

**Predictive Modelling of Teachers' Workload, Classroom Management Practices and
Students' Factors on SS2 Students' Academic Performance in Chemistry in Southwest
Nigeria**

Oluyemi Abiade ADETORO

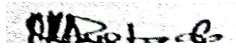
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**In Partial Fulfilment of the Requirements for the Award of Doctor of Philosophy (PhD)
Degree in Measurement & Evaluation**

Certification

This is to certify that Oluyemi Abiade Adetoro with matriculation number LCU/PG/004006 carried out this research work titled “Predictive Modelling of Teachers’ Workload, Classroom Management Practices and Students’ Factors on SS2 Chemistry Students’ Academic Performance in Southwest Nigeria” in the Department of Arts and Social Sciences Education, Faculty of Education, Lead City University, Ibadan, Oyo State, for the award of Doctor of Philosophy Degree (PhD) in Measurement and Evaluation.



Dr. Monilola Dasola Oyetade
(Supervisor)

28/4/2026

Date



Dr. Oluyomi Susan Pitan
(Associate Professor & Head of Department)

28/4/2026

Date

Dedication

This research is dedicated to Omolara, Victoria, Shalom and Samuel Adetoro.

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Even though the above-mentioned institutions and persons have assisted in the process of the research work, I alone stand responsible for the errors, if any, found in the work.

Abstract

This study investigated predictive modelling of Teachers' Workload, Classroom Management Practices and Students' Factors on SSS2 Students' academic performance in Chemistry in Southwest Nigeria. Since most of the variables in behavioural science are categorical variables, there is need to use statistical tools that would correctly categorize data into different groups and predict academic performance from data from which reliable deductions could be drawn. Also, there is dearth of studies on predictive capabilities of AI algorithms in the prediction of students' academic performance of students especially in African contexts. Consequently, the study leveraged machine learning algorithms to investigate the features that could contribute mostly to the performance of machine learning models in the prediction academic performance of students in Chemistry. Four research questions guided the study, and three Theories, Job Demand-Control Theory, Behaviourist Theory and Social Learning Theory provided the needed insights into the study. The study adopted cross sectional research design. The population of the study comprised all the senior secondary school 2 students in the Southwest Nigeria. Multistage clustering sampling technique was used for the selection of participants. The process of data collection involved clustering of six states into three states in the southwest Nigeria. Each of the clustered states was stratified into three senatorial districts, and all the chemistry teachers in the sampled schools were selected for the study. Four research instruments were developed for data collection which include Teacher Workload Rating Scale (TWRS), Teacher Classroom Management Skills Questionnaire (TCMSQ), Students Factors Questionnaires (SFQ), and Chemistry Achievement Test (CAT). The reliability coefficients of the instruments were established by using Cronbach Alpha with reliability coefficients in the range of (0.6-0.75). Data collected was analysed by using machine learning algorithms which include Gradient Boosting Model, Confusion Matrix and SHAP analysis. Results revealed that XGBoost achieved the highest overall test accuracy (0.6622) and a cross-validated F1-score (0.6313 ± 0.01422). However, Gradient Bosting exhibited strength in multi-class prediction F1-score (0.6524). It also achieved the highest Test ROC AUC (0.7714) which indicated a high-performance accuracy in the classification of students on achievement basis. The most influential feature that contributed to the performance of the model in the prediction of students' academic performance in chemistry was Teacher Non-Academic Workload (0.087354). Also, the study revealed that the model correctly predicted the academic performance of 160 students accurately. SHAP analysis (Shapley Additive exPlanations) revealed that Teacher Non-Academic Workload was the most impactful feature in the prediction of student chemistry performance. The study concluded that a teacher's daily workload is a far more powerful driver of students' success. The study recommended among others that urgent intervention is needed to address the issue of teacher's workload in secondary schools.

Keywords: Academic Performance, Teachers' Workload, Management Skills, Students' Factors

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List of Acronyms

Abbreviation	Meaning
STEM	Science Technology, Engineering and Mathematics
TWRS	Teacher Workload Rating Scale
TCMPQ	Teacher Classroom Management Practices Questionnaire
SFQ	Students Factors Questionnaire
CAT	Chemistry Achievement Test
NICMP	Non-Instructional Classroom Management Practices
TAW	Teacher Academic Workload
TNAW	Teacher Non-Academic Workload
TYTE	Teacher Year of Teaching Experience
SHAP	Shapley Additive explanations
THQ	Teacher Highest Qualification
SES	Student Social Economic Status
WASSCE	West African Senior School Certificate Examinations

Chapter One

Introduction

1.1 Background to the Study

Science education has contributed significantly to the strengthening of the economic indices of nations. Most of the developed nations rely on the inputs from science and technology in positioning their economies on the paths of growth and development, this has resulted in upwelling of interests and commitments to STEM education. Chemistry is a component of physical science and has been playing a crucial role in the economic prosperity of nations. So, its study in schools and colleges should be given due attention to enhance effective teaching and learning based on its relevance.

Through the study of chemistry, the concepts of matter in terms of structures and properties are better understood. Consequently, Chemistry is defined as the study of the composition, properties, uses and structure of matter¹. It is the study of composition of matter, its properties and changes it undergoes². In the opinion of the researcher, the knowledge of Chemistry is applied in medicine, pharmacy, metallurgy, textiles industry, glass and cement industries, paints, petroleum, sugar processing industry, plastics and agriculture. The application of chemistry in these areas has contributed to the establishment of manufacturing industries and sustenance of a vibrant economy.

However, a lot of chemical and physical changes that could have been assumed as the wonders of the world have been explained by the knowledge of Chemistry. For example, it is common knowledge that corrugated iron sheets could turn brown when exposed to air and water. The knowledge of Chemistry has helped us to understand the reason for this observation. So, the

need for a sound knowledge of the subject cannot be overemphasized. This was corroborated with this statement that chemistry education is a necessary ingredient for becoming self-reliant, earning a living and contributing towards building a sustainable national development³. The need for a strong science and technology system for the citizenry through emphasis on the pre-requisites for the knowledge-based economy and innovation was reechoed⁴. This observation was also captured in the Policy Brief for Science, Technology and Innovation that Nigeria is operating in a world that is shaped by scientific discovery and revolutionary technologies which are transforming communication, learning and economies ⁵.

It was emphasized that innovations resulting from these discoveries through science and technology are responsible for the establishment of new industries, creation of a wide array of new jobs that otherwise would not have been possible, thus improving the economies of nations and their competitiveness⁵. The reliance of the country's economic development on science and technology was rearticulated in the economic blueprint for the nation tagged vision 20:2020. Therein, manufacturing industries were identified as critical components in the implementation of the objectives of the vision.

Also, it was observed that the objectives of the vision have not been achieved after many years of conception due to poor implementation of the vision⁵. Consequently, Nigeria was ranked 116 out of 140 countries in the global competitiveness index in GDP, markets, money, trade, prices, business and energy⁵. This position was traced to poor quality Mathematics and Science Education in senior secondary schools. This does not speak well of a country that prides herself as the giant of Africa. Since chemistry is a contributor to the prospects of the industrialization of the country through science and technology, there is need to ensure its quality teaching and learning in secondary schools, being the first contact where the subject is first introduced to

learners. So, having a model that could predict how students would fare in learning chemistry will be an intervention that will enhance quality and its sustainability in terms of teaching and learning chemistry in schools. Consequently, this has brought about the need to investigate some factors that are perceived to influence the academic performance of students and establish their predictive capabilities on academic achievement of students in Chemistry.

Though some research had been carried out earlier that was aimed at ensuring quality control and improvement of the teaching and learning of chemistry in schools. For instance, in a study on achieving effectiveness in secondary school classrooms, using constructivist approaches, it was stated that factors such as abstract nature of chemistry, volatility of chemistry concepts, inappropriate and inspiring teaching techniques could affect the stimulation of learners in the learning of chemistry¹. The abstract nature of the subject may promote rote learning and memorization of concepts, which may impede the application of newly acquired skills in a new environment, as learners could easily memorize the chemical concepts to pass examination.

Despite the invaluable contributions of these studies to the teaching and learning of Chemistry, it is evident that much work still needs to be done in a bid to improve the academic achievement of students. For instance, the comparison of grade E₈, the pass grade with grade B₂, the grade that forms the boundary between distinction and credit, from year 2019 to 2024 in the West African Senior Schools Certificate Examination shows that majority of the candidates that passed chemistry with qualifiable grade for admission had C₆.

Table 1.0 Comparison of the Percentage Cumulative Frequencies of Candidates that got E8 with Candidates that got B2 in WASSCE School Candidates, 2019 -2024

2019	2020	2021	2022	2023	2024
B2 66(6.18)	B266(24.07)	B266(11.04)	B265(12.16)	B2 65 (2.63)	B268(23.48)
E833(97.35)	E833(97.35)	E833(96.12)	E832(98.02)	E832(91.64)	E835(96.27)

Source: WAEC

The trends in the performance of candidates in the years under review could be seen in the table. In the year 2019, 66 was fixed as the benchmark for grade B2. However, 6.18 percent of the total candidates that wrote the paper made B2. Also, grade E8 was pegged at 33 and 97.35 percent of the total candidates that sat the paper made that grade out of 762,595 candidates that sat for the paper. From this analysis, it could be inferred that majority of the candidates fell within grade E8 region which indicated that 97.35 of the candidates that sat the examination scored E8 and above. The same trend could be observed in other years, even when grade B2 was reduced by 1 mark from 66 to 65 in the year 2022 and 2023. However, in the year 2024, the performance was better when compared with previous years. The benchmark for grade B2 in 2024 was 68 and 23.48 percent of the total candidates who sat the paper made the grade. The benchmark of grade E8 was 35 and 96.27 of the total candidates who sat the paper made the grade and above. A total of 962,478 sat the examination. Though improvement in performance was noticed in the year 2024, this does not rule out the fact that the performance of candidates in chemistry has not been consistently improved over time.

Consequent upon this development, the researcher is investigating the likely variables that could be responsible for the poor academic achievement of candidates in chemistry, such as teachers' workload, classroom management skills and students' factors.

Teachers' workload is the academic and administrative tasks that teachers carry out in schools to achieve a purpose. Teacher's workload is the totality of academic work and committee

workload that are assigned to a teacher for the attainment of the overall educational objectives in a school⁶. It is seen as the tasks that must be completed within a specified period of time⁷. It is observed that high workload is a challenge among secondary school teachers⁸.

A direct relationship between academic achievement of students and the amount of the workload of teachers was reported⁹. It was equally stated that teachers would not give-in their best in an environment where they would shoulder multiple responsibilities that could affect their performance⁹. Heavy workload on teachers has forced many experienced teachers to resign from teaching profession making it unattractive to the young ones¹⁰.

The components of teachers' workload include planning and writing of lesson notes, filling out diaries, marking of registers, evaluation and recording of test assignments and examination outcomes¹¹. Also, teachers' workload may become heavy because of their likely appointments as Heads of Department and undertaking other appointments which could be in the form of taking up of ad-hoc responsibilities, amongst others¹¹. In addition to workload, classroom management was considered as a likely factor that could affect the academic achievement of students as posited in 'teach thought', an e-book. Classroom management is the conscious manipulation and deployment of several strategies, rules and limitations to create an environment where students can learn effectively¹². Classroom management involves setting clear expectations and consequences, establishment of clear learning goals; provision of flexible learning goals; taking a personal interest in students, usage of equitable and positive class behaviours; utilization of strategies to manage the high needs of students¹³. Classroom management is conceptualized as orderly control of students, the classroom environment and teaching materials to achieve learning objectives which can enhance the academic achievement of students¹⁴. It is viewed as a process that involves the organization of certain academic tasks

which are essential for effective teaching and learning in a specific set-up¹⁵. Classroom management is also conceptualized as the arrangement of teachers and students, seats and creation of proper walkways in the classroom which involves adequate and proper positioning of other classroom furniture to facilitate effective teaching and good learning atmosphere. In addition to this, teachers' instructional effectiveness was considered as a component of classroom management¹⁶.

The components of classroom management were also stated to include learning goals, routines, classroom rules and social expectations, correction and discipline, encouragement, praise and consistency. It was emphasized that encouragement and praise should be used to promote inclusivity which allows every learner to respond positively to learning. The introduction of incentives like treats or short breaks for attentiveness and participation were advocated. In addition to this, classroom rules and social expectations are assumed to significantly reduce disruptive behaviours during teaching and learning¹⁷. Furthermore, the effective application of classroom management practices is foundational to students' academic achievement¹⁸.

The importance of classroom management was explored and includes the establishment of a positive learning environment for learners and productive environment for teachers by allowing learners to work within the specific routines and procedures¹⁹. It was also stated that if classroom routines are working well, it would open door for effective teaching and learning which could be measured in the learning outcomes¹⁹.

Reflecting on the opinions of some teachers that effective classroom management makes teaching easier, because the teacher gets the full attention and concentration of students²⁰. Effective classroom management sets the stage for teaching and learning²¹. Good classroom

management is aimed at setting a tone in the classroom for capturing students' attention which also serves as a necessity for effective teaching and learning¹³.

In addition to this variable, students' factors are also considered as likely factors that could influence the academic achievement of students. It is seen as constructs that are within or outside the control of students which could also influence students' academic achievement. It is argued that factors from the context of school setting and other factors such as attitude towards learning, student self-efficacy and peer relationship could influence the academic achievement of students²². Attitude is the mindset that students have towards learning. A positive attitude to learning could improve students' academic achievement in chemistry²².

These are considered as the chief factors that could affect teaching and learning²³. Beyond this concept, parents' level of education could affect the academic achievement of students²⁴. Time spent in the library, gender and age could also affect students' academic achievement. The popular construct that was held by majority of the researchers about students' factors and academic achievement is family background which is presumed could also affect academic achievement of students as necessary support that is provided by the family could instill necessary confidence in the students²⁵. In line with this opinion, academic achievement of students could be affected by personal and family factors which include socioeconomic factors, class attendance, high school grades, self-efficacy and attitude²⁶.

The impact of the aforementioned factors varies from region to region and differs in cities and rural areas across the country. This difference in observation might be because of diverse data measurement methods and the quality of the content of each study within and outside the country²⁷. Students' academic achievement was linked to students' learning skills, parental

background and peer influence²⁸. It is argued that procrastination and laziness vary in both their essence and the influence they have on human activity²⁹.

From this discussion, it can be deduced that there is still room for improvement if appropriate step is taken and timely intervention is deployed in improving academic achievement of students. However, it was observed that the previous research had significant little impact because they focused on only a few factors that could influence academic achievement of learners, thereby leaving other factors out.

Also, the statistical methods that were deployed in these studies had inherent limitations which restricted the earlier research from comprehensively examining a combination of variables that could influence academic achievement of students in chemistry. Consequent upon this development, their predictive capabilities were constrained and could not effectively predict students' academic achievement to a reasonable degree of accuracy. So, there is a need to use a well-developed modern data analysis technology system that will be able to learn from data and detect patterns to predict students' academic achievement by making use of data from different variables.

Consequently, to address this gap, this study leveraged on the use of advanced machine learning algorithms by training models for prediction of students' academic achievement from teachers' workload, Classroom Management Skills and Students' Factors.

Advanced machine learning algorithm is a choice of data analysis because it can handle vast amounts of data and effectively process multiple variables at a run. This would be achieved by employing sophisticated algorithms and feature engineering methods which will allow the study to build robust predictive models that combine and analyze diverse factors that could influence the academic achievement of students in chemistry. So, this study focused on teachers'

workload, classroom management skills and some students' factors that could influence students' academic achievement. Predictive influence of the variables used in the study was investigated.

1.2 Statement of the Problem

Chemistry is a component of Physical science, and it is important to students that are aspiring to study science related courses in the university and other institutions of higher learning. To achieve this goal, a minimum standard is set for prospective students which is a minimum of a credit pass in Chemistry in the external examinations such as The West African Senior School Certificate Examination (WASSCE) and The National Examinations Council (NECO). To meet up with these minimum requirements, it is therefore important for students to have a good understanding of the subject at secondary school level so that their entry behaviours will help them in higher institutions of learning. This in turn will facilitate the realization of the vision for the National Policy of Science and Technology. But sadly, students still find it difficult to grasp the various concepts of chemistry judging from their poor achievement in public examinations. To address this problem, a lot of research has been undertaken that was aimed at providing empirical solutions to the problem. Some of these studies have narrowed the cause of this problem to the abstract nature of chemistry. Despite these interventions, the academic achievement of chemistry students still needs improvement, especially in public examinations. This suggests that much work still needs to be done. To address this issue, this study explored the capabilities of machine learning algorithms in the prediction of students' academic achievement in chemistry from teachers' workload, classroom management practices and students' factors in Southwest Nigeria. By identifying these factors, the research seeks to provide valuable insights that could help educators and stakeholders improve students'

academic achievement in chemistry. To achieve this purpose, algorithms that are used in machine learning were used in predicting the features of teachers' workload, classroom management practices and students' factors on academic achievement of students in Chemistry. The choice of these statistical tools is due to their ability to handle a vast amount of data at a goal and their high level of precision and accuracy when they are well trained.

1.3 Aim and Objectives of the Study

The aim of this study is to find out the extent to which academic achievement of students in chemistry would be predicted from teachers' workload, classroom management practices and students' factors.

Specifically, the objectives of the study are to:

1. ascertain the level of the comparative performance of machine learning models for predicting chemistry achievement from Teachers' workload, Classroom Management Practices and Students Factors to determine the machine learning model that best predicts chemistry students' academic achievement.
2. determine the features which are most influential in predicting students' chemistry achievement.
3. determine how accurately the best-performing model will classify students into different chemistry achievement categories (low, moderate, and high).
4. determine the specific contributions of individual features to the predictions of students' chemistry achievements.

1.4 Research Questions

Answers were provided to the following research questions.

1. Which machine learning model best predicts secondary school students' academic achievement in chemistry?
2. Which features of teachers' workload, classroom management practices and students' factors are most influential in predicting secondary school students' academic achievement in chemistry?
3. How accurately does the best performing model classify students into different chemistry performance categories (low, moderate, and high)?
4. What are the specific contributions of each of the features to the predictions of students' chemistry achievement?

1.5 Significance of the Study

This study will provide necessary information that will help:

Students and Teachers

The outcomes of the study will help in strengthening the effectiveness of the teaching process in terms of how the classroom environment could be better managed to enhance productivity, while knowing that the learners are heterogeneous in nature. The research is also expected to make significant scientific contribution to the field of science education through the provision of empirical information that will advance the frontiers of knowledge.

Counsellors

To counsel students who have poor attitude and low self-efficacy to the learning of chemistry. Counselling that could help such categories of students could be administered to them.

Policymakers and school administrators

will make use of the study to develop a better educational system that will promote effective teaching and learning. The findings will also contribute to the advancement of knowledge through the inclusion of a new concept of predictive based investigation which could be applied in future for decision making. Also, it will expose the strengths and weaknesses of learning related factors and learning conditions which could be useful for effective planning and classroom management.

School administrators

will find the study useful in ascertaining the number of periods that should be allocated to teachers on a weekly basis to prevent unnecessary workload that could reduce their productivity. Furthermore, the study would serve as a foundational resource for future research endeavors by paving way for continued exploration and advancement in the field of Chemistry Education.

Government

will get useful information for the development of the national roadmap on science education which summarily could help in putting the country on the path of development.

1.6 Scope of the Study

The study focuses on predictive modelling of teachers' workload, classroom management practices and students' factors on students' academic achievement in chemistry in Southwest Nigeria. The region comprises six states, namely Ekiti State, Lagos State, Ogun State, Oyo State, Osun State and Ondo State. A minimum of ten schools were purposively selected from Oyo State, Lagos State and Ekiti State because the population parameters of Oyo are the same with Osun, Lagos with Ogun and Ondo with Ekiti. The population comprises all the senior secondary school² chemistry students in southwest Nigeria.

1.7 Operational Definitions of Terms

Chemistry: A science subject that is taught in senior secondary schools and which comprises metals, non-metals, gases, organic chemistry, analytical chemistry and physical chemistry as topics which students are expected to have learnt before sitting WASSCE and NECO.

Teachers' Workload: A series of school activities that teachers are involved in which could be academic related or non-academic related and are usually undertaken through statutory, delegation and administration. It consists of instructional workload and non-instructional workload. Instructional workload consists of academic activities that teachers undertake in schools while non-instructional activities are related to all activities outside teachers' academic workload.

Classroom Management Practices: The ability of a teacher to take full control of the classroom climate during teaching and learning activities to facilitate achievement of

behavioural objectives. Instructional classroom management skills address the teaching methods and non-instructional classroom management skills address the imposition of rules and discipline in the classroom.

Academic Performance: Describes the scores of candidates in a standardized test. It also describes the measurable performance outcomes or success at the end of students' academic programme.

Students' Factors: Students' attitude towards chemistry, student's self-efficacy and students' peer relationship. Students' attitude deals with the mindset of students towards learning chemistry. Self-efficacy describes the belief that students have in themselves to succeed. Students' peer relationships describe the social relationship among students which could influence their reading habits.

Predictive Model: It is a type of mathematical or computational model that offers recommendations or suggestions to guide decision-making and optimize outcomes in a specific situation based on the quality and sequence of data being analyzed to forecast or give a predictive based decision.

1.8 Limitation of the Study

The focus of the study is on predictive modelling of teacher's workload, classroom management practices and students' factors on academic achievement of students. The study adopted cross sectional research design. The sample size was delimited to the six states of South-West Nigeria due to time and budget constraints which could affect the data set. Ten schools were purposively sampled from the target population in Oyo State, Ten schools in Lagos State and Five schools in Ekiti State across all the senatorial

districts of the states. Purposive sampling method was used to select schools that were centrally located and have large number of chemistry students. States were purposively selected based on the cosmopolitan nature of the states. Questionnaires and achievement test were used for data collection.

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Chapter Two

Literature Review

The review of related literature is discussed under the following sub-headings:

2.1 Conceptual Review

- 2.1.1 The Concept of Teachers' Workload
- 2.1.2 Teachers' Classroom Management Practices
- 2.1.3 Students Factors and Academic Achievement
- 2.1.4 Concept of Age and Students' Academic Performance
- 2.1.5 Concept of Academic Achievement
- 2.1.6 Chemistry Education in Nigeria
- 2.1.7 Machine Learning Algorithm

2.2 Theoretical Review

- 2.2.1 Job Demand-Control Theory
- 2.2.2 Behavioural Theory
- 2.2.3 Social Learning Theory

2.3 Review of Empirical Literature

- 2.3.1 Teachers' Workload and Students' Academic Performance
 - 2.3.1.1 Determinants of Teachers' Workload
 - 2.3.1.2 Teachers' Academic Workload and Students' Academic Achievement
 - 2.3.1.3 Teachers' Involvement in Non-Academic Workload and Students' Academic Performance
- 2.3.2 Classroom Management Skills and Academic Achievement of Students
 - 2.3.2.1 Non-Instructional Classroom Management Skills and Academic Performance of Students
 - 2.3.2.2 Relationship Between Instructional Classroom Management Skills and Academic Performance of Students
- 2.3.3 Students Factors and Academic Performance of Students
 - 2.3.3.1 Students Attitude and Academic Performance of Students
 - 2.3.3.2 Students Self-Efficacy and Academic Performance of Students

2.3.3.3 Students Peer Relationship and Academic Performance of Students

2.4 Conceptual Model

2.5 Summary of Reviewed Literature and Gap

2.1 Conceptual Review

2.1.1 Teacher's Workload

A classroom teacher is a professionally trained person who is involved in classroom practices, a knower and a primary source of knowledge and learning to themselves and others¹. So, creation of an environment for learning has been described as the chief role of a teacher². To perform this role efficiently, professionalism and development of teachers are emphasized as the basic ingredients in enhancing efficiency and productivity³. However, teacher's classroom professionalism may be watered down by a lot of besetting factors such as workload intensification⁴. In the opinion of the researcher, the level of engagement in the academic and non-academic activities in the school may further engage the minds of teachers and the quality of the teacher's productivity which is measured in terms of the academic achievement of students may be reduced.

The general opinion that the teacher's workload includes teaching subjects, administrative duties, supervision of students and other activities has been well established by different scholars which has given credence to the opinion that the work of a teacher is multitasking and stressful⁵. The teacher's workload was discussed in the context of the complexity of assessment procedure and the nature of the curriculum being implemented⁶. The administrative demands in schools could distract teachers from effective teaching⁷. It was also argued that teaching is a difficult task because it encapsulates various stages that are aimed at achieving instructional objectives⁸. Teaching is a task that is structured into planning stage, implementation stage and

appraisal stage. The planning of instructional contents before implementation is very crucial and important for forming the teaching components and development of pedagogy.

