leading to improved learning outcomes for students. The assessment of learner's outcomes has also been more effective and efficient with the implementation of the ADDIE model.

Recommendations

1. Higherinstitutions in Delta State should provide training and capacity building for educators on how to effectively implement the ADDIE instructional model in machine learning courses.
2. Educators should collaborate and share best practices in the application of the ADDIE model to machine learning to enhance teaching and learning outcomes.
3. Higherinstitutions should continuously evaluate the effectiveness of the ADDIE model in machine learning courses and make necessary improvements to enhance student learning outcomes.
4. Higherinstitutions should leverage technology to support the implementation of the ADDIE model in machine learning courses, such as using learning management systems for course delivery and assessment.

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