Comparatively, two categories of teachers were identified by scholars as part-time teachers and full-time teachers⁹. The full-time teachers are fully employed and assume the full responsibilities of a teacher, while part-time teachers have less academic and administrative commitments to the school when compared with full-time teachers. So, their workload is lesser and less stressful⁹. The components of teacher's workload were examined by various scholars, and it was affirmed that it comprises the teaching aspect, administrative aspect and extracurricular activities¹⁰. This makes the preparation of lesson plans, delivery of lesson plan and assessment of student's homework or classwork to form the key components of teacher's workload¹¹.

2.1.1.1. Teacher's Classroom Activities as Components of Workload

Teaching is a process that involves passing knowledge from the teacher to the student and is equally viewed as the combination of various elements within the process where an educator identifies and establishes the learning objectives and develop teaching resources in a bid to implement the teaching and learning strategy¹². In the opinion of the researcher, before learning objectives could be achieved, a lot of instructional activities are directly or indirectly deployed that are aimed at improving the learning process.

In addition to this, the workload of a teacher as an instructor during the learning process reflects the activities they engage in during teaching and learning. These include advisory, mediation, demonstration, coordination, modelling, observation, stimulation, planning of the learning process, time valuer and knowledge of students¹³. In the opinion of the researcher, the teacher

can function in these roles because of the clear understanding of planning of the lesson process which forms the bulk of the mental workload. To buttress this point, it was argued that in planning any instructional activities, questions such as the level of learners to teach, what to teach, how to teach, and what activities to be engaged in should be done during teaching and be meditated upon before teaching and learning begin. From this statement, it could be inferred that a lot of activities at the planning stage of instructions are undertaken by the teacher to ensure effective teaching and learning¹³.

In addition to this, classroom activities contribute to the workload pressure which could be caused by high expectations from various stakeholders. Consequently, it was advocated that mitigation of the challenges of workload would require some strategic measures such as control of working hours, administration of self-discipline and the use of pre-existing resources¹⁴.

Activities of teachers which form the bulk of their workload were expanded to include instructional planning, planning and provision of laboratory instructions which were taken as the major factors that could significantly contribute to teacher's workload¹⁵.

In the opinion of the researcher, implementation of effective classroom activities may be threatened by some challenges such as large teacher-to-pupil ratio and high number of periods that are taken by teachers on daily and weekly basis. It is recommended that the minimum standard of students to teacher ratio in the classroom and the number of periods on daily and weekly basis should be fixed at a minimum of 18 periods per week and a maximum of 22 periods per teacher per week, while teacher to student's ratio should be pegged at 1:35¹⁶. Any system that is above the recommended standard would lead to overutilization of teachers.

2.1.1.2 Non-Academic Workload and Teacher's Productivity

In the opinion of the researcher, non-academic duties are the administrative tasks and responsibilities that teachers undertake in schools which are outside the classroom academic activities. This concept has generated a lot of debates in the school eco system.

The issue of administrative tasks and its attendant effects on the productivity of teachers have dominated the centre of academic discourse and has been documented as part of the factors that could affect the productivity of teachers¹⁸. The multi-dimensional roles of combining classroom activities with administrative assignment may allow teachers to exhibit a dual function in the school system¹⁹. From this statement, the teacher could be assumed to be a master of all trades.

However, it is noted that teachers' tasks vary across schools and are based on staff strength and the number of pupils in the school that are available to undertake pupils related tasks. It is argued that administrative work in schools such as registration of students for admission and other duties are the responsibilities that are imposed on teachers which could affect their performance on the job²⁰. It was asserted that because of the commitment to non-academic duties, academic obligations are carried out as emergencies²¹. Non-academic engagement in schools may prevent teachers from having the time to teach the students in the normal academic programme and may force teachers to organize emergency teaching when examination draws close²². In view of this development, it is advocated that there is need to end the allocation of non-academic responsibilities to teachers to enhance their productivity²³. In addition to this, engagement of teachers in non-academic activities could badly affect quality teaching and learning²³. Administrative workload that could affect teachers' effectiveness include the following school activities.

Keeping schools' records and documentation of data. Teachers are responsible for keeping and updating student attendance records, test scores, behavioural reports, and academic performance reports. These records help school administrators track student progress and identify areas where intervention is needed. Because of the manual way of keeping and updating school records, it makes the process tedious and prone to errors and challenges, particularly in schools without digital management systems²⁴.

Curriculum Implementation and Evaluation

Teachers ensure that the teaching curriculum is effectively executed. This is achieved through the alignment of lesson plans with the national educational standards, updating teaching methodologies, and evaluation of students' cognitive levels. It is argued that Chemistry teachers face challenges due to frequent syllabus modifications by education regulatory bodies, which requires continuous adaptation²⁵.

Participation in Staff Meetings and Committees

One of the administrative duties of teachers are attending staff meetings, academic meetings, and school planning committees. These meetings could focus on curriculum changes, policy implementation, disciplinary measures, and general school administration. These meetings consume valuable time that could be spent on planning lessons and student mentoring. In many Nigerian schools, teachers are also assigned to multiple committees which could increase their non-instructional workload²⁶.

Extracurricular Activities

Teachers are involved in extracurricular activities that include sports, clubs, and student mentorship programmes. These activities contribute to holistic education and add to teachers' workload²⁷. Supervision of Student clubs and other academic related societies have expanded the work of teachers. Many schools require teachers to serve as patrons for student clubs such as science clubs, debate teams, and chemistry societies. While these activities enhance student learning and engagement, they demand additional time and effort from teachers. Also, science teachers, especially those handling chemistry, are often involved in organizing science exhibitions, quiz competitions, and laboratory-based projects. These activities could increase teachers' engagement and occupation²⁷. Teachers are assigned to oversee sports activities, inter-house sports competitions, and fitness programmes. While physical education is essential for student development, it places additional strain on teachers who may already have heavy academic responsibilities²⁸.

In addition to this, provision of support for students through career counselling, personal development, and handling of social issues affecting students' academic performance. Counselling is provided to students that are interested in pursuing careers in science, technology, engineering, and mathematics (STEM). This mentorship includes advising on subject combinations, career paths, and university admission processes²⁹. Counselling that are aimed at managing family related issues, peer pressure, and mental health concerns are offered by teachers due to the dearth of counsellors in schools. So, teachers often step in to offer emotional and psychological support for students. Teachers often organize extramural classes

after school hours. While these remedial classes help struggling students, they increase teachers' workload and reduce their personal time for relaxation and recuperation³⁰.

2.1.1.3 Teacher's Involvement in Extra-Curricular Activities

Extra-curricular activities are non-academic in nature and consist of school clubs, sports, teams, volunteering at local community and student government groups³¹.

The history of extracurricular activities was traced to American College in the nineteenth century when it was first designed and used to complement the curriculum³². Engagement of teachers in extracurricular activities was linked to high workload and fatigue³³. In view of this development, the researcher's view is that to diffuse workload due to extra load from extracurricular activities, teachers may skip some classes as a way of relieving burnouts and stress.

Also, extracurricular activities are planned in a similar way, instructional activities are planned which may indicate equal weighting in terms of planning and execution of programme to achieve what the programme is designed to achieve³⁴. In line with this statement, it is revealed that extracurricular activities are also planned before implementation, and this involves definition of the goals of the activities, planning and supervision which form the basic stages that form the process of extracurricular activities³⁵.

Based on this argument, it could be concluded that double efforts are required to plan instructional activities for the learners and at the same time plan extracurricular activities for them. In the opinion of the researcher, the combined contributory effects of these activities may lead to overwork on the part of the teachers. Beyond this, the task of managing learners during

extracurricular activities so that they are kept within the context of the activity may require the use of stiff measures on learners to get them controlled³⁵.

2.1.1.4 Strategies for Reducing Non-Academic Workload in Schools

In the opinion of the researcher, the bulk of non-academic workload precipitates from administrative tasks in schools. To this effect, schools' administrators should actively appraise schools' administrative procedure to identify areas that need simplification. Deployment of effective and working strategies could mitigate the effect of non-academic workload on teachers. Deployment of robust and user-friendly data management systems can significantly reduce the time spent on manual registration of students, tracking of students' academic performance, and generation of reports³⁶. It is argued that automation of attendance register, grade report sheet, and communication with parents through online platforms can help teachers in the management of non-academic workload and considerably reduce repetitive and time-consuming tasks. Furthermore, these systems can provide real-time insights into student performance, allowing teachers to focus on targeted interventions rather than data collection³⁶.

Consequently, it is recommended that Centralized Communication and Information Technology can be leveraged upon. Effective communication channels should be simplified for effective and seamless processes of non-academic related documents and assignments³⁷. Creation of centralized communication hubs, such as internet facilities or shared online platforms could be used to consolidate information to ensure that teachers have easy access to essential resources³⁷. This approach can also streamline internal communication, fostering a more collaborative and efficient working environment. In addition, employment of adequate administrative support staff can alleviate the burden of teaching staff. This includes assigning staff to handle tasks such as photocopying, management of students' records, scheduling

meetings, and coordinating events³⁸. Delegation of responsibilities would make teachers focus on lesson planning, student interaction, and professional development.

It is well accepted that technology, when implemented strategically, can be a powerful tool for reducing non-academic workload. Utilization of online learning platforms like Google Classroom, Canvas, or Moodle can be used for lesson planning, assessment, and feedback³⁹. Teachers can create and share digital resources, assign and grade online assignments, and provide personalized feedback to students. Furthering on this, building a centralized repository of high-quality digital resources could allow teachers to have access and adapt materials, reducing the time spent on improvisation of resources from scratch.

In another perspective, employment of digital assessment tools can automate the grading process, provide immediate feedback to students, and generate data-driven insights into student learning. Tools like Socrative, Quizizz, and Google Forms offer a range of question types, automated scoring, and data analysis features that can help in freeing up teachers' time to focus on instructional adjustments and individualized support⁴⁰.

Moreover, Utilization of virtual communication tools, such as video conferencing and online messaging platforms can facilitate parent-teacher communication and reduce the need for in-person meetings⁴¹. These tools allow for flexible scheduling and efficient communication, enabling teachers to connect with parents in a convenient and timely manner.

2.1.2 Teacher's Classroom Management Practices

The importance of effective classroom management practices cannot be overemphasized. Study revealed that poor classroom management practices may significantly contribute to poor academic failure of students in public schools⁴². Effective classroom management puts the

teacher in good control of the classroom and equally provides orderliness and safety needed for instructions and learning⁴³. It could help learners to learn, eliminate learning barriers, set the physical, social and emotional learning environment that can support students learning and guide them based on their individual characteristics and needs⁴⁴.

Furthermore, the importance of effective classroom management was established through its link with teaching and learning activities⁴⁵. It is also advocated that classrooms should be judiciously used to support effective classroom management. Further to this opinion, classroom management could be understood through the approach of non-interventionists, the interventionist and interactionist. In addition, it was revealed that the provision of leadership and management that will provide direction, planning, supervision, co-operation and co-ordination of teaching-learning process and provision of comfortable sitting arrangements to facilitate learning are key to effective classroom management⁴⁶.

It is remarked that the success of any educational system depends largely on the effectiveness of classroom management practices⁴⁷. The division of classroom management technique into behavioural classroom management and instructional classroom management was documented⁴⁸.

2.1.2.1 Classroom Management Practices

Classroom management styles are the degree of teacher's relationship with students and the type of control that is exercised by teachers over their students⁴⁹. The role of classroom management style was examined by different scholars and was affirmed that one of the fundamental tenets of classroom management is the teacher's classroom management style

which can promote positive or negative classroom interactions between the teacher and the students⁵⁰.

It is presumed that the overall aim of any classroom management style is to build a conducive classroom climate where teaching and learning can be facilitated. Good classroom climate is strongly associated with classroom environment⁵¹. This is suggestive that the creation of a conducive classroom climate could aid teaching and learning. In the opinion of the researcher, a good classroom climate could be achieved through adoption of effective classroom management styles that will help in controlling disruptive behaviours and other associated vices. Four classroom management styles were identified which could be applied in classroom management and these include authoritarian, authoritative, permissive, and indulgent⁵².

It is believed that Autocratic classroom management style allows the teacher to be the sole authority in the classroom, and it is characterized by the creation of rules for learners and questioning of the rules is not permitted⁵³. The weakness of this type of management style is that learners follow rules only when the instructor is watching them and little is learnt about submission and self-control. This type of style is characterized by anger, fear, humiliation and a desire for revenge⁵⁴. In the view of the researcher, learning may not fully take place under this leadership style as every student may be afraid of the teacher. Boldness to ask questions during learning may be impossible because of the frosty relationship that is perceived to have existed between students and their teachers.

Also, authoritative classroom management, on the other hand in the researcher's opinion, is coined by word authority. It is the classroom management style that provides the opportunity for teachers to lead the students towards achieving the social emotional welfare and learning⁵⁴. The essence of authoritative classroom management style is widely investigated by scholars,

and it was revealed that authoritative classroom management is not meant to control students' behaviour only, but to influence and direct it in a constructive manner which is characterized by permutations and combination of the degree of control and level of involvement⁵⁵.

In addition to this, the components of democratic management styles are itemized, and it is noted that joint decisions are taken in this type of style, objectives are set and shared⁵⁶. This type of management style allows members of the class to participate in policies formation and take decisions on the development that could affect the class. This implies that learners and teachers participate in the administration and management of classroom⁵⁷.

In another perspective, permissive management style is characterized by the freedom that learners must execute what they feel is right and suitable for them. It was further stressed that views are not imposed on the learners, and the mature learners could perform under this leadership style. In the view of the researcher, if the learning environment is not regulated, this type of management style may cause rowdiness in the classroom and may eventually lead to the collapse of classroom management structure⁵⁸.

2.1.2.2 Psychological Dimension of Classroom Management Practices

In the researcher's view, psychological dimension to the understanding of classroom management depicts the stage where the behaviours of a student who resettles from an environment which is not strictly regulated by certain environmental conditions to an environment where reconstruction of behaviours are required through various conditioned environmental stimuli that shape the behaviours of the learner towards positive adaptation.

Psychological dimension in classroom management was examined, and it was affirmed that preventive strategies rather than punishment should be used to reconstruct learner's behaviour to enhance the quality of learning and minimize problem behaviour⁵⁷.

For smooth learning activities, it is important for teachers to factor-in pupils' home conditions in school to take a proactive approach when applying different skills to manage the classroom. Through this, the social and communication level of learners are better understood before socializing them to the learning environment for behavioural control and proper socialization⁵⁷.

2.1.2.3 Behavioural Classroom Management Practices

Behavioral classroom management practices are related to various measures that are put in place by the teacher to regulate, manage and control the behaviours of students to achieve stated behavioural objectives. It is the term that involves a complex interplay of interactions and activities within a learning environment, specifically within the confines of the classroom which includes the emotional state of students, attitude towards learning, interpersonal skills, cultural norms and behavioral tendencies⁵⁸. Understanding classroom behaviours is important in creating an effective learning environment. Behaviours exert a considerable influence on the learning environment, and positive behaviors are regarded as characters which can enhance effective instruction which include active class participation, direct engagement with classroom activities, discussion of tasks, and respect for others which involves display of courteous and considerate behaviour towards educators and fellow students and demonstration of accountability in academic commitments⁵⁹.

It is also conceptualized as the practices that involve setting clear expectations, setting consistent rules, modelling appropriate behaviour, implementation of preventive measures to

preclude disruptive behaviour and employment of intervention strategies when issues arise⁶⁰. Disruptive classroom behaviours are classified as behavioural disorders, and if not well managed, could cause significant impairments in academic, social and occupational functioning⁶¹. The characteristics of behavioural disorder among students at secondary schools involve exhibition of aggressive behaviour towards others, bullying, threatening or intimidating behaviours, physical abuse, deliberate destruction of other's belongings and properties, showing little empathy and concern for the feelings, wishes and well-being of classmates, showing callous behaviour towards others and lack of feelings of guilt or remorse and blaming others for their misdeeds. From the aforementioned items on behavioural problems in the classroom, in the opinion of the researcher, an efficient and robust behavioural management structure is needed for effective management of behavioural disorders in the classroom.

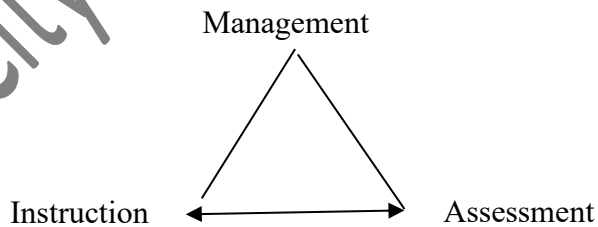
In addition to this, behaviours of students have a significant impact on classroom environment which often causes distraction to learning environment, teaching environment and could cripple the social, educational and holistic growth of the students. In view of this development, it was suggested that students should be motivated with proper discipline and establishment of strategies to improve students' behaviour⁶². However, inability to create boundaries for students can aggravate behavioural issues in the classroom which can impact on the academic performance of students negatively. Consequently, it was recommended that the concept of behaviour should be well understood so that right behaviours can be defined for the students⁶³.

The conceptual view that the management of classroom misbehaviour can be approached through behaviour modification method which involves direct instruction, reinforcement techniques, social praise, material reinforcers and tokens. It can also be approached through

direct instruction or punishment-oriented technique which include verbal reprimand, response cost and time-out⁶⁴.

2.1.2.4 Instructional Classroom Management Practices

The concept of instructional classroom management practices can be explained from the theory of behaviourism. Through this theory, students can respond appropriately to positive or negative stimulus. In this context, the stimulus that elicits responses is embedded in the instructional methods which can be used to maintain discipline in the class to keep the students interested in the learning environment. Classroom management and instruction are inherently interrelated such that the method of instruction, how students are assessed, and the way classroom is managed will affect one another⁶⁵. It is opinionated that the choice of pedagogy can either promote or hinder effective classroom management in such a way that if the pedagogy fails to meet the students' basic needs, it could lead to management problems⁶⁶. Consequently, engagement, satisfaction, well-directed, and meaningful instructional activities can control unruly behaviours in the classroom⁶⁶. The inter-relationship between instruction, management and assessment are well illustrated in the following diagram.



It can be seen in the diagram that classroom management leads to a two-way drive, instruction and assessment. This means that good classroom management will lead to quality assessment and instruction.

In the opinion of the researcher, one of the main objectives in the use of instruction in the management of classroom activities is to facilitate the creation of a conducive classroom environment to enhance quality teaching and learning.

In a related perspective, effective classroom management is facilitated by active and successful engagement in instructional activities. Based on this argument, it was suggested that a well-planned interaction with appropriate pacing, guided practice, attention to individual students, effective and immediate feedback can help teachers to manage the classroom effectively⁶⁷.

In the view of the researcher, active engagement of students in instructional activities can prevent noisemaking in the classroom and other behavioural disorders that can affect effective instructional activities. When students are given classwork or academic tasks, their cognitive senses are well engaged which can bring about more focused and controlled attitudes with the aim of helping teachers in effective management of classroom situation⁶⁸.

2.1.2.5 Factors that Influence Classroom Management Practices

Management practices in the classroom may be formed by the organization of the classroom and teaching materials, effective implementation of lesson plans and time management⁶⁹. Lesson plans have been documented as a vital compass that directs learning activities. So far, its effective implementation allows teachers to ask questions based on previous knowledge before the commencement of learning activities so that they could be taken through the depths of learning which starts with simple recall⁷⁰.

In the opinion of the researcher, effective classroom management is directly linked to the quality of education. Personality traits of teachers, professional and organizational factors and emotional traits of teachers are related factors that could influence classroom management

practices⁷¹. Students' personal needs, code of conduct, and teacher-student relationship are basic factors that are embedded in the concise definition of classroom management⁷¹. Teacher's competency, home environment, socioeconomic status or motivation are listed as factors that should be considered when discussing classroom management practices of teachers⁷². Effectiveness of teaching-learning approaches that are used by teachers during classroom teaching and learning is a factor that could influence classroom management⁷³. School climate is identified as a factor that could influence classroom management skills. It is documented that a school that has a good climate would produce teachers that have high levels of morale, efficacy and satisfaction, and lower levels of burnout, turnover, and absenteeism⁷⁴.

2.1.2.6 Effective Classroom Management through Conflict Resolution Practices

The most important classroom challenges are narrowed to students' disruptive behaviours and classroom management. It is posited that coping with students' classroom disruptive behaviours requires a specialized skill⁷⁵. For smooth delivery of learning, conflict resolution in the classroom could be achieved through cooperative and problem-solving strategies, avoidance strategies and punishment strategies. In keeping disruptive behaviour at bay in the classroom, it is suggested that different strategies should be used. Familiarization with appropriate disciplinary measures could enhance effective discipline⁷⁶.

In the opinion of the researcher, poor conflict resolution in the classroom can make the classroom climate to be in disarray and could affect students' learning, and if not well managed, could degenerate into violence. It is documented that teachers' emotional intelligence in the management of conflict in the classroom is important⁷⁶. Emotional intelligence is defined as the ability to perceive, interpret, demonstrate, control, evaluate and use emotions to communicate and relate with others effectively and constructively⁷⁶. Teachers who have good

emotional intelligence can use conflict management strategies to enhance teaching and learning processes⁷⁷.

2.1.3 Students Factors and Academic Performance

A lot of factors that could influence students' academic performance are documented in literature. Academic achievement of learners plays an important role in the production of best quality graduates who will become great leaders and manpower for the country⁷⁸. In addition to this, self-concept is a construct that can also play a significant role in the academic performance of learners and is a sine qua non for academic performance⁶⁵. Students' factors were considered as internal factors which include health, intelligence, talent, interest, motivation and student learning methods⁵⁹. Factors like attitude, self-efficacy and social interaction of students are classified as psychosocial factors, it is stated that negative psychosocial factors can slow down learning while positive psychosocial factors can facilitate academic achievement of students⁶⁰.

Some scholars gave credence to the fact that psychosocial factors play a great role in the student's academic achievement and are essential for the delivery of a high-quality teaching and learning process which are viewed as psychosocial factors. These are considered as the chief determinants of student academic achievement⁵¹. It is observed that human behaviours are influenced by attitudes which define the level of their involvement in a task or assignment⁶².

Furthermore, peer relationships have been argued at different academic fora as a catalyst that can enhance or inhibit academic performance among secondary school students. Peer relationship is defined as the social interactions and connections that individuals can establish with their peers which include interpersonal relationships, social emotion, and communication

interaction⁵³. It is seen as an influential factor in adolescents' academic achievement. Positive peer relationships have been associated with high level of academic achievement, while negative peer relationships can hinder students' academic progress⁵⁴.

Students' personal factors in the context of learning are considered as factors that are within the students' characteristics which can be psychological, cognitive and behavioural variables⁵⁴. It was revealed that students' factors capture the students' engagement variables that reside within a student's mind⁵¹. Based on this position, the students' variables are related to the way students' minds are reconstructed towards the eagerness to learn or otherwise. Students' personal factors can influence their academic achievement and can also change the dynamics in the socio-contextual factors⁵². Students' personal factors are divided into behavioural strategies, note-taking skills & test-taking strategies⁷⁹.

Behavioural learning strategies were denoted as constructs that could be measured by the extent to which learners are able to manage their own action, motivation, effect and environment which include the people and their surrounding⁷⁹. Behavioural learning strategies were suggested to include time management, test-taking strategies, help-seeking, homework management and note-taking skills⁷⁹.

Test taking strategies are phased into test-preparation strategies, test-preparation awareness and actual test-taking strategies and was revealed that test preparation strategies include the control of one's cognitive functioning, management of work environment and regulation of one's motivation and effort levels⁸⁰.

Learners can suffer from various psychological problems that may severely disrupt their daily functioning in various occasions, and which can be caused by stress, anxiety, depression, lack

of motivation, loneliness and phobia⁸¹. These constructs have been linked to academic performance. According to psychologists, learning is effective if learners can answer the three fundamental questions which are “can I do this activity”? “Do I want to do this activity and why”? And “what do I need to do to succeed”?⁷¹. In addition to this, clarification was made on the constructs that are used with the questions, and it is argued that the question, can I do this activity? It is a question that is related to self-efficacy which describes people’s judgement of their capabilities to organize and execute courses of action required to execute a designated type of performance⁸¹. Consequently, self-efficacy is a psychological factor that can determine the choice of learner’s activity, their effort and their presence in it.

Cognitive ability as a strong student factor can make or mar learning. It is defined as the capability of the human brain’s ability to store information, process and extract information, memory and logical reasoning and thinking transformation⁸¹. Cognitive factors such as comprehension, absorption and creative imagination are aspects of cognitive factors that can influence learning and academic performance⁸². For this study, attitude of students, school social interaction of students and self-efficacy of students are the students’ factors that are being investigated in this study.

2.1.3.1 Students Attitude and Academic Performance

Attitude in the context of learning is the responsiveness and willingness of a student to learn new concepts, skills and activities in the classroom⁸³. Attitude towards learning is a determinant factor for goal setting, problem solving abilities, students’ beliefs towards learning, their internal and external motivation in the process of learning and all the academic performance they perform⁸⁴.

It comprises individualistic, an abstract entity and a kind of intervening variables to explain regularities in behavioural responses. However, in dissecting its components, it was revealed that cognitive, affective or emotion and behavioural make up the bulk of attitudinal exhibitions by students in schools⁸⁵.

Students' attitude plays a vital role in the academic achievement of students. However, emphasis was placed on the need for appraisal of students' attitude as it provides information to students, teachers and curriculum developers to improve quality of instruction⁸⁶.

It is also conceptualized that attitude has a great impact on student's academic performance⁸⁷. Many students have poor grades and low academic achievement because they do not show attention or interest towards their studies through absenteeism, cutting classes and poor participation in classroom activities⁸⁸. It can alter every aspect of a person's life including their education, as it determines their interest, ability and willingness to learn⁸⁹. Negative attitude of students needs to be investigated to enhance the academic achievement of students^{69 70 71 72}.

2.1.3.2 Factors that Influence Students' Attitude Towards Learning

Student's attitude toward learning is influenced by various constructs which are defined by students' characteristics, social, and contextual factors. Attitude can be positive or negative. A positive attitude could lead to increased engagement, motivation, and ultimately, better academic outcomes⁹⁰. On the other hand, a negative attitude can retard learning and contribute to poor academic performance.

Moreover, provision of support and encouragement for students can significantly impact on student's attitude⁹¹. Provision of enabling and inclusive classroom environment where students feel safe, respected, and valued is important for fostering a positive attitude toward learning.

This includes promotion of collaborative and group-based learning among students, management of competition among students, and addressing issues of bullying and discrimination among them⁹¹.

Students are more likely to have a positive attitude towards learning if they see that the instructional contents are relevant to their lives and future goals. Also, engaging in authentic tasks and projects that allow students to apply their knowledge and skills in meaningful ways can enhance their motivation and attitude. Allowing students to have some degree of choice in what and how they learn can increase their sense of ownership and motivation which could result in more positive attitude⁹².

A student's belief in their ability to succeed in a particular subject or task is a strong predictor of their attitude. Encouraging a growth mindset can help students overcome challenges and maintain a positive attitude when facing academic challenges⁹³.

2.1.3.3 Students' Self-Efficacy

Self-efficacy was coined by a psychologist, Albert Bandura. The components of self-efficacy are put as encouragement of learners, fostering of growth mindset, provision of meaningful learning experiences and provision of support to help students to develop skills and strategies that are necessary to navigate academic personal challenges⁹⁴.

It is reported that students that have high self-efficacy will feel confident about their learning abilities, be interested in taking part in classroom activities, use information efficiently for their academic career, be motivated to apply and adapt to new lessons, show strong intrinsic motivation to learn from mistakes and overcome hurdles and inspire others with their way of life and achievement⁹⁵.

Self-efficacy is one of the major factors that are believed to considerably influence academic performance of learners in secondary schools, and it is argued that it accounts for a wide variation between high achieving students and low achieving students⁹⁶. For clearer understanding of the concept of the construct, characteristics of high self-efficacy as highlighted are strong sense of self confidence, self- evaluation and self- awareness, willingness to take risks or step outside the comfort zone, ability to solve tough problems or complete challenging tasks, high motivation to reach specific goals, resilient, that is, ability to recover from setbacks, a deep sense of passion and good state of mental health⁹⁷.

In the opinion of the researcher, it is a construct that is non-cognitive in nature but provides good information on the worth of individuals in their ability to take up challenges and face difficult cognitive tasks during teaching and learning activities. It is also conceptualized as a construct that has its scope transcending cognitive skills, but a function of students' beliefs. The researcher posited that three issues are related to self-efficacy, they are confident to write, anxiety and students' interest⁹⁷.

2.1.3.4 Student's Peer Relationship

Peer relationships are defined as the social interaction and connection that individuals can establish with their peers, which include interpersonal relationships, social emotion and communication interaction⁹⁸. It could be seen to have a profound impact on students' academic outcomes, as peers can serve as a source of both positive and negative influence. It is remarked that positive peer relationships can lead to higher levels of academic achievement, while negative peer relationships can hinder students' academic progress⁹⁹.

Students can interact with one another to discuss difficult topics, difficult subjects, concepts and strategies for high academic achievement. Similarly, the onerous nature of learning has made peer relationships become one of the most important relationships among high school students¹⁰⁰. Number of friends, the academic performance of friends and high quality of friendship are identified as key indicators of peer relationship. In addition to this, peer relationship improves the physical and mental fitness of students¹⁰⁰.

It is remarked that beside students' families, school is an important micro system that can shape children's cognitive and socioemotional development⁹⁸. On a contrary view, it was remarked that peer experiences are important parts of the school context for children and early adolescents, which can significantly contribute to their school liking, academic achievement and wellness⁹⁷.

However, from the perspective of psychology, it is acknowledged that when children reach adolescent age, they prefer to spend more time with their peers and less time with their families. Based on this perspective, it was posited that adolescents within a peer group tend to be like one another in behaviour and attitude which explain the reason for homophily adolescents that is adolescents who are like one another spend time together. Furthermore, it was posited that adolescents who spend time together can shape each other's behaviors and attitude¹⁰⁰.

The researcher views this concept in terms of homogeneity of academic ability of students, which gives explanation to why students with equal academic ability relate with one another which can bring about peer relationship.

2.1.4 Concept of Age and Students' Academic Performance

In the opinion of the researcher, it is generally believed that older students are more matured and so could perform better academically. Older students perform better than other students because of their cognitive development and emotional maturity. Older students possess better attention spans, problem-solving skills, and self-regulation abilities, all of which can positively impact academic success¹⁰¹.

Students who are older than other students could put on behaviours that could lead to social isolation, feelings of being out of place, or even behavioral issues, all of which can negatively affect academic engagement and performance¹⁰². In addition to this, Students who are older due to having repeated a class may face academic and social stigmas. Repeating a class could negatively affect self-esteem and motivation which could complicate academic challenges¹⁰³.

Students whose date of birth is close to the cut-off date for school entry may be younger than their peers. While some studies suggest that these students may be disadvantaged because they may face some academic challenges at the beginning of their academic journey, particularly in subjects that require strong foundational skills¹⁰⁴.

2.1.5 The Concept of Academic Performance

In the opinion of the researcher, academic performance is the quantitative description of human behaviours after a period of instructional activities. The quality of skills a learner has acquired in a formal setting which can be measured quantitatively to know whether learning has taken place or not. This position is consistent with the opinions of some scholars about academic achievement. It is considered as the scores of students in any educational programmes, which is influenced by cognitive and non-cognitive attributes¹⁰⁵.

Students' academic performance could be assessed using teacher ratings, tests and examinations. It is seen as the standard against which student, school, curriculum and teacher's ability and the mastery of the subject matter are measured. The importance of academic performance in educational settings has been emphasized by different scholars. For instance, it provides a measure of students understanding and mastery of subjects which give both students and educators a clear sense of progress and areas that need improvement. In addition to this, it could serve as a gateway to higher education opportunities, scholarships and competitive programmes. Academic achievement may also help to find in boosting student's confidence¹⁰⁶.

Conversely, in research, there have been misconceptions around academic performance, academic achievement and learning outcomes which make the three concepts to be used interchangeably. In clarifying these concepts, academic performance is defined as the observable or measurable behaviour of a person in a particular situation. It is documented in literature that academic performance can be determined by conducting performance tests on the learners. However, in the context of research, it is regarded as the observable and measurable behaviour of a student in a particular situation¹⁰⁷. From this concept, it can be inferred that academic performance of a student is usually presented as scores at any time which could be obtained from a teacher made test. In contrast, a concise definition of academic performance was given as the performance outcomes that indicate the extent to which a person has accomplished specific goals which form the focus of activities in instructional environment, which include school, college and university system¹⁰⁸.

Learning outcome is defined as the statement of the knowledge, skills and abilities that an individual student should possess and can demonstrate upon completion of a learning experience or sequence of a learning experiences⁸³. It comprises certain features that define it,

such being realistic, reliance on active verbs in the future tense, being well framed in terms of the programmes instead of specific classes that the programme offers, sufficiency in learning outcomes, alignment with the programme curriculum, should be simple and not compound. It should focus on learning products and not the learning process. In addition to this, it is stated that educational objectives should be consulted as useful guides for developing a comprehensive list of students outcomes¹⁰⁷.

2.1.6 Chemistry Education in Nigeria

Chemistry is a fundamental science subject that serves as the backbone for careers in medicine, engineering, pharmacy, and other science-based professions. It provides students with essential knowledge about chemical reactions, the composition of substances, and various industrial applications¹⁰⁹. Despite its significance, students in Nigeria and other developing countries often struggle with chemistry, resulting in low academic performance in national and regional examinations. The West African Examinations Council (WAEC) and the National Examinations Council (NECO) report over the last decade consistently indicate that many students perform poorly in chemistry due to factors such as inadequate instructional methods, poor laboratory facilities, and students' lack of motivation¹¹⁰. The persistent underperformance in chemistry calls for an in-depth investigation into its underlying causes and potential solutions. By examining the interplay between teachers' workload, classroom management skills, and student factors, this study seeks to provide a holistic understanding of the determinants of chemistry achievement in secondary schools in Southwest Nigeria.

2.1.7 Chemistry Education and its Challenges in Nigeria and Issues Affecting It

2.1.7.1 Misconceptions of Difficult Concepts

One of the major challenges in chemistry education has been identified as students' misconceptions of difficult topics which could affect learning. Some topics in chemistry are abstract which makes their learning to be challenging. Some of these topics were listed to include atomic structure, chemical bonding, reaction mechanisms, and thermodynamics, which students often find difficult to visualize and understand¹¹¹. Many students rely on rote memorization rather than conceptual understanding, leading to confusion and difficulty in applying knowledge to problem-solving situations¹¹².

Research has shown that common misconceptions persist even after instruction. It is documented that students often struggle with the particulate nature of matter, mistakenly believing that atoms and molecules behave like macroscopic objects¹¹³. In addition, chemical equilibrium is often misunderstood as a static state rather than a dynamic process of forward and reverse reactions occurring at the same rate¹¹⁴. These misconceptions make it challenging for educators to ensure meaningful learning and conceptual clarity.

2.1.7.2 Poor Laboratory Facilities and Practical Training

Practical activities are key important parts of chemistry, as they provide a long-lasting learning experience for the learning of theoretical concepts¹¹⁵. However, it is documented that the bane of many schools that offer chemistry especially in developing countries is lack of well-equipped laboratories, chemicals, and safety equipment, thereby limiting students' opportunities to get involved in practical activities¹¹⁶.

Also, the absence of practical experiences can make chemistry education look abstract and difficult to relate to real-world applications. It was established in a study that students in schools with well-equipped laboratories performed significantly better in chemistry assessments than those with limited or no access to laboratory facilities¹¹⁷. Students miss out on developing essential scientific skills such as observation, data analysis, and critical thinking when they are not well exposed to practical part of chemistry¹¹⁷.

2.1.7.3 Instructional Strategies and Teaching Methods

The traditional teaching method remains pronounced in many chemistry classrooms, despite evidence that it is less effective when compared with other teaching methods¹¹⁸. Traditional teaching methods do not allow for the engagement of students in critical thinking and problem-solving, leading to low retention rates and poor attitude to the subject. Research established that students learn better when instruction incorporates inquiry-based learning, problem-based learning, and cooperative learning strategies¹¹⁹.

In addition to this, teachers' pedagogical content knowledge plays a significant role in how chemistry is taught and learnt in schools. Many teachers are faced with the challenge of explaining difficult chemistry topics to students which could affect their understanding¹²⁰. In a study, it was concluded that professional development programmes that focus on innovative teaching strategies are often limited, which further exacerbates the issue¹²⁰.

2.1.7.4 Limitations of the Curriculum and Overloaded Contents

A curriculum contains the learning activities that learners are expected to learn over a period. It is observed that chemistry curriculum in many educational systems is often overloaded with

different learning contents compared to the allocated time on the timetable to effectively teach and learn the contents. This makes students memorize a large amount of information within a short period¹²¹. Also, the emphasis on content coverage rather than its understanding could lead to poor learning. This makes students focus on passing examinations rather than developing a long-term scientific literacy¹²¹. It is noted that chemistry curriculum does not capture real-world situations, making the subject seem detached from everyday life¹²². Students often struggle to see the relevance of chemistry beyond the classroom which could reduce their motivation to engage with the subject¹²³.

2.1.7.5. Negative Attitudes Toward Chemistry

It was reported that many students have a negative attitude to chemistry which could be caused by various factors leading to low motivation and engagement¹²⁴. Negative attitudes toward chemistry often stem from early learning experiences, where students find the subject challenging due to its abstract nature and mathematical requirements. A study found that students who struggled with mathematics were more likely to develop a fear of chemistry, leading to poor academic achievement¹²⁵. In addition to this, teachers play a crucial role in shaping students' perceptions of chemistry. When educators fail to make the subject engaging or relevant, students may develop anxiety and a lack of confidence in their ability to succeed in chemistry¹²⁶.

2.1.8 Machine Learning Algorithms

Learning is a process that involves acquisition of new knowledge, modification of the existing behaviours. The concept of learning is not restricted only to students and classroom learning

process and teachers¹²⁷. In the opinion of the researcher, machines are also programmed to learn by using data for computational activities. It is a tool of artificial intelligence that enables computers to learn from datasets. It allows computers to modify their actions to be more accurate and precise. In machine learning, accuracy is an evaluation metric that measures the overall correctness of a model's prediction¹²⁸.

In another perspective, it represents the ratio of correctly predicted instances to the total number of instances in the dataset¹²⁸. Literature revealed that the concept of the human nervous system was used in the creation of a group that built a machine for the recognition of letters of alphabets¹²⁹. Machine learning was called the perception by its creator and used both analogue and discrete signals which include a threshold element that converts analogue signals to discrete one¹²⁹.

Also, it involves a process which allows a computer programme to learn from a dataset with respect to some tasks and some performances¹³⁰. It is documented that it encapsulates a multi-disciplinary field that has a wide range of research domains that reinforces its existence¹³⁰. It is designed to allow for predictive purposes. It is also co-related with mathematical optimization which relates models, applications and frameworks to the field of statistics. Complex problems in the field of education could be analyzed using machine learning.

The use of machine learning in processing large databases is called data mining. In data mining, a large volume of disorganized data is processed to construct a simple model with valuable use which has high predictive accuracy. The process of data mining is systematic, and it involves selection of data, processing of data to eliminate differences and inconsistencies between data¹³¹. The applications of machine learning are well documented.

This involves its use in retail business, finance, and manufacturing. Machine learning models are used for optimization, control, and troubleshooting. In medicine, learning programmes are used in medical diagnosis. In telecommunications, call patterns are analyzed for network optimization and maximization of quality of service. In science, large amounts of data in physics, astronomy, and biology can only be analyzed fast enough by computers. It is used to teach a system to learn and adapt to changes so that the system designer does not need to foresee and provide solutions for all possible situations. It is used to find solutions to many problems in vision, speech recognition, and robotics. It is also applied in the design of computer-controlled vehicles to steer correctly when driving on a variety of roads. It is concerned with the use of the right features to build the right models that achieve the right tasks¹³².

There are several types of machine learning, and each of them has special characteristics and applications. Types of machine learning algorithms are Supervised Machine Learning, Unsupervised Machine Learning and Reinforcement Learning¹³³. Supervised machine learning involves training a model using labelled data, where each input comes with a corresponding correct output¹³³. It is a type of machine learning where a model is trained on labelled data, this means that each input is paired with the correct output. The model learns by comparing its predictions with the actual answers provided in the training of data and improvement of accuracy.

The goal of supervised learning is to make accurate predictions when given a new and unseen data¹³³. Supervised learning can be applied in various forms, including supervised learning classification and supervised learning regression, making it a crucial technique in the field of artificial intelligence and supervised data mining. A fundamental concept in supervised machine learning is learning a class from examples. This involves building a model with where

the correct label is known, such as learning to classify diagrams. The model then learns the distinguishing features of each class and applies this knowledge to classify new images. Where supervised learning algorithm consists of input features and corresponding output labels. The process is through data training. In this case, the model is provided with a training dataset that includes input data (features) and corresponding output data (labels or target variables)¹³³.

The algorithm processes the training data, learning the relationships between the input features and the output labels. This is achieved by adjusting the model's parameters to minimize the difference between its predictions and the actual labels¹²⁷.

Concisely, unsupervised learning is defined as a branch of machine learning that deals with unlabelled data. Unlike supervised learning, where the data is labelled with a specific category or outcome, unsupervised learning algorithms are tasked with finding patterns and relationships within the data without any prior knowledge of the data's identity. Unsupervised machine learning algorithms find hidden patterns without any human intervention.

The training model has only input parameter values and discovers the groups or patterns on its own¹²⁸. Reinforcement learning is a machine learning technique that trains software to make decisions to achieve the most optimal results. It mimics the trial-and-error learning process that humans use to achieve their goals. Software actions that work towards your goal are reinforced, while actions that detract from the goal are ignored¹²⁸. Reinforcement learning algorithms use a reward and punishment paradigm in processing data. They learn from the feedback of each action and self-discover the best processing paths to achieve final outcomes. The algorithms are also capable of delayed gratification¹²⁸. The best overall strategy may require short-term sacrifices, so the best approach they discover may include some punishments or backtracking

along the way. Reinforcement learning is a powerful method to help artificial intelligence systems achieve optimal outcomes in unseen environments.

2.1.8.1 The Concept of Predictive Modelling

Predictive modelling refers to the use of machine learning techniques to forecast future outcomes based on historical and real-time data. In education, predictive models are used to analyze patterns in student performance, identify at-risk students, and suggest interventions that can enhance learning outcomes¹³⁴. These models utilize data from multiple sources which include student demographics, teacher-related factors, classroom behaviours, and prior academic records to make predictions about students' future academic achievements. Predictive modelling has become increasingly relevant in educational research due to the rise of big data analytics and artificial intelligence. Institutions worldwide are leveraging on predictive analytics to improve decision-making in areas such as curriculum planning, student retention, and academic performance forecasting¹³⁵.

2.1.8.2 Types of Predictive Models in Educational Assessment

In educational assessment, various computational techniques are used to analyze data and make informed forecasts about students' outcomes, teaching effectiveness, and overall academic performance. These models vary in complexity and applicability, ranging from traditional statistical methods to advanced machine learning algorithms. The choice of predictive model depends on the type of data that is available, the relationships among variables, and the specific educational problems being addressed. The major predictive models used in educational research include regression analysis, decision trees, neural networks, support vector machines,

and Bayesian networks. Each of these techniques has distinct advantages and limitations in predicting students' academic achievement in chemistry and other subjects.

Regression Model

In the opinion of the researcher, one of the mostly used predictive modelling analytics in education is regression models. It examines the relationships between dependent and independent variables to determine how different factors contribute to academic outcomes. In the context of chemistry education, regression analysis can assess the extent to which teachers' workload, classroom management skills, and student-related factors influence chemistry scores. For instance, a multiple regression model might analyze the impact of teacher-student ratios, laboratory resources, and teaching experience on students' examination performance.

Regression models also allow for the quantification of the strength of these relationships, helping educators and policymakers identify key drivers of student success. Linear regression is commonly applied when relationships between variables are assumed to be proportional, whereas logistic regression is often used when the outcome variable is categorical, such as whether a student will pass or fail a chemistry exam¹³⁶.

Decision Tree Models

Classification of data into smaller subsets based on certain conditions or decision rules is achieved through the deployment of this model. This approach is particularly useful for predicting student success or failure by analyzing multiple factors such as attendance, participation, and prior grades¹³⁷. Decision trees operate by splitting the dataset into branches until a decision outcome is reached. For example, a decision tree may classify students into

three categories they are high-performing, average, and at-risk, which is dependent on their engagement levels and study habits. It is argued that an advantage of decision trees is their interpretability, which educators can easily understand the decision rules that classify students into different performance levels. It can sometimes lead to overfitting, meaning they perform well on training data but fail to generalize effectively to new student datasets¹³⁷.

Artificial Neural Networks

A more advanced technique employed in educational data mining is artificial neural networks. These models simulate human cognitive processes by using interconnected layers of artificial neurons to analyze complex patterns in student performance data¹³⁸. Neural networks are effective in handling large datasets with nonlinear relationships. In chemistry education, neural networks can predict student achievement by considering multiple input variables, including prior grades, teacher workload, classroom resources, and socioeconomic factors¹³⁸. These models excel in capturing subtle interactions between variables that might not be evident through traditional statistical methods. It is documented that neural networks require substantial computational power and large amounts of labelled data for training. Their complexity can also make them difficult for educators to interpret compared to more transparent models like decision trees or regression¹³⁸.

Support Vector Machines

Another predictive modelling technique commonly used in education is support vector machines. They are classification models that analyze student data and categorize learners into different groups, such as high achievers, moderate performers, and students with learning

challenges¹³⁹. It is reported that it works by constructing an optimal decision boundary or hyperplane. It is documented that it can be used in the classification of students based on their historical academic records, attendance, and engagement levels¹⁴⁰. Its ability to handle high-dimensional data makes them suitable for educational research, where multiple student-related factors could influence academic achievement. In chemistry education, it can help predict which students are likely to struggle with laboratory-based assessments versus theoretical content. These predictions allow educators to tailor interventions for specific student groups. Despite their accuracy, they require careful tuning of hyperparameters and may be computationally intensive for large-scale educational datasets¹⁴⁰.

Bayesian Networks

It represents a probabilistic modelling approach that accounts for uncertainties in student performance. Unlike deterministic models, which assume fixed relationships between input and output variables, Bayesian networks incorporate probabilities to model how different educational factors influence learning outcomes¹⁴¹.

This approach is useful when data contains missing values or when relationships among variables are uncertain. For instance, a Bayesian network can estimate the probability of a student passing chemistry based on prior grades, attendance, and teacher effectiveness, even when some of these data points are missing. Bayesian networks also help identify key predictors of academic success by calculating conditional probabilities for different student characteristics. It was reported that the chief challenge with Bayesian networks is the complexity involved in defining the dependency structures between variables, which requires expert domain knowledge¹⁴².

Studies have demonstrated the effectiveness of these predictive modeling techniques in improving educational outcomes. Predictive model is used to identify students at risk of failing chemistry and recommended targeted interventions¹⁴³. Their study showed that decision trees and neural networks provided the highest accuracy in predicting student success, while regression analysis offered the most interpretable results for educational policymakers. Similarly, it was found that Bayesian networks were highly effective in identifying key determinants of academic performance in science subjects, by allowing for early intervention strategies¹⁴³.

2.1.8.3 Sources of Data for Predictive Modelling in Education

Predictive modelling in education is only as effective as the data it relies on¹⁴⁴. The availability, accuracy, and comprehensiveness of data play a fundamental role in determining the reliability of predictions regarding student performance, teacher effectiveness, and overall educational outcomes¹⁴⁴. Data sources in education come from multiple dimensions, ranging from student academic records to teacher-related factors, classroom environments, socioeconomic conditions, and psychological behaviours. By integrating these diverse data sources, predictive models can offer deep insights into learning trends by allowing for data-driven interventions that enhance academic achievement, particularly in subjects like chemistry¹⁴⁴.

One of the most crucial sources of data for predictive modelling is student academic records. These records provide a historical perspective on student performance and serve as a foundation for forecasting future achievement. Examination scores, test results, and coursework grades are used to analyze performance trends that help to identify students who may need additional support. Consistent low scores in science related subjects may indicate difficulty in grasping

fundamental concepts, necessitating targeted remedial programs¹⁴⁵. Beyond numerical grades, academic records also include attendance data, which has been widely recognized as a strong predictor of student success. Frequent absenteeism is often linked to poor performance, and predictive models can flag students with irregular attendance patterns for early intervention¹⁴⁶.

Additionally, participation in class activities and laboratory experiments provides valuable insight into student engagement levels. Chemistry, being a practical-oriented subject, requires active participation, and students who actively engage in laboratory work tend to perform better than others¹⁴⁷. Predictive models analyze engagement patterns to recommend personalized instructional strategies that cater for different learning needs.

Another critical dimension of data sources is teacher-related information. The effectiveness of teaching significantly influences student performance, making teacher-specific data integral to predictive analytics in education. Teachers' qualifications, years of experience, and subject specialization contribute to instructional quality, with research indicating that experienced and well-trained teachers positively impact students' learning¹⁴⁸. Predictive models utilize this data to assess how teacher expertise correlates with student outcomes in chemistry. Workload distribution is another factor that affects teaching effectiveness. Overburdened teachers may struggle to provide personalized attention to students, leading to gaps in learning. By analyzing teacher workload data, schools can ensure balanced subject allocations and manageable class sizes, optimizing the overall learning experience¹⁴⁹. Teacher effectiveness is also measured through student feedback, classroom observations, and grading patterns. Consistent grading patterns reflect fairness and accuracy, while inconsistencies may indicate areas where additional training is required¹⁵⁰.

Additionally, data on teacher-student interactions, including mentorship and academic counselling sessions, provide insights into how personalized support influences student success¹⁵¹. The classroom environment and school resources are also essential data sources that could shape educational outcomes. Classroom dynamics, such as student-teacher ratios could influence the level of attention students receive. Overcrowded classrooms can lead to decreased engagement, while smaller class sizes often yield better academic performance¹⁵². Predictive models analyze class size data to determine optimal learning conditions. The availability of laboratory equipment and learning materials is particularly important in science education. Schools with well-equipped chemistry laboratories tend to produce students with stronger practical skills. Predictive modelling can be used to assess how laboratory accessibility affects chemistry learning and whether resource availability correlates with performance in practical assessments¹⁵³. Additionally, the integration of digital learning tools, such as e-learning platforms and simulations, is becoming increasingly relevant. Data from online learning systems provide valuable insights into student study habits, content preferences, and areas where additional support may be needed. Predictive analytics can leverage this information to tailor digital learning experiences to individual student needs¹⁵⁴.

Socioeconomic and demographic factors form another category of data that plays a vital role in student achievement. Parental education level has been shown to influence student performance, as children from highly educated families often receive additional academic support at home¹⁵⁵. Predictive models could incorporate this data to understand how home environments contribute to learning outcomes. Similarly, family income and financial stability impact access to educational resources such as textbooks, private tutoring, and internet connectivity for online learning. Financially disadvantaged students may face difficulties

keeping up with academic requirements, and predictive models can identify such students for scholarship or intervention programmes¹⁵⁶. The home learning environment is another significant factor; students with dedicated study spaces and access to educational materials perform better academically. Schools can use predictive analytics to design programmes that support students from less conducive home learning environments, ensuring that all students have equal opportunities to succeed¹⁵⁷.

Beyond academic and socioeconomic factors, psychological and behavioural data provide deeper insights into student learning patterns. Motivation levels, interest in specific subjects, and learning styles all contribute to academic achievement. Some students excel with visual learning aids, while others perform better through active experiments or group discussions. Predictive models assess these learning preferences and recommend personalized teaching strategies¹⁵⁸. Study habits and time management skills are also strong indicators of academic success. Students who maintain structured study routines and allocate sufficient time for revisions tend to perform better than those with poor time management¹⁵⁹. Additionally, behavioural patterns such as class participation, extracurricular involvement, and emotional well-being could impact student performance. Stress and anxiety can negatively affect learning, and predictive analytics can help schools identify students who may require counseling or psychological support¹⁶⁰.

Integration of diverse data sources enables predictive modelling to offer a holistic view of student performance. However, despite its potential, data collection in education presents several challenges. Data quality and availability remain major concerns, as many educational institutions lack comprehensive student information management systems¹⁶¹. Incomplete or

inconsistent data can compromise the accuracy of predictive models. Ethical and privacy concerns also arise, as handling sensitive student data requires strict security measures to prevent unauthorized access or misuse¹⁶². Additionally, resistance to technology adoption among educators and administrators may hinder the effective implementation of predictive analytics in schools¹⁶³. Addressing these challenges requires investment in secured data management systems, teacher training on data driven decisions, and the establishment of ethical guidelines for data usage in education¹⁶⁴.

Sources of data for predictive modelling in education are dependent on a combination of academic, teacher-related, classroom, socioeconomic, and psychological data sources. Each of these elements contributes to a deeper understanding of student learning dynamics, which allows for empirical based interventions that enhance academic achievement. While challenges such as data quality, privacy concerns, and resistance to technology exist, the benefits of predictive analytics in education far outweigh the limitations. With continuous advancements in data science and artificial intelligence, predictive modelling has the capability to improve education, offer personalized learning experiences, improving teacher effectiveness, and optimization of classroom management strategies¹⁶⁴. Schools that effectively harness predictive analytics will be better equipped to support students, enhance learning outcomes, and ensure that every student is carried along in the process of learning.

2.2 Theoretical Review

2.2.1 Job Demand-Control Theory

The proponent of this theory was Robert Karasek in 1979. The theory outlines the impact of work characteristics on stress, health and occupational wellbeing. The theory postulates that

work-related stress can result from the interaction between several psychological job demands that relate to workload, which can be cognitive and emotional demands, interpersonal conflict and job control relating to decision authority. The theory focuses on psychological workload and the nature of work demand on work related psychological distress and stress. From this conception, it can be inferred that the theory shows that high work demand can result in psychological distress and physical fatigue. The theory has laid a background on the presumed relationship that exists between teacher's workload and students' academic achievement.

2.2.2 Behaviourist Theory

This theory is an aspect of psychology that focuses on how people learn through their interaction with the environment. The theory became operational through the idea that all behaviours are acquired through conditioning, which forms the principle of reinforcement and punishment. According to this theory, learning is viewed as a change in observable behaviour that results from experience. In line with this philosophy, behaviourists such as John B. Watson and B.F. Skinner argued that psychology should be a science of observable and measurable events and behaviours, and that mental state and cognitive processes are irrelevant or inaccessible. Through this theory, it was proposed that environmental stimuli can shape behaviour, and that learning occurs through a process of operant conditioning which involves reinforcing or punishing based on their outcomes.

For instance, a learner that is praised for answering a question correctly is more likely to repeat that behaviour in the future. On the other hand, if a student is punished for wrongdoing, they are less likely to repeat their behaviour in the future. According to this theory, classroom management could be effective if the behaviours that promote calmness and better classroom coordination are promoted through praise, reward and good classroom organization while the

behaviours that negatively affect learning such as noise making and truancy are discouraged using negative reward. Based on this theory, it is argued that the use of positive reinforcement encourages desirable behaviours and fosters a positive learning environment. In addition to this, behaviourist strategies include positive reinforcement and negative reinforcement. Positive reinforcement entails offering rewards or incentives to strengthen desired behaviours. Examples of this type of reinforcement include verbal praise, stickers, tokens and tangible rewards. On the other hand, negative reinforcement is expressed in the form of removal of unpleasant stimulus to facilitate occurrence of pleasant behaviours. For example, a reduction of the amount of homework for a student who performs well in a test.

2.2.3 Social Learning Theory

The proponent of social learning theory is Albert Bandura. The theory emphasized observational learning and the influence of cognitive processes on behaviours. Social learning theory argues that an individual can learn by observing others and imitate their actions. It also considers the role of internal mental processes in learning.

In addition to this, the theory provides clear understanding on how people are motivated and can motivate others, how they perform and how they learn new skills. The theory also explains how personalities can change due to influence from others. For example, the attitude of a student to the use of the library can be positively influenced by observing other students who make use of library facilities to get themselves prepared for examination. This attitude can be emulated by other students to reinforce their learning. The model of the theory comprises the following components:

Cognitive factors – Knowledge, expectations and attitudes

Environmental factors- Social norms, access in community, influence on others

Behavioural factors – skills, practice and self-efficacy

2.3 Review of Empirical Studies

2.3.1 Teacher's Workload and Student's Academic Performance

The impact of workload on teachers' efficiency and academic performance in public schools, was explored. A qualitative case study approach was used, and a total of 30 semi-structured interviews were conducted with 15 teachers and 15 students using qualitative content analysis. The findings revealed that teacher workload had a significant impact on student academic achievement, teacher's efficiency and effectiveness¹⁰⁸. Teacher's workloads in relation to their job performance with a particular focus on secondary schools in Nigeria. Strategies for effective management of teacher's workload were interrogated. The study revealed that teachers often get stressed up and experience burnout due to heavy workload. Consequently, it was recommended that workshops and seminars should be organized to train teachers in time management. It was also recommended that ICT facilities should be used to complement teaching and learning activities¹⁶⁵.

Investigation into teacher's workload and its efficacy in primary schools was conducted. The potential additional work areas that put burden on primary school teachers were also investigated. The study employed mixed method design. Survey questionnaires and interviews were used to collect data; 79 participants were randomly selected for the study. The findings revealed that teachers' high workload has a negative impact on classroom teaching and learning due to limited time for planning lesson and tasks assessment¹⁶⁶.

From the relationship between workload and teachers' effectiveness in secondary school in Uganda using a descriptive survey design. Questionnaire and interview were used for data collection. Pearson correlation was used for data analysis to determine the level of statistical relationship between workload and teacher's effectiveness. Findings revealed that there is a weak significant correlation between teachers' workload and their effectiveness in secondary schools¹⁶⁷. It was observed that teachers in Tharaka Nithi Country, Kenya were faced with numerous stressors that led to burnout which could limit their abilities to meet up with teaching obligations.

Consequently, a study was conducted to examine the influence of workload on teachers' burnout in Tharaka. Descriptive survey design was used and 378 teachers and 31 principals from 31 schools participated in the study. Questionnaires and interviews were used for data collection. Frequencies, percentages, mean and standard deviation and Pearson correlation were used for data analysis. Findings revealed that there is a positive significant correlation between teachers' burnout and workload. It was concluded that workload contributed to teachers' burnout¹⁶⁸.

Pupil-teacher ratios is a factor that could contribute to teacher's workload and its impact on academic performance in public primary schools in central division of Machakos County, Kenya was studied. The study targeted 78 primary schools. However, 24 schools were sampled for the study. The study adopted descriptive survey design. Simple regression was used to determine the correlation between pupil-teacher ratio and pupil's academic performance. The findings of the study revealed that pupil-teacher ratio significantly influenced the performance of pupils in national examination¹⁶⁹.

Teachers' workload and its implications on students' academic performance in secondary schools in Akoko Northeast Local Government Area of Ondo State was investigated. The study adopted descriptive design of the survey type and stratified random sampling technique was used to select 12 schools. 6 public and 6 private schools. The participants included 120 teachers and 12 principals. A self-constructed questionnaire was used for data collection, and five hypotheses guided the study. Pearson's product moment correlation and T-test at $p < 0.05$ level of significance were used for data analysis. The results showed that there was a negative correlation between teachers' workload and students' academic performance. The findings indicated that the teachers' workload was high in teaching activities¹⁷⁰.

The effect of teachers' workload on students' academic performance in community secondary schools was investigated, four research objectives guided the study, and descriptive survey design, a mixed method approach. qualitative and quantitative approaches were used in the study. The survey and interview were used for data collection. Random and purposive sampling techniques were used for selection of participants. The study revealed that the teacher's workload was heavy and had a negative effect on students' academic performance in community secondary schools¹⁷¹.

2.3.1.1 Determinants of Teachers' Workload

Some studies have been carried out to determine the depth of the contributions of the perceived determinants of teachers' workload. To this end, it was argued that class size and timetable loads could influence teacher's job performance, descriptive survey design was adopted for the study. Administrative workload questionnaire and teachers' job performance questionnaire were used for data collection. Descriptive statistics, path analysis, ANOVA and multiple

regression were used for data analysis. It was reported that class size and timetable loads had significant positive contributions to teachers' job performance¹⁷².

A study on workload, stress and resilience of primary school teachers with a focus on teachers perceived changes in workload and stress levels as well as other factors that may have made teaching challenging over the years were surveyed. It was reported in the study that curriculum changes, administrative demands and employment related changes like job mobility contributed to teachers' workload. In addition to these factors, it was revealed that overcrowded curriculum is one of the significant contributors to the increased stress levels among teachers. Consequently, the study concluded that teachers with 16-25 years of teaching experience reported a high workload compared with teachers with fewer years of experience¹⁷³.

Also, investigation into the causes and effects of teachers' shortage in Nigerian schools was carried out. Descriptive survey design was used for the study. The sample size consisted of 25 administrators and 250 teachers selected from 25 public secondary schools in Osun State. Proportional stratified sampling technique was used to select the sample schools. The study revealed that teachers were overworked with assignments due to shortage of teachers. Large class size was also reportedly linked with shortage of teachers¹⁷⁴.

In a study, the relationship between teachers' factors vis-à-vis teachers' qualifications, teachers' workload, teaching methodology and students' academic performance was established. Descriptive survey research design was adopted, and 30 teachers were sampled for the study. Ten schools were sampled out of the twenty-four secondary schools in Ibadan Southwest Local Government Area. The findings of the study showed that there was no relationship between teachers' workload and students' academic performance in Economics¹⁷⁵.

A study focused on the comparison of teachers' workload in public secondary schools with their counterparts in private secondary schools was carried out. A sample of 100 teachers from both government and private secondary schools were used for the study. The research adopted a descriptive survey design. Data was collected by administering questionnaires to the respondents. Data was analyzed by using frequency, t-test and ANOVA. Findings revealed that teachers in public schools are more flexible and satisfied with their working hours compared with their counterparts in private schools¹⁷⁶.

2.3.1.2 Teachers' Academic Workload and Students' Academic Performance

Teachers' academic workload involves the development of classroom assignments for learners, evaluation of students' continuous assessment (CAT), provision of individualized attention to weak students and the coverage of the teaching syllabus. In a study that involved the investigation of teachers' factors and their influence on students' academic performance in secondary schools in Nyandarua, County, Kenya, one hundred and fifty-three teachers were randomly selected from eighteen schools in three districts. Data was collected using a questionnaire that was developed by researchers. Linear regression and one-way ANOVA were used to test the relationship between teachers' weekly teaching workload, administration of students' classroom assignment, evaluation of students' continuous assessment which defined the teachers' academic workload and students' academic performance¹⁷⁷.

The effect of academic workload on academic productivity in Nigeria was examined, the data for this study were collected through a questionnaire that was developed for this purpose and was administered to 257 academics in faculty of education. Academic workload was measured by academics' services, either professional or non-professional in the last three years. The study

adopted both descriptive and logistics regression for data analysis. The findings showed that academic workload significantly affected academic productivity¹⁷⁸.

A study revealed that excessive workload negatively impacts teachers' job satisfaction, leading to burnout and reduced effectiveness in delivering instruction. The study was conducted among secondary school teachers in Norway, revealed that workload-related stressors such as large class sizes, administrative duties, and excessive assessments hindered teachers' ability to engage with students effectively¹⁷⁹.

Similarly, a study on cross-national study examining the effects of teacher workload on student achievement across multiple countries. The study found that countries where teachers experienced a more manageable workload demonstrated higher student performance on standardized tests. This suggests that reducing excessive teaching responsibilities can create a more supportive learning environment conducive to student success¹⁸⁰. Analysis was carried out on how workload influences chemistry teachers' instructional quality and student performance. Findings revealed that excessive lesson planning, marking of assignments, and administrative tasks negatively affected chemistry teachers' ability to deliver engaging and hands-on science lessons. As a result, students in classes where teachers experienced high workloads performed poorly in chemistry compared to those taught by teachers with more balanced schedules¹⁸¹.

2.3.1.3 Teachers' Non-Academic Workload and Students' Academic Performance

The conflict of teachers' academic workload with non-academic workload was investigated by different scholars. In the researcher's opinion, there seems to be strong debate as to whether non-academic activities would influence academic performance of students or not. In view of

this development, investigation on the effects of teachers' administrative workload on their ability to undertake class instruction, note preparation and feedback on students' homework was done. Using a variable instrumental method, it was revealed that teachers with greater administrative workloads are less likely to spend time on instructional preparation. According to the study, this finding was significant for public schools¹⁸².

Teachers' non-academic responsibilities and quality of teaching were examined. The argument was because if the quality of teaching is poor, students would have a poor grasp of the knowledge contents which could have a negative effect on their academic performance. To this end, the impact of non-academic responsibilities of teachers on the quality of teaching was examined, descriptive research design was adopted in the study. It was revealed that non-academic responsibilities significantly influenced the quality of teaching in schools¹⁸³.

There is an insight into the extent to which extracurricular activities can add to the academic workload of teachers. In view of this development, the non-academic responsibilities of teachers in relations to the quality of instructions were examined. Descriptive research design was deployed in the study. The study found that extracurricular activities contributed to the workload of teachers and had a considerable negative impact on teaching standards. The study concluded that excessive administrative obligations could cause anxiety, depression, overburden, lack of interest in teaching, cancelling of lectures, poor time management, overwork and lack of time for self-improvement¹⁸⁴.

The surge in non-academic workload has significant implications for teacher wellbeing and effectiveness. Overwhelming administrative demands contribute to increased stress, burnout, and decreased job satisfaction¹⁸⁵.

A study established a direct relationship between high workload and teacher efficacy. It was reported that teachers who experience high levels of stress due to excessive workloads reported lower levels of self-efficacy in their ability to teach effectively¹⁸⁶. This reduced self-efficacy could result in decreased enthusiasm, less innovative teaching practices, and ultimately, a decline in the quality of instruction. Further, excessive workload can lead to teachers working longer hours, impinging on their personal time and potentially impacting their health and wellbeing¹⁸⁷.

The reduction in teacher effectiveness caused by excessive non-academic workload inevitably impacts student academic achievement. When teachers are less prepared and less engaged in their teaching, students suffer the consequences. Studies have found a negative correlation between the amount of time teachers spend on administrative tasks and student performance on standardized tests¹⁸⁸. This indicates that diverting teachers' time and energy away from instruction directly hinders student learning outcomes.

2.3.1.4 Comparison of Non-Academic Workload Across Different School Settings

Investigation into teachers' instructional workload management and students' academic performance in private and public secondary schools was conducted. Descriptive statistics of survey type were adopted, stratified random sampling technique was used in the selection of schools for the study. Six public and six private schools were sampled. A questionnaire was used for data collection. Pearson's product moment correlation and T-test at $p < 0.05$ level of significance was employed for data analysis. Results revealed a significant difference in teachers' workload between public and private secondary schools ($t\text{-cal} = 2.346$). It was also revealed that the workload is high in teaching activities¹⁸⁹. A qualitative analysis of non-teaching workload by forty rural teachers in China was conducted. The study revealed that the

impact of management and control logics employed in the schools led to increased work burden on rural teachers. Excessive concentration of administrative power, insufficient proactive measures taken by schools were identified as some of the factors that contributed to high workload in the school¹⁹⁰.

A comparative study on the factors determining teachers' performance in urban and rural areas of Ijebu-Ode, Ogun State was carried out. Descriptive research methods were adopted while the target population involved teachers, pupils, and the school-based management committee in public primary schools. The sample size consisted of 140 respondents. Composition of participants revealed that 80 teachers (40 rural teachers and 40 urban teachers); 40 pupils (20 rural pupils and 20 urban pupils); and 20 school-based management committee in primary schools (10 rural participants and 10 urban participants). The sample was drawn from 10 public primary schools (5 rural schools and 5 urban schools) out of a total of 42 primary schools in Ijebu Ode LGA. Three instruments were used for data collection from the participants. T-test was used to statistically test the mean score of the dependent variables for the two independent groups. The findings of the study revealed that teachers in urban public schools performed better than teachers from rural public schools on three indicators which were quality teaching, coverage of the syllabus and instructional design, while teachers from rural schools performed better than teachers in urban school on two indicators which include teachers' workload and evaluation of pupils' assignments¹⁹¹.

2.3.2 Classroom Management Skills and Academic Performance of Students

The influence of classroom management skills on academic achievement of students has been widely reported in literature. For instance, a study was carried out on effective classroom management and students' academic performance in secondary schools in Uyo Local

Government Area. Four research questions and four null hypotheses were formulated to guide the study. Survey design was adopted for the study. The target population for the study comprised SS 1 students in the selected Local Government Area. A questionnaire was developed for data collection. Chi-square was used for data analysis. There was a significant difference in the academic performance of the students based on verbal instruction, corporal punishment, instructional supervision and delegation of authorities to learners¹⁹².

Influence of classroom management skills was investigated using public secondary schools. Descriptive research design was adopted for the study. Stratified sampling technique was used to select one hundred and fifty teachers for the study. Mean and standard deviation were employed for data analysis. Findings revealed a significant relationship between classroom discipline and academic performance of students¹⁹³.

Furthermore, the impact of classroom management on students' academic achievement at secondary school level was explored. The population of the study comprised 240 secondary school teachers which were randomly selected. The data was analyzed using Pearson coefficient correlation. Regression analysis was used to test the hypothesis. The study revealed a positive relationship between classroom management and students' achievement¹⁹⁴.

Classroom management is a complex concept that has a crucial effect on the learning process of every student. Driven by this conviction, the effect of classroom management on learners' achievement was investigated. The researcher classified the determinants of classroom management into classroom environment, teacher training and seminar exposure, behaviour and discipline, leadership and styles. The study concluded that for learners' academic achievement to be good, classroom management must be well applied. It was recommended

that teachers should be aware that having good information about their students is very important in effective teaching and learning¹⁹⁵.

Furthermore, the influence of teacher classroom management skills on academic performance of pupils in public and private primary schools in Ibadan North Local Government Area of Oyo State was assessed. Descriptive survey research design was adopted for the study. Multi-stage sampling technique was adopted for the selection of samples for the study. A total of 200 respondents were purposively selected from both public and private primary schools. A questionnaire was used for data collection, and six research questions and six hypotheses guided the study. The data collected were analyzed using frequency table, percentages and Pearson's product moment correlation coefficient. The findings of the study revealed a positive but low relationship between teacher classroom management skills and academic performance¹⁹⁶.

Empirical research has also highlighted the impact of classroom management skills on students' academic performance. In a study, it was found that teachers who implemented proactive classroom management strategies, such as setting clear expectations, maintaining discipline, and using positive reinforcement, had students with higher academic achievement¹⁹². The research, which included over 500 middle and high school classrooms, showed that classrooms with well-structured management practices reported fewer behavioral disruptions and higher student engagement levels. Further research was explored, and the link between classroom management and student motivation was investigated. The study used high school science students as a population. Study revealed that effective classroom management fosters a positive learning climate, leading to increased student interest and improved academic outcomes. Chemistry students were taught by teachers who employed interactive and structured classroom strategies showed better performance on laboratory tasks and conceptual understanding¹⁹³.

A study examined classroom management strategies in secondary schools and their impact on chemistry students' learning outcomes. The study found that classrooms with structured management practices, such as routine class schedules, well-defined behavioral expectations, and active student participation resulted in higher student achievement. The research recommended that teacher training programmes should emphasize classroom management skills to enhance instructional effectiveness. Student-related factors, such as motivation, socio-economic background, and prior knowledge, significantly influenced academic achievement in chemistry¹⁹⁴.

2.3.2.1 Non-instructional Classroom Management Practices and Academic Performance of Students

It was argued that many disciplinary incidents that occur in the classroom originate from the insufficiency of teachers' classroom management practices to manage learners with behavioural challenges. In view of this development, a study was conducted on 450 teachers. Data was analyzed by employing t-test. The study revealed a significant relationship between the dimensions regarding classroom management skills of teachers and disciplinary behaviours of students¹⁹⁵.

The management of classroom behaviours for improved academic achievement was also advanced by verification of the management of classroom behaviours for improved academic achievement was advanced through a study that was conducted on the social behavioural and academic outcomes of a large diverse samples of middle school students within an urban context. The samples included 102 teachers and 1,450 students in sixth to eight grades. The study adopted a two-level hierarchical linear model to examine the overall treatment effects on

student behaviour and academic outcomes. Also, mediation analysis was used to examine a hypothesized putative mechanism for observing academic outcomes.

However, null effects were observed for students prosocial and disruptive behaviours and self-regulation skills as well as reading comprehension and broad math performance. It was revealed that behavioural control increased students' concentration in the classroom¹⁹⁶.

Furthermore, verbal instruction, instructional supervision and delegation of authority to learners in the management of students' classroom behaviours were deployed in a study on effective classroom management and students' academic performance. The study adopted a one-group pre-test, post-test quasi experimental design and survey questionnaires to elicit responses from 32 respondents. Three research questions and three research hypotheses were formulated to guide the study. Descriptive statistics and chi-square were used for data analysis. Findings revealed that the mean performance of students in Biology increased significantly¹⁹⁷.

2.3.2.2 Relationship Between Instructional Classroom Management Practices and Academic Performance of Students

The relationship between instructional classroom management practices and academic performance of students has been reported in different studies. For instance, research on the relationship between the quality of teaching and classroom management was undertaken. The study also explored instructional inputs in shaping classroom management. Findings revealed that some of the participants focused on the classroom management approach by leveraging on instructional inputs to help in the management of classroom learning environment¹⁹⁸.

In a paper on effective teaching and classroom management as a tool for quality education, emphasis was placed on pupil centered instructional approach for effective engagement of

learners during teaching and learning. Provision of guidance to learners, motivation and provision of enabling classroom environment were mentioned as components of learners centered teaching. The paper concluded that effective preparation of lesson plans, lesson presentation and classroom organization could help in achieving the instructional objectives of teaching and learning activities which are measured through academic performance of students¹⁹⁹.

A study was carried out on the relationship between teachers' implementation of classroom management practices and students' behaviour in elementary school. The indices of classroom management practices were active instruction and supervision of students, opportunities for students in their response and feedback. Latent class analysis was used in the study. Four groups of teachers from 1,242 teacher-student days in 65 elementary schools with a group of teachers demonstrating a very low rate of classroom management practices were statistically less engaged which affected their academic performance¹²⁰.

The extent to which teacher instructional management strategies, classroom management effectiveness and learners' academic achievement in English Language in Nigeria influenced students' academic performance was investigated. It was revealed that there exists a positive significant relationship between teacher instructional management strategies, classroom management effectiveness and students' academic performance in public secondary schools.

2.3.3 Students Factors and Academic Achievement of Students

2.3.3.1 Students Attitude and Academic Performance

The relationship between students' attitude and academic performance in statistics was explored. Correlational research design was adopted in this study. Sample size comprised 560

students that were enrolled in a business statistics course. The components of attitude that were investigated comprised affective, cognitive competence, value, interest, difficulty and effort. Pearson's correlation was used to test the significant relationship between the attitude components and the academic performance of students in the course. Findings revealed that effective, cognitive competence, value, interest and effort have a significant positive relationship on academic performance of students²⁰⁰.

The impact of learning attitude on students' academic performance in Literature-in-English in secondary schools, Lagos State was investigated, descriptive survey research was adopted. Two hundred and forty teachers and students were randomly selected from senior secondary schools from Badagry Local Government Area of Lagos State. A structured questionnaire with a 4-point Likert rating scale was developed to elicit information from the respondents. The study revealed a significant relationship between learning attitude and academic performance in Literature-in- English among secondary school students²⁰¹.

Attitude as a predictor of academic achievement in GSE 112 (Library Studies) among students in Federal Colleges of Education in southern Nigeria was examined. Purposive sampling technique was adopted for the sampling of five conventional colleges of education in Southern Nigeria. Simple random sampling techniques were adopted in administering questionnaires to 1,340 in each of the five colleges. Two research instruments which comprised questionnaire and achievement test were used. Two research questions and two hypotheses guided the study. It was revealed that students' attitude towards GSE 112 was positive while their academic achievement on the course was on average. Also, it was revealed that there was no significant relationship between students' attitude and academic achievement in GSE 112²⁰².

Confirming the influence of attitude on the academic performance of students, a survey of influence of attitude on academic achievement of Physics students in Nigeria was carried out. Ex-post facto and correlational research designs were adopted for the study. The population of the study comprised all senior secondary school three students that took Physics in 2012/2013 academic session. Physics Attitude Questionnaire (PAQ) and Physics Attitude Performance Test (PAPT) were administered on the selected students. Frequencies and percentages were used to determine students' attitude and the level of academic performance between male and female students. Pearson product moment correlation coefficient (r) was used to determine the relationship between attitude and academic performance. Findings revealed that there was no relationship between attitude and academic performance in Physics²⁰³.

2.3.3.2 Students Self-Efficacy and Academic Performance

Correlation between self-efficacy, mastery experience, vicarious experience, social persuasion, emotional arousal with academic performance was studied. A 40-item survey measuring sources of mathematics self-efficacy was administered to 178 third-year engineering students. Academic performance that comprised mathematics grade point average (GPA) scores were collated. Findings revealed that sources of self-efficacy were correlated with mathematics achievement scores as well as cumulative GPA of electronics-related engineering diplomas²⁰⁴.

The relationship between academic self-efficacy and academic performance among university undergraduate students was analyzed using samples that were drawn from public and private universities by using a stratified sampling technique. A questionnaire on self-efficacy was used for the collection of data from participants drawn from faculties of education, humanities and science. Descriptive and inferential statistics were used to analyze the differences and relationship between academic self-efficacy and academic performance among university

undergraduate students. The results revealed that there is a statistically significant relationship between academic self-efficacy and academic performance among university undergraduate students²⁰⁵.

A study was conducted on the relationship between motivation and self-efficacy on learners' academic performance in Physics. Learner's Theory of Operant Conditioning and Bandura's Social Cognitive Theory were used in the study. A correlational survey research design was adopted for the research. The number of participants was 375 senior secondary three physics learners. Learner's psychosocial factors scales were used for data collection. Simple linear regression was used for data analysis. The results showed that self-efficacy had significant positive relationships with learners' performance in physics²⁰⁶.

2.3.3.3 Students Peer Relationship and Academic Performance

The influence of peer group on adolescent students' academic performance in secondary schools in Tanzania was investigated. A total of 144 participants made up of 120 students and 24 teachers participated in the study and were purposively selected from two secondary schools which comprised government and private schools. The instruments used for data collection were interview checklists and questionnaires. Both qualitative and quantitative approaches were adopted in the study. Findings revealed that peer group relationships had both positive and negative influence on adolescent students' academic performance at the selected schools with government schools more influenced than private schools. It was concluded that peer's relationship, socialization and environment had a great influence in determining students' academic performance²⁰⁷.

Peer group and parental support were correlated with academic performance of senior secondary students in Southwest Nigeria. The study adopted ex-post facto design and descriptive research design of survey type. The population comprised all senior secondary school students in South-West Nigeria. The sample of the study consisted of one thousand, one hundred and fifty senior secondary school students; three states of the six states in the southwest were covered in the study. Questionnaire and inventory were used for eliciting information from the respondents. Two null hypotheses were formulated to guide the study. Findings revealed that there was a positive significant relationship between peer group and the academic performance of students²⁰⁸.

The effect of peer-to-peer relationship on social life and academic performance of English Language students was investigated. Pre-test, post-test control group, quasi-experimental design with 2x2x2 factorial matrix was adopted. Students were randomly assigned to treatment group, purposive sampling technique was used in the selection of sample for the study and four instruments were used for data collection, and they were English Language Achievement Test (ELAT), Peer-to-Peer Guide (PPG), Social Life Inventory (SLI) and direct observation. Findings revealed that there was a significant difference in the post and social life between students that were exposed to peer-to-peer strategy and those exposed to conventional strategy²⁰⁹.

A survey study was conducted on the influence of peer group on the academic performance of undergraduate students in selected departments in Babcock university, Ogun State. Descriptive and ex-post facto designs were adopted in the study. A questionnaire was used for data collection; one hundred and sixteen students were sampled from five departments in the school of education and humanities using stratified random sampling methods. Data was analyzed

using Pearson product moment correlation coefficient and linear regression analysis. The result of the study revealed that peer group has significant influence on academic performance of undergraduate students²¹⁰.

2.3.3.4 Capabilities of Predictive Models in Predicting Academic Performance of Students

Predictive modelling has become an essential tool for analyzing and forecasting students' academic performance based on multiple factors. Recent studies have demonstrated its effectiveness in identifying academically challenging students and improving educational outcomes. A predictive model was developed using machine learning techniques to analyze chemistry students' academic performance. The model incorporated variables such as attendance, homework completion, and classroom participation to predict students' final grades. The study found that predictive modelling was highly accurate in identifying students who needed additional support, allowing educators to intervene early²¹¹. Similarly, a study explored the use of data-driven predictive models in secondary school chemistry education. Decision tree and neural network models were applied to evaluate student performance patterns. The study concluded that predictive analytics could help teachers allocate resources more effectively and design personalized learning interventions for struggling students²¹². A study was conducted on the application of artificial intelligence, AI in predicting chemistry student outcomes. The study found that AI-based predictive models, trained with historical student data, were able to accurately forecast student performance based on variables such as class participation, previous test scores, and study habits. These findings suggest that integrating AI into the educational system could enhance students' support strategies and overall academic activities.

2.4 Conceptual Model

The conceptual model of this study shows the diagrammatic representation of the key concepts which involves the variables of the study, independent variables. The independent variables are Teacher's workload (Academic workload and Non-academic workload); Classroom management skills (Instructional classroom management skills and non-instructional classroom management skills) and Students factors (Attitude, Self-efficacy and Peer relationship). The dependent variable is SS 2 students' academic achievement in Chemistry. The model was used to guide research questions based on the existing theories. It was also used to establish the relationships that exist between independent variables and dependent variables which provided the framework for the investigation of the research question.

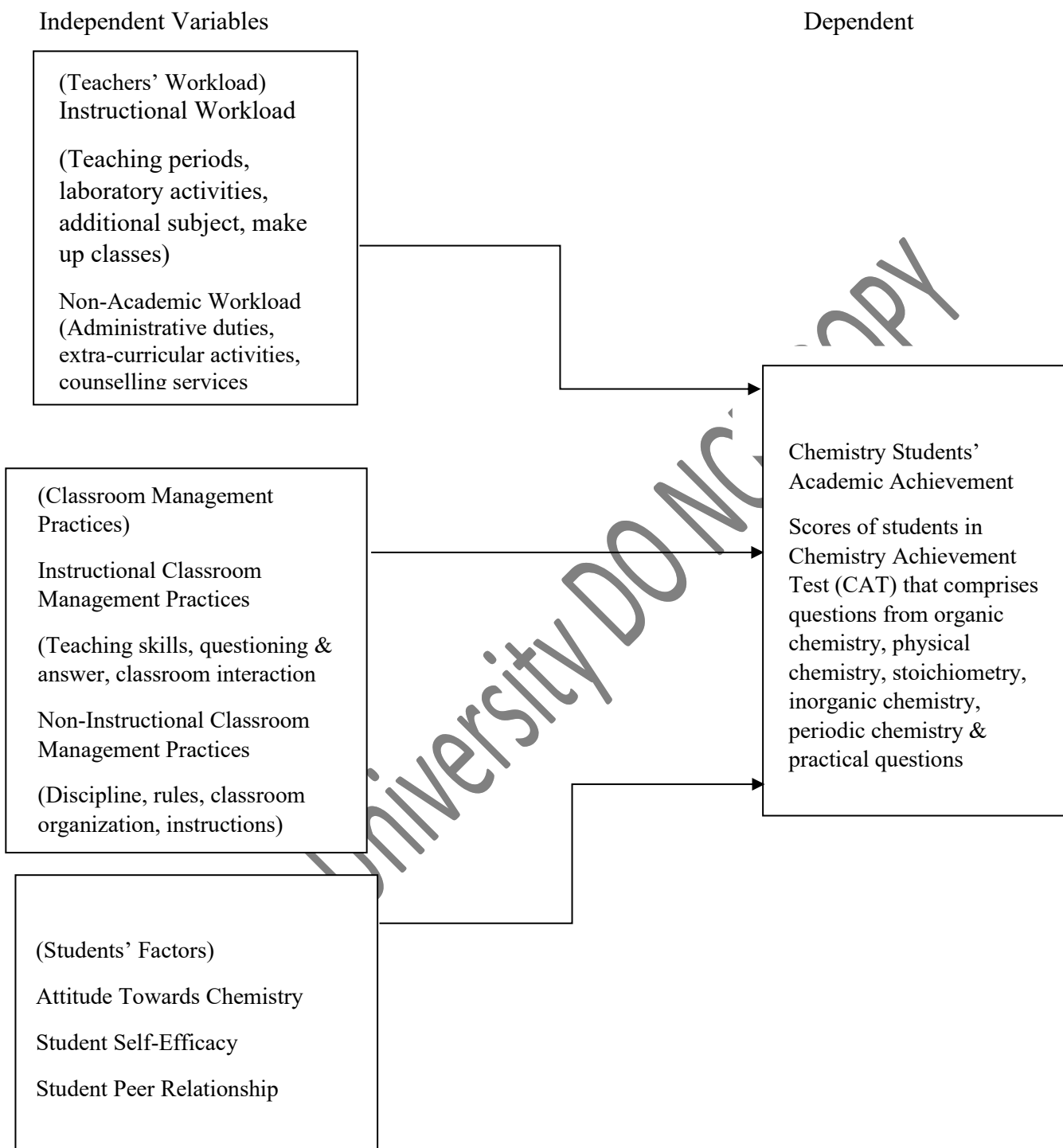


Fig 2.1 Conceptual framework of the study

Source: Researcher, 2025

Dependent and Independent Variables

The basis for this study is to develop an empirical based model from the research variables that could significantly influence the academic achievement of Chemistry students. In this study, the predictor variables are classroom management skills with two levels, teacher's workload with two levels and students' factors with three levels. The dependent variable is the academic achievement of SS 2 students in Chemistry. The moderating variable is the type of school which is assumed could affect the causal relationship between the independent variables and dependent variables. The foundation of the study was laid on the theoretical framework which provided a useful blueprint for the formulation of the research questions upon which the study is anchored. In the study, the type of school is taken as a dichotomous variable which will be in two levels, public school and private school. In line with this blueprint, the conceptual model is designed to provide a graphic illustration and support for the study. This means that briefly, the relationships between the independent variables and dependent variables are better understood through the pictorial representation of the conceptual model. On the other hand, the dependent variable is the quantitative description of the students' academic achievement in chemistry which described quantitatively the students' responses in the chemistry achievement test.

2.5 Summary of Reviewed Literature and Gap

Reports and findings of the variables of study are documented in literature with varying statistical methods of analysis (ANOVA, ANCOVA, Regression) and designs (Experimental, mixed methods, survey). It was documented that teachers' workload influences academic achievement of students using ex-post facto research design. Information abounds in literature on how the productivity of teachers could be affected due to overloaded tasks which make them

give less of their best. Correlation between administrative duties of teachers and students' academic achievement were reported in literature. Different methods of analysis such as frequency counts, inferential and descriptive statistics were used for data analysis.

Reports on classroom management on academic achievement of students are captured in the literature. Literature revealed that most of the studies on classroom management skills had their data collected by using questionnaires. Literature revealed that instructional management skills significantly influenced the academic achievement of students. On students' factors, few reports were documented in the literature on students' peer relationship. Literature established a significant relationship between attitude and students' academic achievement. In addition to this, literature reported that students' self-efficacy significantly influenced students' academic achievement. However, there were no sufficient reports in the literature that revealed the impact of the teachers' workload, classroom management skills and students' factors on academic achievement of students. There were no sufficient studies that investigated the comparative influence of multiple variables on students' academic achievement. There is dearth of studies on the comparative analysis of AI algorithms for the prediction of students' academic achievement. This brings a better insight into their capabilities in the prediction students achievement test based on the available dataset. Despite these insights, several research gaps remain. First, most studies on predictive modelling were conducted in non-African environment, that is the dataset lacked African contents, particularly, Nigeria. Second, while predictive modelling has shown a promising capability in improving academic outcomes, its implementation in Nigerian secondary schools remains underexplored. Addressing these gaps in this study would provide a more comprehensive understanding of the models that could best predict chemistry achievement in secondary schools by focusing on the

features that could enhance the models' performance in the prediction of students' academic achievement. The usage of AI algorithms in this study brings an advantage of evaluating different predictive features of the study and their attendant impacts on academic achievement of students with the hope of assessing the implications of the findings on teaching and learning chemistry.

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Chapter Three

Methodology

The study focused on predictive modelling of teachers' workload, classroom management practices and students' factors on academic achievement of students in chemistry. This chapter deals with research design, population of the study, sample and sampling techniques, description of the research instruments, validation of research instruments, reliability of the research instruments, method of data collection and data analysis.

3.1 Research Design

This study adopted cross sectional research design. The study leveraged on models that linked a combination of features of the study among a sample of participants. This design allowed data to be collected at a single point in time, and with no manipulation of the features of study.

3.2 Population of the Study

The population of the study comprised all the senior secondary school 2 chemistry students in the Southwest, Nigeria.

3.3 Sample and Sampling Techniques

The study adopted multi-stage clustering sampling techniques in the selection of participants. There are six states in Southwest Nigeria. They are Lagos State, Ogun State, Oyo State, Osun State, Ondo State and Ekiti State. The researcher clustered the six states into three states that include Lagos State, Oyo State and Ekiti State. The states were clustered because of the similarity in their population parameters. Both private and public schools were purposively selected from each of the states to give room for more chemistry students and teachers to

participate in the study, and to ensure that participants were sampled from urban and rural settlements.

The population was stratified into three senatorial districts. All the chemistry teachers in the sampled schools were purposively selected for the study. The schools were selected based on the type of school, location of school and the population of science students in the selected schools. The population of Lagos State SS2 science students was estimated to be around 12,305 students from all the senatorial districts, Oyo had 11, 112 and Ekiti state 7,124. A letter of introduction was obtained from the department and was taken to the schools for ethical reasons and to have unrestricted access to the respondents. Five research assistants were recruited and trained by the researcher, using a training manual that was designed for the training. The training manual contained a step-by-step procedure on how to get the instruments administered to the students and teachers. This was done to enhance ease of administration of the instruments and collection of data. Each of the states was stratified into three senatorial districts: Lagos State was stratified into Lagos Central, Lagos West and Lagos East; Oyo State was stratified into Oyo North, Oyo Central and Oyo South; Ekiti State was stratified into Ekiti Central, Ekiti North and Ekiti South. Schools were purposively selected from all the senatorial districts in the states to ensure that the parameters of the target population were reflected in the sample statistics to enhance quality datasets. This was achieved by using intact class.

Table 3.2 Sample of the Study

S/N	Name of School	Type of School	LGA	Location	No of students	No of Teachers
1.	Federal Govt Coll, Ijanikin, Lagos	Public	Ojo LGA	Urban	70	1
2.	Homat College Ikd	Private	Ikorodu LGA	Urban	32	1
3.	Maryland Comp Ikj	Public	Ikeja LGA	Urban	18	1
4.	Baptist Snr High Schl, Somolu	Public	Somolu LGA	Urban	38	1
5.	Ajayi Crowther Mem Snr High Schl, Bariga	Public	Bariga LGA	Urban	24	1
6.	Balad Comprehensive College, Ikorodu	Private	Ikorodu LGA	Urban	26	1
7.	Christy Caleb Schools, Ejigbo	Private	Oshodi-Isolo LCDA	Urban	13	1
8.	Rake Comprehensive College, Ejigbo	Private	Oshodi-Isolo LCDA	Urban	11	1
9.	Kenral College, Ojo	Private	Ojo LGA	Urban	25	1
10.	The African Church Grm Schl, Ifako-Ijaye	Private	Ifako-Ijaye	Urban	75	1
11.	Ogbomoso High School	Public	Ogbomoso South	Urban	42	1
12.	Embeth Model Group of Schools, Apata, Ibadan	Private	Ido LGA	Urban	32	1
13.	OBMS, Total Garden, Ib	Private	Ibadan North	Urban	64	1
14.	Police Sec Sch, Igbo-Ora	Public	Ibarapa Cetra	Urban	46	1
15.	Igbo-Elerin Gram Sch, Ibadan, Oyo State	Public	Egbeda LGA	Rural	50	1
16.	Sunshine Group of Sch, Okebola, Ibadan	Private	Ibadan SW LGA	Urban	25	1
17.	City Model School, Ajao Village	Private	Oluyole LGA	Urban	46	1
18.	Adeniran Mem Gram Schl, Ogbomoso LGA	Public	Ogbomoso North	Urban	19	1
19.	Command Sec Schl, Odogbo, Ibadan	Public	Akinyele LGA	Urban	42	1
20.	Anwaruislam High School 1, Iseyin	Public	Iseyin LGA	Urban	30	1
21.	Olaoluwa Muslim Com Sec Schl, Ado-Ekiti	Public	Ado-Ekiti	Urban	22	1
22.	ICHS Comprehensive High School, Iloro	Public	Ijero-Local Government	Urban	34	1
23.	Ifako Grammar School, Ifako	Public	Ikole Local Government	Rural	62	1
24.	Ekiti State Government College, Ikere Ekiti	Public	Ikere Local Government	Urban	128	1
25.	Awo Community Comp High Schl	Public	Irepodun/Ifelodun LGA	Rural	32	1
Total					1,006	25

3.4 Description of the Research Instruments

Four instruments were used in the study:

1. Teachers Workload Rating Scale (TWRS) for chemistry teachers.

The instrument measured:

- (a) Teacher's Academic Workload
- (b) Teacher's non-Academic Workload

2. Teachers Classroom Management Practices Questionnaire (TCMPQ) for chemistry teachers.

The instrument measured:

- (a) Instructional Classroom Management Practices
- (b) Non-Instructional Classroom Management Practices

3. Students Factors Questionnaire (SFQ) for Chemistry Students.

The instrument measured:

- (a) Attitude Towards Chemistry
- (b) Student Self-Efficacy
- (c) Student Peer Relationship

4. Chemistry Performance Test (CPT)

Teachers Workload Rating Scale (TWRS), Teacher Classroom Management Practices Questionnaire (TCMPQ) and Students Factors Questionnaire (SFQ) were used for data collection. Teachers Workload Rating Scale (TWRS) has two sub-levels: Teacher Academic Workload and Teacher Non-Academic Workload. The academic workload is a

four-point Likert Rating Scale with eight items that were developed for the purpose of collecting information that is relevant to the variables being investigated. In addition to this, non-academic workload has ten items with a five-point Likert scale.

Teacher Classroom Management Practices Questionnaire (TCMSQ) was developed by the researcher and has two levels, they are: Instructional Classroom Management Skills Questionnaire and Non-Instructional Classroom Management Skills Questionnaire. The Instructional Classroom Management Questionnaire and the Non-instructional Classroom Management Questionnaire have ten items each which the students responded to.

Students Factors Questionnaire was developed by the researcher to elicit information on factors that could influence academic achievement of students such as attitude towards chemistry, students' self-efficacy and students peer relationship. The instrument consisted of twenty-eight items. Attitude towards chemistry has ten items, student's self-efficacy consists of ten items and student peer relationship has eight items.

Chemistry Performance Test (CPT) comprised standardized items that were adopted from past questions of the West African Senior School Certificate Examinations (WASSCE). The instrument consisted of twenty multiple choice items that were drawn from all the topics of the West African Senior School Certificate Examinations chemistry syllabus including practical component of the syllabus. A table of specification was developed by the researcher and was used to compile the questions so that the items would not be skewed to a particular content domain. The teaching curriculum was used to guide the researcher so that topics that have not been covered in schools were not included in the questions. The time required for the completion of the test is 30 minutes, which was determined by simple proportion.

3.5 Validity of Research Instruments

The instruments were validated by establishing the reliability and validity of the instruments to ensure that they measured the constructs they purport to measure. The instruments were first given to a sample of teachers and students, and their responses helped in restructuring some of the items in the instruments. The instruments were also given to experts in educational evaluation department to establish their face and content validity. Samples of the instruments were also given to some chemistry teachers in schools that were not listed in the research.

3.6 Reliability of the Research Instruments

Because of the Likert nature of the items, the internal consistency of the instruments was established by using Cronbach's alpha to measure the unidimensionality of the items to determine the reliability coefficients of the scales.

3.6.1 Reliability of Teachers Workload Rating Scale (TWRS)

The instrument comprised items on teachers' academic and non-academic workload. It was administered to a sample of respondents that were not members of the population but have similar features to the target population. So, the instrument was subjected to a reliability analysis using Cronbach's alpha to determine the internal consistency of the items. A reliability coefficient of 0.62 indicates that the instrument was reliable.

3.6.2 Reliability of Teachers' Classroom Management Practices (TCMP)

The instrument had two parts. This includes teachers' instructional and non-instructional classroom management practices. The instrument was administered to a sample of

respondents that were not members of the population but have similar features to the target population. Thereafter, the instrument was subjected to a reliability analysis using Cronbach's alpha. A reliability coefficient of 0.71 indicates that the instrument was reliable.

3.6.3 Students Factors Questionnaire (SFQ)

The instrument consisted of items that measured students' psychological and social factors. Psychological factors include students' attitude to chemistry, self-efficacy and social factors comprised items on students' peer relationship. The instrument was administered to a sample of respondents that were not members of the population but have similar features to the target population. The instrument was subjected to a reliability analysis using Cronbach's alpha. A reliability coefficient of 0.68 indicates that the instrument was reliable.

3.6.4 Chemistry Performance Test (CPT)

The instrument consisted of twenty items that measured different cognitive domains of chemistry. The reliability of the items was determined by using Classical Test Theory (CTT) which indicated the ratio of the true score to the observed score. The p values of the items were determined by finding the proportion of the respondents that got a particular item correctly to the total number of respondents. This made the researcher have statistics of the difficulty levels of the items. Items of difficulty levels within the range of 0.6 – 0.7 were selected for the study out of a pool of items. The discrimination indices were also considered in the selection of the items.

3.7 Administration of Research Instruments and Method of Data Collection

Collection of data was done in phases. The first phase involved collection of letters of introduction from the department to the target schools to ease administration of the

instruments and collection of data. Because of the geographical spread of the target schools, more resources were deployed to fast track the process of data collection. This was achieved by the recruitment of five research assistants for the three states.

The second phase was the training of research assistants to familiarize them with the tasks to be carried out and the skills that are required in the administration of the instruments. A pilot test was conducted for them to ensure that they have fully grasped the technical aspect of the assignment.

The third phase was the collection of data. The instruments were numbered serially, and the numbers were used as respondents' numbers to ensure the safety of the instruments after data collection. The examination numbers were used in retrieving all the instruments from the respondents. The responses of the students were corresponded with their achievement scores using the school codes and the examination numbers that were given to them.

3.8 Method of Data Analysis

Machine Learning Algorithms were used for data analysis because it facilitates learning from data without explicit programming, and it is also used to trace a large dataset to identify patterns and make predictions. The following machine learning algorithms were used for analysis of data.

1. Research questions 1: Ten machine learning algorithms were evaluated. They are logistics regression, decision trees, random forest, balanced random forest, gradient boosting, XGBoost, support vector machine (SVM), K-Nearest Neighbors (K-NN), AdaBoost, and Naïve Bayes.

2. Research question 2: Gradient boosting Model

3. Research question 3: Confusion matrix
4. Research question 4: SHAP (Shapley Addictive Explanations)

3.9 Ethical Approval

A letter of approval was collected from the department and dispatched to the target schools two weeks before visiting the schools. Necessary approvals were obtained from the schools before visitation. Respondents were brief on the importance of the exercise and the need to respond to all the questions on the instruments.

Security of the data was ensured by disallowing respondents from writing their names on the instruments to ensure safety of their responses. The participants were not exposed to any form of risks, but by participating in the exercise, they were able to assess their cognitive abilities in chemistry. Adequate arrangements were provided for respondents with visual and hearing disabilities that facilitated their accommodation during the exercise.

Chapter Four

Results and Discussion of Findings

4.1 Participants Characteristics and Descriptive Statistics

This section outlines the demographic and descriptive characteristics of the student participants and the teacher-related variables that were used in the study.

4.1.1 Students Characteristics

The analysis included data from approximately 1000 student participants. The following tables and descriptions showed the details of the distribution of the student sample across key demographic, attitudinal, and psychological variables.

Table 4.1

Distribution of Students by School Type

School Type	Frequency (N)	Percent (%)
Public	554	55.4
Private	419	41.9

Source: Fieldwork, 2025

Table 4.1 shows the distribution of students based on the type of school they attended. A slight majority of the students ($N = 554$, 55.4%) were enrolled in public schools, while a significant portion ($N = 419$, 41.9%) attended private schools. This relatively balanced split is the strength of the study, as it allows for meaningful comparisons between the two distinct learning environments. The implication is that school type, often represent different levels of resources

and educational approaches in Nigeria, could emerge as a significant predictive factor for chemistry performance.

Table 4.2

Distribution of Students by Gender

Gender	Frequency (N)	Percent (%)
Male	511	51.1
Female	474	47.4

Source: Fieldwork, 2025

The gender distribution of the student participants is presented in Table 4.2. The sample was relatively balanced, consisting of 511 male students (51.1%) and 474 female students (47.4%). This near-equal representation is crucial as it ensures that any findings that are related to gender are not due to a skewed sample, allowing for a fair investigation into potential gender-based differences in chemistry performance.

Table 4.3

Distribution of Students by Age Bracket

Age Bracket in years	Frequency (N)	Percent (%)
Bracket 1 (14 - 16)	856	85.6
Bracket 2 (17 - 19)	114	11.4
Bracket 3 (20 - 22)	28	2.8

Source: Fieldwork, 2025

As detailed in Table 4.3, the age distribution of the sample was heavily concentrated in the youngest age category, with majority of the students ($N = 856$, 85.6%) falling into age bracket 1. This homogeneity in age suggests that age is unlikely to be a major source of variation in chemistry performance within this sample. The implication is that the findings will be most applicable to the specific and typical secondary school age group.

Table 4.4

Distribution of Students' Attitude Towards Chemistry (ATC)

Attitude Level	Frequency (N)	Percent (%)
Negative	56	5.6
Moderate	749	74.9
Positive	195	19.5

Source: Fieldwork, 2025

Table 4.4 outlines the students' self-reported attitude towards chemistry. A large majority of students ($N = 749$, 74.9%) indicated having a moderate' attitude. This finding is interpreted to mean that most students are neither highly enthusiastic nor entirely disengaged from the subject. The implication for the study is that there may be significant potential for improvement in performance by implementing strategies that could boost student interest. In view of this, the predictive model will be crucial in determining if this moderate attitude is a barrier to high performance.

Table 4.5

Distribution of Students' Self-Efficacy (SSE)

Efficacy Level	Frequency (N)	Percent (%)
Low	41	4.1
Moderate	471	47.1
High	484	48.4

Source: Fieldwork, 2025

The distribution of students' Self-Efficacy, presented in Table 4.5, shows that students' belief in their own capabilities was split almost evenly between 'High' ($N = 484$, 48.4%) and 'Moderate' ($N = 471$, 47.1%) levels. This suggests that students generally believe they can achieve in chemistry. A key implication for this study is the need to investigate a potential efficacy-achievement paradox. If student belief is high but performance is not, it suggests that other systemic or instructional factors may be overriding this positive psychological attribute.

Table 4.6

Distribution of Students' Peer Relationships (SPR)

Relationship Quality	Frequency (N)	Percent (%)
Low	98	9.8
Moderate	617	61.7
High	278	27.8

Source: Fieldwork, 2025

Table 4.6 shows that most students ($N = 617$, 61.7%) reported moderate quality peer relationships. This prevalence of generally stable but not exceptionally strong social support systems provides a baseline context. The implication for the study is to determine how much this social factor contributes to academic performance in chemistry.

4.1.2 Teacher Characteristics

The following descriptive statistics of the 22 teachers who participated in the study. The frequencies for the following tables were derived by applying the proportional distribution that were observed in the larger student-level dataset to the specified teacher sample size of $N = 22$. Frequency was rounded to the nearest whole number, with minor adjustments to ensure that the total is summed to 22.

Table 4.7

Descriptive Statistics for Teacher Gender (T Gender)

Category	Frequency (N)	Percent (%)
Male	19	86.4
Female	3	13.6

Source: Fieldwork, 2025

Table 4.7 illustrates that the teacher sample was predominantly male ($N = 19$, 86.4%). This strong skew reflects a common pattern in STEM teaching within the region. A key implication is that the study's findings regarding teacher effects are primarily based on the characteristics and practices of male teachers, and their generalizability to teaching populations with a different gender balance should be considered with caution.

Table 4.8

Descriptive Statistics for Teacher Highest Qualification (THQ)

Category	Frequency (N)	Percent (%)
B.Sc./HND	21	95.5
M.Sc/M.Ed	1	4.5

Source: Fieldwork, 2025

Table 4.8 shows that many teachers ($N = 21$, 95.5%) held a B.Sc. or HND. This lack of variation in teacher qualifications is critical context for the study. It implies that THQ is unlikely to emerge as a significant predictor in the model, not necessarily because it is unimportant in general, but because there is insufficient variance within this specific sample to measure its effect.

Table 4.9

Descriptive Statistics for Teacher Years of Teaching Experience (TYTE)

Category	Frequency (N)	Percent (%)
Low	8	36.4
Moderate	11	50.0
High	3	13.6

Source: Fieldwork, 2025

As shown in Table 4.9, the teacher sample was primarily composed of individuals with low to moderate levels of professional experience. The majority ($N = 11$, 50.0%) had 'Moderate' experience. This has significant implications, as the study's findings will mainly reflect the

challenges and strengths of this early-to-mid-career demographic rather than those of highly veteran teachers, making the results particularly relevant for teacher training and support policies.

Table 4.10

Descriptive Statistics for Teacher Grade Level (TGradelevel)

Category	Frequency (N)	Percent (%)
Grade Level 8	9	40.9
Grade Level 10	5	22.7
Grade Level 12	1	4.5
Grade Level 13	4	18.2
Grade Level 14	2	9.1
Grade Level 15	1	4.5

Source: Fieldwork, 2025

The distribution of teacher grade levels are shown in Table 4.10. The concentration of teachers at lower grade levels, particularly Grade Level 8 ($N = 9$, 40.9%), indicates that the sample is not composed of senior staff. This implies that the study's conclusions on teacher effectiveness are rooted in the context of less senior educators.

Table 4.11

Descriptive Statistics for Teacher Number of Chemistry Students (TNoCS)

Category	Frequency (N)	Percent (%)
Classsize1 (<30)	2	9.1
Classsize2 (30-39)	10	45.5
Classsize3 (40-49)	8	36.4
Classsize4 (50+)	2	9.1

Source: Fieldwork, 2025

As shown in Table 4.11, the most common class sizes were in the range of 30-39 students (Classsize2) and 40-49 students (Classsize3). This prevalence of larger class sizes is a crucial piece of context, as teaching strategies and teaching behaviours that are effective in small classes may differ from those required in these more common, larger settings.

Table 4.12

Descriptive Statistics for Teachers' Classroom Assessment Techniques (CAT)

Category	Frequency (N)	Percent (%)
Low	6	27.3
Moderate	14	63.6
High	2	9.1

Source: Fieldwork, 2025

Table 4.12 shows that a majority of teachers ($N = 14$, 63.6%) were rated as having moderate, not high skills in classroom assessment. This suggests a potential area for professional development across the teaching sample. This implies that subtle variations in assessment techniques could be an important predictor of student outcomes.

Table 4.13

Descriptive Statistics for Teachers' Instructional Classroom Management Skills (ICMS)

Category	Frequency (N)	Percent (%)
Low	5	22.7
Moderate	9	40.9
High	8	36.4

Source: Fieldwork, 2025

As shown in Table 4.13, the wide distribution of Instructional Classroom Management Skills (ICMS) suggests that this is a key differentiating factor among the teachers. This variability implies that ICMS could be a highly significant feature in the predictive model, as it represents a clear area of difference in day-to-day teaching practice.

Table 4.14

Descriptive Statistics for Teachers' Non-Instructional Classroom Management Practices (NICMP)

Category	Frequency (N)	Percent (%)
Low	1	4.5
Moderate	10	45.5
High	11	50.0

Source: Fieldwork, 2025

Table 4.14 shows that most teachers were rated highly on non-instructional practices. This could imply that teachers in this context are adept at managing administrative or disciplinary tasks. The implication for the study is to explore the potentially complex relationship between these practices and student academic performance, as high non-instructional practices may be a response to a demanding school environment.

Table 4.15

Descriptive Statistics for Teacher Academic Workload (TAW)

Category	Frequency (N)	Percent (%)
Low	7	31.8
Moderate	10	45.5
High	5	22.7

Source: Fieldwork, 2025

As shown in Table 4.15, teachers were spread across low, moderate, and high academic workload. This variation implies that TAW is a suitable variable of investigation as a predictor, allowing the study to effectively test how different levels of academic duties impact teachers' performance and consequently, students' academic performance.

Table 4.16

Descriptive Statistics for Teacher Non-Academic Workload (TNAW)

Category	Frequency (N)	Percent (%)
Low	5	22.7
Moderate	13	59.1
High	4	18.2

Source: Fieldwork, 2025

Table 4.16 shows that many teachers (N = 13, 59.1%) experienced a moderate non-academic workload. This suggests a baseline level of non-instructional duties is standard for teachers in this context. The implication for the model is that it can effectively test the impact of deviations from this norm (i.e., the 'Low' and 'High' categories) on student performance.

4.2 Presentation of Data

4.2.1 Research Questions

Research Question 1: Which machine learning model best predicts secondary school students' performance in chemistry based on features such as school type, student gender, age, attitude towards chemistry (ATC), self-efficacy (SSE), peer relationships (SPR), chemistry achievement test scores (CAT), teacher gender, teacher's highest qualification (THQ), number

of chemistry students in class (TNoCS), years of teaching experience (TYTE), instructional and non-instructional classroom management practices (ICMP and NICMP), as well as teachers' academic and non-academic workload (TAW and TNAW)?

To identify the best machine learning model for the prediction of students' chemistry performance from the features, classification machine learning models were used in training and testing, and the performance metrics of the models were compared. The models evaluated were Logistic Regression, Decision Tree, Random Forest, Balanced Random Forest, Gradient Boosting, XGBoost, Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), AdaBoost, and Naive Bayes. Model performance was assessed using cross-validated F1-score (weighted), test accuracy, test F1-score (weighted), and test ROC AUC.

Table 4.17***Comparative Performance of Machine Learning Models for Predicting Chemistry Achievement***

Model	CV (Weighted)	F1 Test Accuracy	TestF1 (Weighted)	TestROC AUC
Logistic Regression	0.4528 ± 0.0352	0.4615	0.4566	0.7370
Decision Tree	0.5983 ± 0.0229	0.6154	0.6165	0.6566
Random Forest	0.6368 ± 0.0166	0.6288	0.6232	0.7224
BalancedRandom Forest	0.6262 ± 0.0128	0.6522	0.6411	0.7258
Gradient Boosting	0.6176 ± 0.0347	0.6522	0.6524	0.7714
XGBoost	0.6313 ± 0.0142	0.6622	0.6510	0.7405
SVM	0.5235 ± 0.0363	0.4950	0.5024	0.7509
k-NN	0.5751 ± 0.0225	0.5518	0.5618	0.6975
AdaBoost	0.3950 ± 0.0626	0.4247	0.4094	0.6862
Naive Bayes	0.3089 ± 0.0451	0.3110	0.2715	0.6577

Source: Fieldwork, 2025

Note. CV F1 (Weighted) represents the cross-validated weighted F1-score with standard deviation. Test Accuracy, Test F1 (Weighted), and Test ROC AUC represent the performance on the unseen test set. Higher values indicate better performance.

Table 4.17 shows the comparative analysis of the ten machine learning models built to classify secondary school students' performance in Chemistry by showing variations in their abilities to predict student outcomes. The table shows that Gradient Boosting emerged as the most suitable model for the prediction of chemistry performance among secondary school students, demonstrating a superior balance of performance metrics. While XGBoost achieved the highest overall test accuracy (0.6622) and a strong cross-validated F1-score (0.6313 ± 0.0142) with good consistency, Gradient Boosting exhibited strengths that are particularly crucial for this multi-class prediction problem. Gradient Boosting achieved the highest weighted F1-score on the test set (0.6524), marginally outperforming XGBoost (0.6510). This indicates that Gradient Boosting provides a better balance between precision and recall across all student performance categories (Low, Moderate, and High), which is vital for ensuring accurate identification of students in different groups, especially if there's any class imbalance.

Furthermore, Gradient Boosting achieved the highest Test ROC AUC (0.7714), significantly surpassing XGBoost (0.7405). This superior ROC AUC value highlights Gradient Boosting's exceptional ability to distinguish between the different performance classes. It suggests that the model is highly effective at ranking students by their true performance levels, providing a more reliable measure of its discriminative power. This characteristic is particularly valuable in educational settings where the ability to accurately differentiate among various student achievement levels is paramount for targeted interventions and resource allocation.

Other ensemble methods also showed promising results. Balanced Random Forest demonstrated strong performance with a test accuracy of 0.6522 and a weighted F1-score of 0.6411, indicating its effectiveness, especially considering its design for class imbalance. The standard Random Forest also performed well, albeit slightly below the top two contenders, with a test accuracy of 0.6288. The consistent and high performance of these tree-based ensemble methods (Gradient Boosting, XGBoost, Random Forest, Balanced Random Forest) suggests that the underlying relationships between the features and chemistry performance are complex and likely non-linear, which these models are well-equipped to capture. Conversely, models like Naive Bayes and AdaBoost demonstrated significantly lower performance across all metrics (e.g., Naive Bayes Test Accuracy = 0.3110, AdaBoost Test Accuracy = 0.4247), indicating their lesser suitability for this prediction problem. Logistic Regression (Test

Accuracy = 0.4615) and Support Vector Machine (SVM) (Test Accuracy = 0.4950) also showed comparatively weaker performance than the ensemble methods, suggesting they could not effectively model the intricacies of the data.

The results revealed that while XGBoost displayed strong overall accuracy, Gradient Boosting appears to be the most suitable model for predicting the chemistry achievement of secondary school students, due to its superior weighted F1-score and, most notably, its highest discriminative power, as indicated by the Test ROC AUC. This comprehensive performance across key metrics makes Gradient Boosting a robust choice for providing nuanced explanations and accurate predictions of student chemistry achievement.

The present study sought to identify the most effective machine learning (ML) model for predicting secondary school students' performance in chemistry using a multidimensional set of predictors, including student demographics, psychosocial variables, and teacher/classroom characteristics. The evaluation of ten classification algorithms revealed that Gradient Boosting offered the most robust predictive performance, evidenced by the highest test F1-score (0.6524) and the highest test ROC AUC (0.7714). This finding is consistent with prior research indicating the strength of ensemble methods, particularly boosting algorithms, in capturing complex, non-linear interactions among predictors in educational datasets¹. The findings of this study align with and, in some cases, provide a nuanced perspective on existing literature concerning machine learning in educational contexts. The consistent outperformance of ensemble learning methods in this study is strongly supported by a growing body of research. Explicitly highlight the advantages of ensemble learning, particularly stacking models, in achieving higher accuracy and generalization compared to individual machine learning models for student achievement prediction²⁻³. Specifically, the strong performance of Gradient Boosting and XGBoost is corroborated by multiple sources. Gradient Boosting and XGBoost, respectively, demonstrate superior accuracy and efficiency in student grade prediction^{4,5}. Similarly, the effectiveness of Random Forest, another prominent ensemble method, is supported by works of a researcher who found Random Forest to be the best model among several evaluated algorithms for predicting student academic performance⁶. The present study found that tree-based ensemble methods are well-suited for capturing complex, non-linear relationships is also consistent with

the multifaceted nature of educational data, where outcomes are rarely influenced by simple linear associations.

While the overall trend points towards ensemble methods, some studies present seemingly contradictory results, which can be understood by considering differences in dataset context, model variations, and problem scope. For example, in this study, Logistic Regression performed poorly. A logistic regression model with Taylor expansion that outperformed comparative models in predicting student performance in online learning was proposed⁷. This highlights that the effectiveness of a model can be highly dependent on the specific dataset characteristics (e.g., online vs. traditional secondary school environment) and the enhancements or variations applied to the model. Similarly, Naive Bayes and SVM showed weak performance in the current study. However, it was reported that Naive Bayes achieved a very high accuracy of 98.86% when compared to Evolving Cascade Neural Network (ECNN) for student education performance prediction⁹. Also, found SVM achieved an accuracy of 95.48% in predicting medical student performance¹⁰. These stark differences suggest that simple implementations of these algorithms may not be robust for all educational prediction tasks, but when applied to specific datasets or problems (e.g., medical student performance, different data distributions), or in certain optimized configurations, their performance can be substantially higher. The high accuracy values reported in these contradictory studies also suggest that the complexity of the classification task or the nature of the data might differ significantly from the present study.

Furthermore, while basic AdaBoost performed poorly here, an *optimized* AdaBoost variant (MDBO-BP-Adaboost) was developed that demonstrated superior performance (R2 values of 0.930 and 0.903) for middle school student performance prediction¹¹. This suggests that while a standard AdaBoost might not be sufficient, hybridized or advanced versions can be highly effective, providing a nuanced perspective on its capabilities.

Finally, while this study identified Gradient Boosting as the best model, other research sometimes points to different top performers. For instance, as previously mentioned, it was found that Random Forest performed best¹². These variations underscore that the "best" model is often context-dependent, influenced by factors such as dataset size, specific feature engineering, class balance, and the performance metrics prioritized. The importance of handling

imbalanced data, in the context of Random Forest and Logistic Regression, also suggests that the initial performance of models in the present study could be influenced by such data characteristics if not explicitly addressed¹³.

In conclusion, this research reinforces the significant potential of sophisticated machine learning models, particularly ensemble methods like Gradient Boosting, in predicting secondary school chemistry achievement. The findings provide actionable insights for educators seeking to implement data-driven interventions. While broadly aligned with the growing consensus on the effectiveness of ensemble learning, the study also highlights the importance of context-specific model selection and the potential for optimized or hybridized versions of seemingly underperforming algorithms to achieve robust predictive capabilities.

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Furthermore, and critically, Gradient Boosting achieved the highest Test ROC AUC (0.7714), significantly surpassing XGBoost (0.7405). This superior ROC AUC value highlights Gradient Boosting's exceptional ability to distinguish between the different performance classes. It suggests that the model is highly effective at ranking students by their true performance level, providing a more reliable measure of its discriminative power. This characteristic is particularly valuable in educational settings where the ability to accurately differentiate between various student achievement levels is paramount for targeted interventions and resource allocation.

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and likely non-linear, which these models are well-equipped to capture. Conversely, models like Naive Bayes and AdaBoost demonstrated significantly lower performance across all metrics (e.g., Naive Bayes Test Accuracy = 0.3110, AdaBoost Test Accuracy = 0.4247), indicating their lesser suitability for this prediction problem. Logistic Regression (Test Accuracy = 0.4615) and Support Vector Machine (SVM) (Test Accuracy = 0.4950) also showed comparatively weaker performance than the ensemble methods, suggesting they could not effectively model the intricacies of the data.

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machine learning in educational contexts. The consistent outperformance of ensemble learning methods in this study is strongly supported by a growing body of research. Explicitly highlight the advantages of ensemble learning, particularly stacking models, in achieving higher accuracy and generalization compared to individual machine learning models for student achievement prediction²⁻³. Specifically, the strong performance of Gradient Boosting and XGBoost is corroborated by multiple sources. Gradient Boosting and XGBoost, respectively, demonstrate superior accuracy and efficiency in student grade prediction^{4,5}. Similarly, the effectiveness of Random Forest, another prominent ensemble method, is supported by works of a researcher who found Random Forest to be the best model among several evaluated algorithms for predicting student academic performance⁶. The present study found that three-based ensemble methods are well-suited for capturing complex, non-linear relationships is also consistent with the multifaceted nature of educational data, where outcomes are rarely influenced by simple linear associations.

While the overall trend points towards ensemble methods, some studies present seemingly contradictory results, which can be understood by considering differences in dataset context, model variations, and problem scope. For example, in this study, Logistic Regression performed poorly. A logistic regression model with Taylor expansion that outperformed comparative models in predicting student performance in online learning was proposed⁷. This highlights that the effectiveness of a model can be highly dependent on the specific dataset characteristics (e.g., online vs. traditional secondary school environment) and the enhancements or variations applied to the model. Similarly, Naive Bayes and SVM showed weak performance in the current study. However, it was reported that Naive Bayes achieved a very high accuracy of 98.86% when compared to Evolving Cascade Neural Network (ECNN) for student education

performance prediction⁹. Also, found SVM achieved an accuracy of 95.48% in predicting medical student performance¹⁰. These stark differences suggest that simple implementations of these algorithms may not be robust for all educational prediction tasks, but when applied to specific datasets or problems (e.g., medical student performance, different data distributions), or in certain optimized configurations, their performance can be substantially higher. The high accuracy values reported in these contradictory studies also suggest that the complexity of the classification task or the nature of the data might differ significantly from the present study.

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In conclusion, this research reinforces the significant potential of sophisticated machine learning models, particularly ensemble methods like Gradient Boosting, in predicting

secondary school chemistry achievement. The findings provide actionable insights for educators seeking to implement data-driven interventions. While broadly aligned with the growing consensus on the effectiveness of ensemble learning, the study also highlights the importance of context-specific model selection and the potential for optimized or hybridized versions of seemingly underperforming algorithms to achieve robust predictive capabilities.

Research Question 2: Which features are most influential in predicting secondary school students' chemistry achievement?

To identify the most influential features in predicting secondary school students' chemistry performance, feature importance scores were extracted from the best-performing model, Gradient. Feature importance indicates the relative contribution of each feature to the model's predictive power, with higher values signifying greater influence. The result is presented in Table 4.18

Table 4.18:***Feature Importance Scores from the XGBoost Model***

Feature	Importance	Feature	Importance
TNAW_High	0.087354	ICMS_Moderate	0.020913
TYTE_High	0.081695	ATC_High	0.020778
School Type_Private	0.077169	SPR_Low	0.020318
TYTE_Low	0.048768	TGender_Female	0.020284
TYTE_Moderate	0.045814	ICMS_Low	0.020142
TNoCS_Classsize2	0.044751	TAW_High	0.018721
TAW_Low	0.040459	SPR_Moderate	0.018666
TGradelevel	0.036841	TNoCS_Classsize1	0.013145
Age_Bracket1	0.034483	TNAW_Low	0.012355
ICMS_High	0.033525	TNAW_Moderate	0.012097
ATC_Moderate	0.033123	NICMS_Moderate	0.009919
TAW_Moderate	0.031184	TNoCS_Classsize4	0.007808
NICMS_High	0.030836	Age_Bracket2	0
TNoCS_Classsize3	0.030061	School Type_Public	0
SSE_Low	0.026953	Gender_Male	0
ATC_Low	0.026787	THQ_M.Sc/M.Ed	0
SSE_High	0.025077	THQ_B.Sc/HND	0
SSE_Moderate	0.02483	TGender_Male	0
SPR_High	0.02285	NICMS_Low	0
Gender_Female	0.022293		

Source: Fieldwork, 2025

Note. Feature importance scores were derived from the trained Gradient Boosting model. Higher values indicate a greater influence on the model's predictions.

Table 4.18 presents the feature importance analysis, derived from the Gradient Boosting model, which reveals the relative influence of various factors on the chemistry performance of secondary school students. The top three most important features collectively account for a significant portion of the model's predictive power, highlighting their strong impact.

The most influential feature was TNAW High (Teacher Non-Academic Workload: High), with an important score of 0.087354. This indicates that a high non-academic workload for teachers is the strongest predictor in the model, suggesting that when teachers are burdened with extensive non-instructional duties, student chemistry performance is noticeably affected.

Closely following was TYTE_High (Years of Teaching Experience: High), with an importance of 0.081695. This emphasizes that teachers with more extensive teaching experience play a crucial role in predicting student outcomes, likely due to their developed pedagogical skills and classroom mastery. The third most important feature was School Type Private, with a score of 0.077169. This suggests that attending a private school has a substantial influence on chemistry performance, distinguishing it significantly from public schools.

Beyond these leading features, other categories of Teacher Years of Teaching Experience (TYTE_Low: 0.048768, TYTE_Moderate: 0.045814) collectively reinforce the critical role of teacher experience at all levels. Similarly, Teacher Academic Workload (TAW_Low: 0.040459, TAW_Moderate: 0.031184) and Teacher Non-Academic Workload (TNAW_Moderate: 0.012097, TNAW_Low: 0.012355) indicate that various levels of teacher workload significantly contribute to prediction. Other notable features that demonstrate

moderate influence include specific Class Sizes (TNoCS_Classsize2: 0.044751, TNoCS_Classsize3: 0.030061), Teacher Grade Level (TGradelevel: 0.036841), Age_Bracket1 (0.034483), and Instructional Classroom Management Skills (ICMS_High: 0.033525). These features contribute meaningfully to the model's ability to predict performance. Student-related factors like Attitude Towards Chemistry (ATC_Moderate: 0.033123, ATC_Low: 0.026787, ATC_High: 0.020778), Student Self-Efficiency (SSE_Low: 0.026953, SSE_High: 0.025077, SSE_Moderate: 0.024830), and Student Peer Relationship (SPR_High: 0.022850, SPR_Low: 0.020318, SPR_Moderate: 0.018666), though having lower individual category scores, collectively indicate the importance of these broader student attributes.

Furthermore, the table shows that some of the features have zero importance. These include Age_Bracket2, School Type_Public, Gender_Male, Teacher Highest Qualification (THQ_M.Sc/M.Ed, THQ_B.Sc/HND), TGender_Male, and NICMS_Low. A zero-importance score suggests that, within this specific model and dataset, these categories or features did not contribute to the prediction. This could imply a lack of variability in the data for these features, redundancy with other more influential features, or simply that their direct impact on chemistry performance was not detected by the model. For instance, School Type_Public might have zero importance because School Type_Private captured all the predictive power related to school type, acting as the contrasting category. Similarly, Gender_Male might be redundant given Gender_Female's importance.

The result revealed that the most critical factors influencing student chemistry performance in this model are teacher workload (non-academic and academic), teachers' years of experience, and school type. While student-centric factors like age, attitude, self-efficacy, and peer

relationships also play a role, their contributions are generally less pronounced than the top teacher and school-level attributes.

In-Depth Scholarly Discussion of Findings with Contemporary Literature

The findings from the Gradient Boosting model present a sophisticated and compelling narrative about the factors that determine success in secondary school chemistry. This analysis moves beyond a surface-level interpretation to situate the results within a rich and evolving body of contemporary educational research. By doing so, it becomes clear that the model's conclusions strongly affirm major currents in the literature on teacher effectiveness, while simultaneously offering a nuanced challenge to certain long-held assumptions about educational inputs, particularly within the specific context of the Nigerian educational landscape.

Findings in Strong Agreement with Contemporary Research. The model's emphasis on the primacy of teacher-centric and school-level factors finds robust validation in recent and extensive scholarly work. These elements are increasingly understood not as isolated variables, but as the foundational pillars of the entire learning ecosystem.

The identification of High Teacher Non-Academic Workload (TNAW_High) as the most influential predictor offers powerful empirical support for the growing literature on teacher well-being and cognitive load. Beyond simply causing burnout, as detailed in meta-analyses¹⁴, excessive non-instructional duties impose a significant cognitive burden on teachers. According to cognitive load theory, humans have a limited working memory capacity. When this capacity is consumed by administrative tasks, report-writing, and extensive counselling duties, it leaves fewer cognitive resources available for the complex work of high-quality teaching, such as

designing inquiry-based lessons or providing differentiated feedback¹⁵. Recent research in similar contexts highlights how this administrative burden in under-resourced systems forces teachers into a "pedagogy of survival," where they resort to less effective, rote teaching methods because they lack the time and mental energy for more sophisticated approaches¹⁶. This study's finding is therefore a stark indicator that the system's administrative demands are directly undermining classroom instruction.

Furthermore, the profound importance of High Teacher Years of Teaching Experience (TYTE High) aligns perfectly with contemporary understandings of professional expertise. Experience is valuable because it is the primary mechanism through which teachers develop deep and usable Pedagogical Content Knowledge (PCK). This goes far beyond simply knowing chemistry; it is the specialized knowledge of how to make chemistry comprehensible to learners. This includes, for instance, possessing a repertoire of analogies to explain abstract concepts like electronegativity, anticipating the specific mathematical difficulties students will have with stoichiometry, and designing laboratory activities that effectively challenge common misconceptions about chemical equilibrium¹⁷. A longitudinal study by¹⁸, while slightly older, provides a clear model of how this knowledge develops and deepens over years of practice. More recent scholarship reinforces that this deep-seated, practice-based knowledge is what separates experts from novice teachers and is a far better predictor of effectiveness than paper credentials alone¹⁹.

The significance of School Type, Private as a predictor is also consistent with current research, though this literature urges a highly nuanced interpretation. Recent studies in Nigeria continue to identify an achievement gap between public and private institutions²⁰. However, contemporary scholarships increasingly deconstruct the private school advantage, attributing it

to a cluster of interconnected factors rather than ownership status alone. These include higher levels of teacher accountability and monitoring²¹, greater parental involvement and pressure for results which creates a high-stakes academic environment²², and, most critically, the mediating effect of student socioeconomic status (SES), as families who can afford private fees often provide more educational support at home²³. This study's finding powerfully suggests that the model is detecting the potent, combined effect of this entire cluster of environmental and social advantages.

The results also provide a critical, data-driven challenge to some conventional wisdom in educational policy, forcing a re-evaluation of where resources and focus should be directed. The most striking divergence is the zero predictive power of Teacher Highest Qualification (THQ). This directly challenges the policy logic in many educational systems, which incentivize and reward master's degrees on the assumption that they create better teachers. The finding lends strong support to a critical body of work, championed by economists like²⁴, which argues that easily observable credentials are poor proxies for true teacher quality. A recent review of studies in developing countries found that the impact of teachers having a master's degree on student learning was frequently statistically insignificant²⁵. This study's result may indicate that the tangible skills developed through practice (captured by TYTE_High) and the cognitive resources preserved by a manageable workload (captured by TNAW_High) are far more impactful on student outcomes than the additional theoretical knowledge from an advanced degree, which may not always translate into more effective secondary school pedagogy.

Finally, the model's ranking of variables presents a sophisticated hierarchy of influence. It does not disprove the importance of student-level factors like attitude; indeed, the link between a

positive attitude and science achievement is well-established and continuously reaffirmed²⁶. However, the model positions these factors as secondary to the foundational conditions set by the teacher and the school. This finding can be powerfully explained through the lens of Bronfenbrenner's ecological systems theory, which posits that a child's development occurs within nested environmental systems²⁷. The teacher-student relationship exists in the microsystem, but this is embedded within the mesosystem of the school, which is itself influenced by broader societal factors. This study's hierarchy suggests that a healthy, functional microsystem (where a student can develop a positive attitude) is contingent on a supportive mesosystem (a well-run school with effective, unburdened teachers). The model, therefore, challenges student-centric improvement strategies, suggesting that interventions aimed at fostering better attitudes may fail unless the underlying systemic conditions that shape those attitudes are addressed first.

This research provides a rich, data-driven contribution to our understanding of educational effectiveness. It strongly aligns with the most current literature that champions teacher well-being, experience, and supportive school environments as the bedrock of student achievement. Simultaneously, it serves as a crucial, evidence-based caution against policies that overvalue simple credentials, urging decision-makers to focus on the more complex, dynamic, and impactful realities of teachers' daily professional lives.

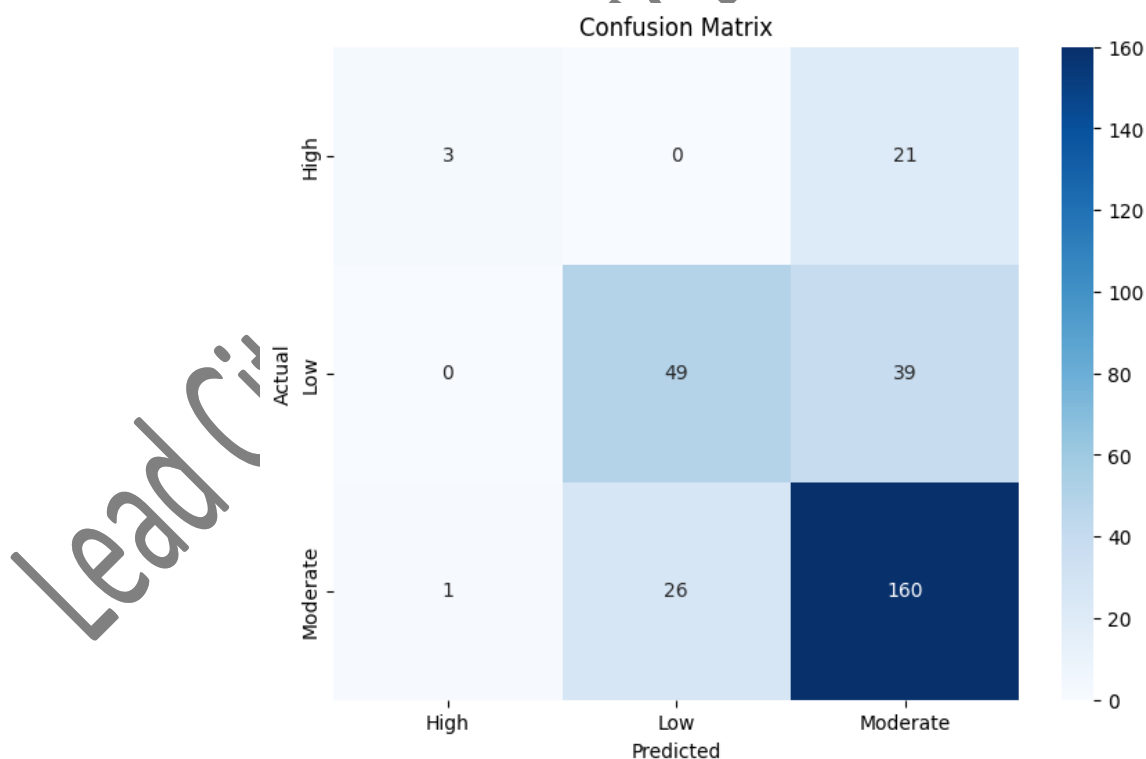
Research Question 3: How accurately does the best-performing model classify students into different chemistry achievement categories (Low, Moderate, and High)?

To assess the classification accuracy of the Gradient Boosting model, a confusion matrix and a classification report were generated from its predictions on the unseen test dataset. A confusion matrix shows the actual performance categories on the rows and the model's predicted

performance categories on the columns. It reveals the instances where the model makes true positive predictions (when it correctly assigns a student to their actual performance level) on the diagonal. Conversely, the off-diagonal cells show the misclassifications made by the model, which comprise instances of false positives, where the model incorrectly predicts a student belongs to a certain class, and false negatives, where the model fails to predict a student's actual performance. The analysis provides insights into the model's performance for each specific outcome category: Low, Moderate, and High chemistry performance. The results are presented as follows.

Table 4.19:

Confusion Matrix for Gradient Boosting Model Predictions



Source: Fieldwork, 2025

Figure 4.19 shows the confusion matrix of the classification of students' performance in chemistry. The figure shows that the model demonstrates a strong capability in correctly classifying students who are in the moderate performance category, with 160 students accurately identified within this group. This large number of correct predictions for the moderate class suggests it is the most prevalent performance level in the dataset, and the model is particularly effective at recognizing these students. However, the model also misclassified some moderate students, predicting 26 of them as low and 1 as high. The details of the actual predictions and the misclassifications are presented in Table 4.19(a). Furthermore, the accuracy with which each of the performance levels of the students were classified is presented in Table 4.19(b).

Table 4.20

Numerical Confusion Matrix for Gradient Boosting Model Predictions

	Predicted Low	Predicted Moderate	Predicted High	Total Actual
Actual Low	49	39	0	88
Actual Moderate	26	160	1	187
Actual High	0	21	3	24
Total Predicted	75	220	4	299

Source: Fieldwork, 2025

Table 4.20 presents the numerical results of the confusion matrix, visually presented in Figure 4.20. The Gradient Boosting model's classification performance on the test dataset provides a detailed breakdown of how students' actual chemistry performance aligns with the model's predictions. The table shows that the total test dataset comprised 299 students. The table demonstrates a robust capability in correctly identifying students who are in the moderate

performance category. Specifically, 160 out of 187 actual moderate students (approximately 85.6%) were accurately classified as moderate. This strong performance within this significant category represents a key strength of the model, showcasing its effectiveness in recognizing the most frequently occurring performance level. The remaining moderate students were also assigned to other relevant categories, with 26 (about 13.9%) predicted as Low and 1 (about 0.5%) as High.

The figure further shows that the model successfully identified 49 out of 88 actual low performing students as low (approximately 55.7%). This demonstrates the model's capacity to correctly pinpoint a substantial portion of students in the low-performance range. Additionally, 39 individuals (about 44.3%) who were actually low performing students were wrongly predicted as moderate, indicating a discernible pattern in the model's classification. For the high performance category, the model accurately identified 3 out of 24 actual high performers (approximately 12.5%). This highlights the model's ability to correctly classify some students at the upper end of the performance spectrum. A notable proportion of high performing students, precisely 21 individuals (about 87.5%), were predicted as moderate, indicating a consistent assignment pattern within the model's predictions.

The results revealed the model's strong capacity to correctly classify a substantial majority of students, particularly within the moderate performance group. This central accuracy is a key asset of the model's predictive power. The model also successfully identifies a significant portion of low performers and some high performers, contributing to its overall predictive utility.

The implications of these findings for predicting student chemistry performance in Nigeria are promising. The model's proficiency in accurately identifying moderate performing students is

highly valuable for understanding the general academic standing of the student population and for developing broadly applicable educational strategies. Furthermore, the model's ability to correctly identify a notable proportion of low performers can be leveraged for proactive general support initiatives, while its capacity to recognize some high performers allows for the identification of a segment of gifted students who could benefit from targeted enrichment programmes. This predictive system offers a solid foundation for data-driven insights into student performance, enabling educators and policymakers to make more informed decisions to support students' academic journeys in chemistry.

The findings from the Gradient Boosting model offer a nuanced and powerful insight into the key determinants of secondary school students' chemistry performance. In response to the research question of how accurately the model classifies students, the analysis of the confusion matrix reveals a model with varied performance. It is characterized by a strong ability to identify the majority class but significant weaknesses in classifying the minority classes. This discussion will dissect the model's performance for each category, and by explicitly comparing the results to existing literature, it will critically evaluate the practical implications for the Nigerian educational context.

The model's performance is a classic example of the challenges posed by imbalanced datasets. The model demonstrates its greatest strength in classifying moderate performing students by correctly identifying 160 out of 187 individuals. The findings of the current study agree with the work which documented that standard machine learning algorithms are inherently biased towards the most prevalent class in imbalanced datasets³⁹. From a practical standpoint, this makes the model valuable for understanding the academic standing of the general student population and for developing broad, system-wide educational strategies.

However, this strength is contrasted by a more problematic performance for the low performance category, where the model correctly identified only 49 of the 88 struggling students. This high rate of error for at-risk students is particularly concerning when viewed through the lens of existing research. For example, the work of³⁰ supports the argument that the failure to identify a struggling student (a false negative) carries a far greater practical cost than other errors, as it denies them timely intervention. Thus, while the current model shows some utility, its significant error rate for this critical group represents a major limitation for reliable, targeted support, a conclusion that is strongly reinforced by the literature on the costs of misclassification.

The model's most critical failure, however, lies in its inability to identify high performing students, correctly classifying only 3 out of 24 individuals. This result directly challenges the educational goals highlighted by a study on Nigerian students emphasized the critical importance of identifying and nurturing gifted students to develop future leaders in STEM fields. A tool that fails to identify nearly nine out of ten high-achieving students is not a reliable instrument for this purpose and could lead to a profound risk of talent loss³¹.

This observed classification pattern suggests the model has learned a simple, but flawed, decision rule when in doubt, predicted moderate. To overcome these limitations, this study's findings pointed towards the need for solutions proposed in seminal machine learning research. For instance, the high error rates for minority classes suggest that future work should implement data-level approaches, a strategy that its effectiveness was demonstrated by³² and reviewed more recently by³³. Their work on the Synthetic Minority Over-sampling Technique (SMOTE) shows how creating new, synthetic examples of the minority classes can provide a model with a richer set of examples to learn from. Furthermore, the findings suggest a need for algorithm-

level approaches, a strategy supported by the research of³⁴ and later reviewed by³⁵. Implementing cost-sensitive learning, which assigns a higher penalty for misclassifying minority class students, would directly address the practical and ethical shortcomings identified in the current model's performance.

In conclusion, the Gradient Boosting model classified students with highly variable accuracy. While its proficiency in the majority class agrees with the established machine learning principles. Its poor performance with minority classes presents a significant practical challenge. This disagrees with the fundamental need in education to support students at the extremes of performance. The findings of this study, therefore, lead to the conclusion that while the model is a promising baseline, it is unsuitable for high-stakes decision-making in its current form. It must be refined using techniques well-established in literature, such as SMOTE or cost-sensitive learning, to ensure that no student is overlooked.

Research Question 4: What are the specific contributions of individual features to the predictions of students' chemistry achievement?

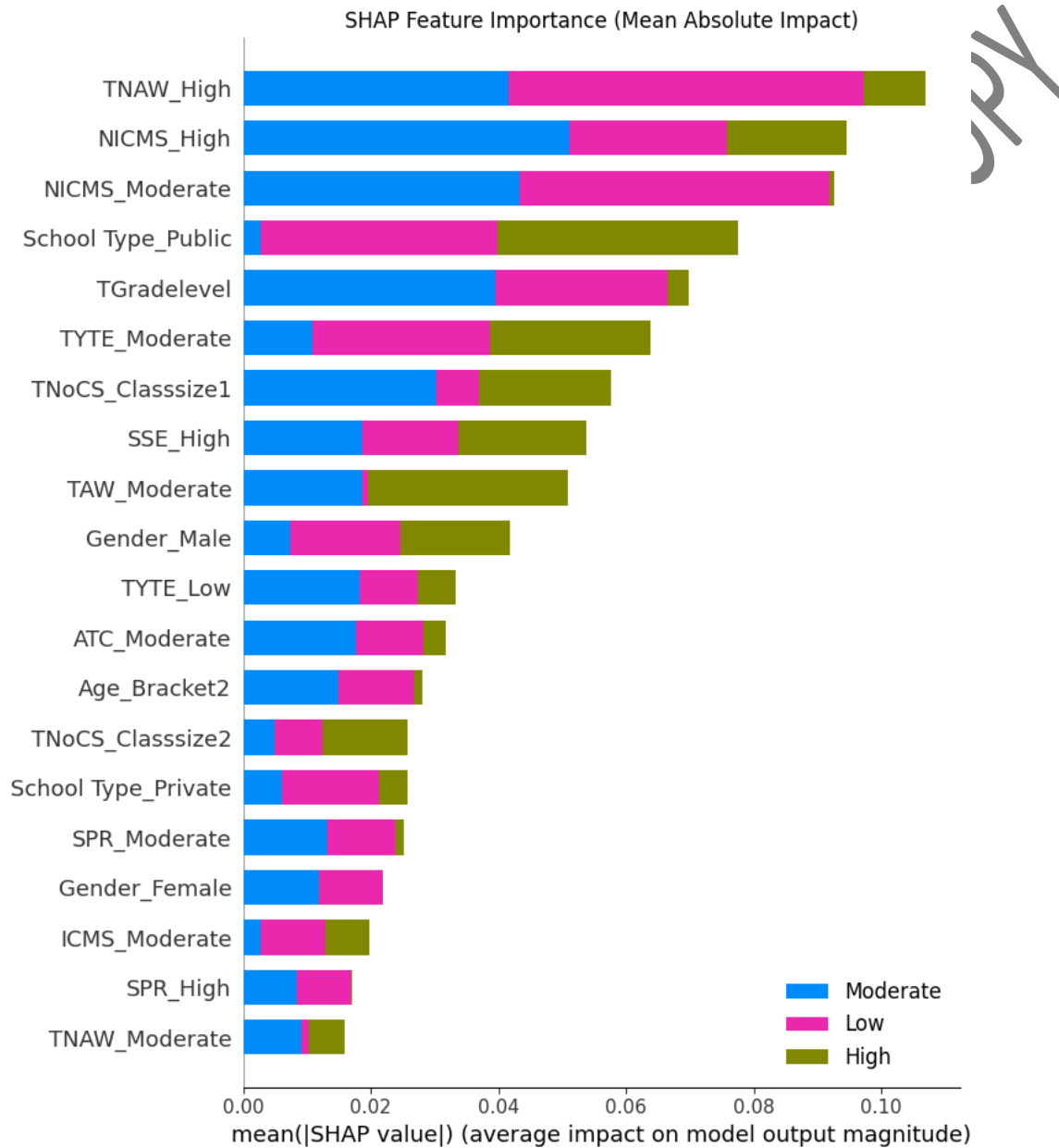
To understand the Gradient Boosting model's decision-making process at a granular level and identify the specific contributions of individual features to its predictions for student chemistry performance, a SHAP (Shapley Additive Explanations) analysis was conducted. SHAP values quantify the impact of each feature on the model's output, enabling the interpretation of how individual feature values influence the prediction for each class. Figure 4.4 visually represents the mean absolute SHAP value for each feature, broken down by the class it primarily predicted. The figure shows the SHAP Feature Importance plot, which provides a comprehensive explanation of how individual features specifically contribute to the Gradient Boosting model's predictions for student chemistry performance. The length of each bar indicates the overall

average magnitude of impact a feature has on the model's output, while the coloured segments within each bar detail which performance classes (moderate, low, high) are most influenced by that feature's contribution. The x-axis is labelled ($|\text{SHAP mean value}|$ average impact on model output magnitude). The legend indicates moderate chemistry performance, blue indicates moderate chemistry performance, magenta indicates low chemistry performance: olive green indicates high chemistry performance.

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Figure 4.4:

SHAP Feature Importance (Mean Absolute Impact) of Gradient Boosting Model



Source: Fieldwork, 2025

This plot shows the average magnitude of impact each feature has on the Gradient Boosting model's output. The coloured segments within each bar indicate the proportion of that impact that is attributed to predicting the 'Moderate' (blue), 'Low' (magenta), or 'High' (olive green) chemistry achievement classes.

Figure 4.4 shows the SHAP Feature display, which is a horizontal bar chart where each bar represents a feature. The length of the bar indicates the mean absolute SHAP value (average impact on model output magnitude). Each bar is segmented by colour: blue for 'Moderate' chemistry performance, magenta for 'Low' chemistry performance, and olive green for 'High' chemistry performance. The features are ranked from most impactful (top) to least impactful (bottom) based on their total bar length. The top features are TNAW High (Teacher Non-Academic Workload: High), NICMS High (Non-Instructional Classroom Management Skills: High), NICMS_Moderate (Non-Instructional Classroom Management Skills: Moderate), School_Type_Public (School type: Public), TGradelevel (Teacher grade level), TYTE_Moderate (Years of Teaching Experience: Moderate), TNoCS_Classsize1 (Number of chemistry students in class: less than 20), SSE_High (Student Self-Efficacy: High), TAW_Moderate (Teachers' Academic Workload: Moderate), and Gender_Male (gender of student: Male).

The result revealed that high Teacher Non-Academic Workload is the single most impactful feature in the prediction of students' chemistry achievement. Its substantial mean absolute SHAP value significantly contributes to the model's prediction of Moderate and Low student performance, with a notable portion of its influence directed towards the 'Moderate' class. This demonstrates how a high non-academic workload for teachers distinctly predisposes students to perform poorly in chemistry.

Furthermore, the result showed that high Non-Instructional Classroom Management Skills and moderate Non-Instructional Classroom Management Skills are highly influential. Both feature categories show a strong contribution to the prediction of Moderate and Low student performance, indicating how varying levels of non-instructional classroom management skills play a crucial role in shaping these outcomes. The finding implies that, as the non-instructional classroom management skill of teachers gets higher, the performance of their students becomes poorer.

The result also revealed that public school attendance stands out as a significant contributor, with its impact predominantly observed in the prediction of Moderate and Low performance in chemistry. This highlights the model's ability to leverage school environment characteristics in its predictions. The result showed that the chemistry performance gets poorer if they attend public school. Similarly, Teacher Grade Level and moderate Years of Teaching Experience exert notable influence, primarily impacting the prediction of moderate and low performance, showcasing the value of teacher experience and position. This implies that the lower the position and experience of a teacher, the poorer the performance of their students in chemistry.

Further down the ranking, the result indicated that having fewer than 20 Students in a chemistry class is a consistent contributor to the predictions of chemistry performance among the secondary school students. Its impact is predominantly observed in the prediction of moderate and low performance in chemistry, implying that students in classes of this specific size are more predisposed to achieving moderate or low chemistry performance. Similarly, high Student Self-Efficacy was influential in predicting low to moderate chemistry performance. This suggests that even with high self-efficacy, students are more likely to achieve moderate or low

chemistry performance, indicating that other factors might be more dominant in determining higher outcomes.

Moderate Teacher Academic Workload was also impactful in predicting moderate and Low performance. This implies that with a moderately high academic workload, students are more predisposed to achieving moderate or low chemistry performance, suggesting that a moderate workload might not be sufficient to drive higher outcomes, indicating that low academic workload might be just what is needed to make students perform excellently in chemistry. Furthermore, being a male significantly predisposes a student to achieving poorly or fairly in chemistry. This implies that male students are more predisposed to achieving moderate or low chemistry performance. Across almost all features, the most substantial portion of their impact (represented by the blue segment) is on the prediction of moderate student performance, followed by a discernible impact on Low performance (magenta segment). This consistent pattern reveals the model's robust capacity to discern and predict these two significant performance levels, indicating that the model's primary explanatory power lies in differentiating between moderate and low outcomes.

The results showed that when a student is taught by a chemistry teacher that has high non-academic workload, who simultaneously demonstrates high or moderate non-instructional classroom management skills, and teaching in a public school setting especially where the instructor holds a lower grade level or moderate years of teaching experience, and the class size is fewer than 20 students, such a student, even when possessing a strong sense of self-efficacy, is consistently predisposed to perform within the low to fair range in chemistry. This implies that for a student to perform higher in chemistry, strategic adjustments to these influential elements are imperative. This involves a concerted effort to alleviate high teacher non-academic

workloads, refine non-instructional classroom management skills towards optimal effectiveness, and implement targeted enhancements within public school environments. Such deliberate and well-calibrated strategic adjustments possess the potential to significantly elevate student performance, moving them beyond the foundational low to moderate levels and empowering them to aspire towards and achieve higher academic success.

4.2.2 Discussion of Findings

Research Question 4 seeks to dissect the Gradient Boosting model's decision-making process by examining the specific contributions of individual features to its predictions. The SHAP (Shapley Additive Explanations) analysis provides a sophisticated, granular view that goes beyond simple feature importance, revealing how and to what extent each feature pushes a prediction towards a specific class (low, moderate, or high). The results powerfully illustrate that the model's explanatory power is overwhelmingly concentrated on identifying the drivers of low and moderate chemistry performance. Furthermore, the analysis revealed several counterintuitive relationships that demand a critical, theory-guided interpretation, moving beyond simplistic cause-and-effect conclusions.

Confirmation of Environmental and Teacher-Related Barriers

The SHAP analysis provides strong, specific evidence for how systemic factors create barriers to high achievement. The finding that high Teacher Non-Academic Workload (TNAW_High) is the single most impactful feature, primarily driving predictions towards low and moderate outcomes, provides compelling support for the conclusions of³⁶ on teacher burnout. The SHAP plot visualizes precisely how this single factor acts as a strong negative force on student outcomes. Similarly, the impact of School Type Public in pushing predictions towards Low and

Moderate performance agrees with the research by³⁷ in the Nigerian context. The SHAP values quantify the public-school disadvantage that was identified in earlier stages of this research, showing it to be a key element in the model's predictive logic. The influence of TGradelevel and moderate Teacher Years of Teaching Experience (TYTE Moderate) further reinforces this narrative, aligning with the work of³⁸ by demonstrating that characteristics associated with less experienced or junior teachers are strong predictors of non-optimal student performance.

While some findings confirm existing literature, several key features present paradoxical relationships that challenge conventional wisdom and require deeper scholarly analysis. First, the finding that high Non-Instructional Classroom Management Skills (NICMS_High) strongly predicts Low and Moderate performance is profoundly counterintuitive. A literal interpretation, as suggested in the text provided, would mean that better management skills lead to worse outcomes. This would directly disagree with a vast body of educational research that links effective classroom management to improved student achievement. A more plausible, critical interpretation is that NICMS High is not a causal factor but rather a proxy for a challenging school environment. This interpretation finds support in the work of³⁹, who studied teacher practices in under-resourced systems. It is likely that teachers working in difficult schools with more disciplinary issues and lower-performing students are forced to develop exceptionally high non-instructional coping and management skills out of necessity. Therefore, the high NICMS does not cause poor performance; instead, the challenging environment likely causes both the low student performance and the development of these specific teacher skills.

Second, the small class with less than 20 students (TNoCS_Classsize1) predicted Low and Moderate performance, presents another paradox. This finding appears to contradict the conclusions of the extensive literature on the benefits of smaller class sizes for student

achievement. A probable explanation in the Nigerian context is student sorting. It is highly likely that these very small classes are not standard but are remedial classes created specifically for students who are already struggling academically. In this case, the small class size is an effect or an administrative response to low performance, not a cause of it. The SHAP analysis has correctly learned this association but interpreting it causally would be a serious error.

Third, perhaps most significantly, the finding that high Student Self-Efficacy (SSE High) contributes to predicting low and moderate academic performance is a direct and startling paradox. This presents a significant challenge to the conventional understanding of self-efficacy as a driver of success, as proposed by⁴⁰. Two scholarly interpretations explained this. The first may find agreement with research on the Dunning-Kruger effect⁴¹, which suggests that individuals with lower competence in a domain often overestimate their ability. The students may report high self-efficacy precisely because they are unaware of their own knowledge gaps. An alternative and equally powerful explanation supports an ecological systems perspective, consistent with the theories of Bronfenbrenner and⁴². This revealed that the negative environmental factors identified by the model (high teacher workload, challenging school type, etc.) are so powerful that they effectively suppress and override the potential benefits of a student's individual psychological strengths like self-efficacy. The SHAP values compellingly showed that even when a student possesses high self-efficacy, the weight of these other negative features could be enough to push the prediction down to a moderate or low outcome.

The most striking insight from the SHAP plot is the near-total absence of olive-green bars, representing contributions to high academic performance predictions. This revealed that the model has learned a great deal about the factors that could lead to failure or mediocrity but has learned almost nothing about the pathways to excellence. The dataset and the features within it

are predominantly characterized by risk factors and barriers. The final summary in the provided text correctly synthesizes this. For instance, a student is predisposed to low-to-fair performance when a confluence of negative factors is present. The implication is that achieving high performance requires the removal of these negatives. This deficit-model perspective, while valuable, highlights a gap in the data's ability to explain what positively drives exceptional academic performance.

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Chapter Five

Conclusion

This final chapter brings together the different threads of the research project. After the detailed dive into the data and models in chapter four, the goal here is to step back and look at the bigger picture with the aim of summarizing the key results, writing the main conclusions, and discussing the implications of this work. This chapter answers so what question, framing the study's findings within the wider conversation in education and technology. This study focused on the use of the power of modern machine learning to get a clearer picture of what drives performance in secondary school chemistry. The researcher investigated the performance of ten different algorithms, feeding them with a rich set of data that went beyond just student grades to include their attitudes, teachers' workloads and experience. The hope was not only to build a model that could predict student performance but also to use it to understand which of these many factors truly matter the most. The result of the analysis in Chapter Four was significant, and at times surprising, insights. It became clear that a group of models called ensemble methods specifically Gradient Boosting did the best job. But more importantly, study revealed that the most powerfully predicted students' performance was not necessarily student-focused at all. The biggest factors were the teachers' working conditions. At the same time, the analysis showed that the model, for all its power, had a blind spot when it came to identifying the students at the very top and those in the struggling category.

5.1 Summary of Findings

When all the data was analyzed, a clear picture began to emerge. The Best Tool for the Job: Of the ten different machine learning models tested, Gradient Boosting was the clear winner. It wasn't just about having the highest overall accuracy; its real strength was in its ability to tell different student performance levels apart, which was reflected in its top scores on metrics like the F1-score (0.6524) and ROC AUC (0.7714). What Really Matters? The model pointed to a clear set of priorities. The factors that had the biggest impact on student performance were all related to the school environment and the teacher's professional life. The three most powerful predictors were high teacher non-academic workload, extensive teacher experience, and whether the student attended a private school.

In what might be a surprise to many, a teacher's formal degree (whether a B.Sc, M.Sc, etc.) had zero predictive importance in the model. It simply was not a factor in predicting student success in this context. An Uneven Picture of Accuracy: The model was very good at identifying students in the Moderate performance category, getting it right about 85.6% of the time. But it struggled with the students on the edges. It correctly identified only about half (55.7%) of the low performing students and was almost completely blind to the high performers, identifying only 12.5% of them correctly. A Model Focused on Risk, Not Success: When a tool called SHAP was used to explain the model's decisions, we learned a lot about what puts students at risk of low or moderate performance. Things like heavy teacher workload or attending a public school were strong signals for these outcomes. However, the model learned almost nothing about what it takes to achieve excellence; it couldn't identify a clear pathway to high academic achievement.

5.2 Conclusion

The study leads to a few critical conclusions. First, while these sophisticated machine learning models are powerful tools, they are not a magic bullet for education. The Gradient Boosting model can give us a good sense of the average student's trajectory, but its unreliability in spotting the students who need the most help or the most enrichment makes it a risky tool for making important decisions about individual students. In its current form, it is not ready for high-stakes deployment. Second, the research has equally revealed that what drives learning in schools is beyond teachers' qualifications and students' factors. The story told by the data is that the conditions of the school environment are paramount. A teacher's daily workload and years of hands-on experience were far more powerful drivers of student success than the degrees hanging on their wall. Finally, the findings suggest that a student's individual mindset may be positive but could be overwhelmed by a negative or unsupportive environment. Even students with high self-efficacy were predicted to have moderate or low performance when other negative factors were present. It suggests that a student cannot thrive, no matter how motivated they are, if they are learning in a system that does not support learning.

5.3 Recommendations

The most urgent task is to address teacher's workload in senior secondary schools. Reducing the burden of non-academic duties on teachers should be a top priority, as it was the major factor affecting students' academic performance in chemistry. Hiring and professional development should focus more on practical experience and demonstrated skill rather than just on credentials. The data suggests that years in the classroom are a much better indicator of effectiveness than advanced degrees.

In building these models, the issue of class imbalance must be addressed. Techniques like SMOTE or cost-sensitive learning are essential to make the models better at seeing the students in the minority, the high and low performers. We need to be critical when interpreting these models. When a model says small class size or high management skill predicts poor outcomes, we need to dig deeper and ask if it's really measuring what we think it is, or if it has just learned a proxy for a remedial class or a difficult environment

School administrators should work out a blueprint for even distribution of both academic and non-academic responsibilities to teachers. This would help in mitigating the negative influence of teachers' workload on effective teaching and learning. This can be achieved by getting non-academic staff involved in non-academic activities.

5.4 Contribution to Knowledge

This research pushes the conversation forward in education in a few important ways. A better Methodological Toolkit: Instead of just picking one algorithm, this study tested a whole suite of them, showing that the best model is not always the one with the highest accuracy. It makes a strong case for using metrics like the F1-score and ROC AUC to find models that are good in the classification of students based on performance. But it didn't stop there. By using a new technique called SHAP to open the black box of the model to see how it was making its decisions, revealing its bias toward predicting moderate and low outcomes.

Challenging Old Theories: The results have something important to say about long-held educational theories. The idea that a more qualified teacher is always a better one was directly challenged by the data, which showed that formal degrees had zero impact on predictions. The study also gave a real-world example of Bronfenbrenner's ecological systems theory. The

surprising finding that high student self-efficacy could lead to a prediction of lower performance provides a powerful illustration of how a negative school environment can effectively cancel out a student's positive mindset.

A Story Specific to Its Context: This work shows why context is important. Findings that seem bizarre on the surface make sense in the understanding of the local reality of the Nigerian school system. The seemingly negative effects of high classroom management practices or small class sizes are likely not what they appear; instead, they are probably signs of teachers adapting to difficult environments or students being placed in remedial groups. This is a crucial reminder that we cannot just parachute these models into different parts of the world and expect them to work the same way.

Clear Guidance for Policy: The study offers clear, evidence-based advice. The message for policymakers is to stop focusing so much on teacher credentials and start focusing on teacher conditions. The data provides a strong argument for reducing workloads and investing in the public school system. It also serves as a warning about the responsible use of AI in schools. Simply deploying this model to make decisions about students would be a mistake, as its biases could end up hurting the very students who need the most support.

5.5 Suggestion for Further Studies

The generalizability of the study could be improved by expanding the scope of future study to other geopolitical zones of the country for more robust data. Other teacher-related and student-related features should be used in future study to determine the performance metrics of the machine learning algorithms. Furthermore, study on other machine learning algorithms should be considered in the future for the determination of the predictive capabilities of students'

academic performance in other subjects. A longitudinal study may be explored for studies on observation of the population to establish the sequence of events that drive learning in secondary schools. In addition to this, techniques like SMOTE or cost sensitive learning could be adopted in further studies to make the model better by identifying the students in the minority group.

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Appendix
Questionnaire
Lead City University Ibadan
Faculty of Education and Social Science
Department of Arts & Social Science Education (Measurement & Evaluation Unit)
Teachers Workload Rating Scale (TWRS)

Dear sir/ma,

The researcher is a student at Lead City University, Ibadan, and is carrying out research on some factors that could influence the academic achievement of students in chemistry. Kindly respond to all the questions in this instrument.

This instrument is constructed to elicit information on Teachers Academic Workload and Non-Academic Workload in secondary schools. The information should be treated with utmost confidentiality and should be used solely for research purposes.

Please respond to the questions by ticking (✓) the boxes. Write your responses where required and rate the items in the table based on the degree of occurrence.

Thank you.

SECTION A: DEMOGRAPHIC DATA

School Type: Public ☐ Private ☐

Gender: Male ☐ Female ☐

Grade Level:

Education District:

Highest Qualification: B.Sc. / HND ☐ M.Sc./M.E ☐ Ph.D ☐

Number of Chemistry Students in a class ☐ ☐ ☐ ☐
less than 20 20-30 31-40 41 and above

Number of Chemistry Teachers in the school:

Years of Teaching Experience: ☐ ☐ ☐
Less than 10 11-20 21 and above

Are you a part time or permanent teacher?

SECTION B: Teachers' Academic Workload

S/N	Item	Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree
1.	Too many teaching periods						
2.	Covering for absent colleagues						
3.	Organization of make-up classes for students						
4.	Students' assignments are brought home for marking because they are many						
5.	Assist students with their classwork						
6.	Teaching of other science subjects						
7.	Covering of more than 30 teaching periods a week						
8.	Involved in setting-up the laboratory for practical activities						

SECTION C: Teacher Non-Academic Workload

S/N	ITEM	Never	Rarely	Sometimes	Often	Very often	Always
1.	Updating of students' attendance records						
2.	Special administrative duties are assigned to me by the principal						
3.	Organization of extra-curricular activities for students						
4.	I am involved in newly admitted students' orientation programme						

5.	I attend the meeting of the timetable committee						
6.	I supervise the conduct morning assembly						
7.	I counsel students when the need arises						
8.	I supervision external examinations such as WASSCE and NECO						
9.	I attend to parents complaints about their children						
10.	I prepare students for inter-house sports competitions						

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4.	I distribute tasks to students during teaching					
5.	I point at students to answer questions					
6.	I instruct students to read from the chalkboard					
7.	I move round the class while students write					
8.	I discourage chorus answers					
9.	I inspect students' notebooks while writing					
10.	I review what students have learnt for learning deficiencies					

Non-Instructional Classroom Management Practices

	Item	Never	Rarely	Sometimes	Often	Always
1.	I set rules that guide classroom activities					
2.	I punish students for disobeying classroom rules					
3.	I discipline disruptive behavior in the classroom					
4.	Students' misconduct during teaching are overlooked					
5.	I leave students to form their opinions in the classroom					
6.	I do not discipline students for breaking classroom rules					
7.	I talk on self-control in the classroom					
8.	I discourage classroom disorganization					
9.	I encourage students to take permission before leaving the classroom					
10.	I emphasize the need to pay attention during classroom activities					

Lead City University Ibadan
Faculty of Education and Social Science
Department of Arts & Social Science Education (Measurement & Evaluation Unit)

Students Factors Questionnaire
(SFQ)

Dear Student,

Research is being conducted on some factors that could influence academic achievement of students in chemistry. To achieve this purpose, this instrument is designed to elicit necessary information from you. Please respond to every item in the instrument by ticking (✓) each item based on the degree of occurrence of the attribute you are rating. Please be assured that the information that would be elicited from you will be solely used for research.

Thank you for your cooperation.

SECTION A: DEMOGRAPHIC DATA

School Type: Public ☐ Private ☐
Gender: Male ☐ Female ☐
Age: ☐ ☐ ☐ ☐
14-16 17- 19 20-22 Above 22

SECTION B: Attitude Towards Chemistry

S/N	Item	Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree
1.	Some chemistry topics are difficult to understand						
2.	Enjoy chemistry practical class						
3.	Am happy when writing chemistry assignment						
4.	Knowledge of chemistry helps me to understand other subjects						
5.	Only super brilliant students can understand chemistry						

6.	There is preference for chemistry practical when compared to essay						
7.	Reading chemistry textbooks is interesting						
8.	Calculation aspect of chemistry makes me to lose interest in the subject						
9.	Chemical equations in chemistry are difficult to understand						
10.	Chemistry is the most difficult science subject						

SECTION B: Student Self-Efficacy

S/N	Item	Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree
1.	Chemistry questions can be solved by trying and retrying						
2.	Chemistry examination can be passed						
3.	Difficult chemistry questions are easily abandoned						
4.	Good grades can be obtained in Chemistry						
5.	Solving of chemistry questions can be done through determination						
6.	Practical activities are carried out easily with my basic knowledge						
7.	Regular attendance in chemistry class has helped my understanding						
8.	Hard work pays off						
9.	Any questions in chemistry can be answered correctly						
10.	Unexpected event can effectively be dealt with						

SECTION C: Student Peer Relationship

S/N	Item	Never	Rarely	Sometimes	Often	Very Often	Always
1.	I share academic challenges with my friends						
2.	I follow my classmates to the school library						
3.	I discuss with my friends about many academic topics						
4.	My friend's poor attitude to reading discourages me from reading						
5.	The brilliance of my friends inspires me to work harder						
6.	My friends discourage me from doing my classwork						
7.	My friends inspire me when they answer questions in the classroom						
8.	I enjoy talking to my friend instead of doing my chemistry assignment						

CHEMISTRY EXAMINATION SYLLABUS

SECTION A

CONTENT	NOTES
1.0 INTRODUCTION TO CHEMISTRY (a) (i) Measurement of physical quantities. (ii) Scientific measurements and their importance in chemistry. (b) Scientific Methods	(1) Measurement of mass, length, time, temperature and volume. (2) Appropriate SI units and significant figures. (3) Precision and accuracy in measurement. Outline the scientific method to include: Observation, hypothesis, experimentation, formulation of laws and theories.
2.0 STRUCTURE OF THE ATOM (a) Gross features of the atom. (b) (i) Atomic number/proton number, number of neutrons, isotopes, atomic mass, mass number.	(1) Short account of Dalton's atomic theory and limitations, J.J. Thompson's experiment and Bohr's model of the atom. (2) Outline description of the Rutherford's alpha scattering experiment to establish the structure of the atom. Meaning and representation in symbols of atoms and sub-atomic particles.

CONTENT	NOTES
(ii) Relative atomic mass (A_r) and relative molecular mass (M_r) based on Carbon-12 scale. (iii) Characteristics and nature of matter. (c) Particulate nature of matter: physical and chemical changes. (d) (i) Electron Configuration (ii) Orbitals (iii) Rules and principles for filling in electrons.	(1) Atomic mass as the weighted average mass of isotopes. Calculation of relative mass of chlorine should be used as an example. (2) Carbon-12 scale as a unit of measurement. Definition of atomic mass unit. Atoms, molecules and ions. Definition of particles and treatment of particles as building blocks of matter. Explain physical and chemical changes with examples. Physical change- melting of solids, magnetization of iron, dissolution of salt etc. Chemical change- burning of wood, rusting of iron, decay of leaves etc. Detailed electron configurations (s,p,d) for atoms of the first thirty elements. Origin of s,p and d orbitals as sub-energy levels; shapes of s and p orbitals only. (1) Aufbau Principle, Hund's Rule of Maximum Multiplicity and Pauli Exclusion Principle. (2) Abbreviated and detailed electron configuration in terms of s, p, and d.

CONTENT	NOTES
3.0 STANDARD SEPARATION TECHNIQUES FOR MIXTURES (a) Classification of mixtures. (b) Separation techniques (c) Criteria for purity.	Solid-solid, solid-liquid, liquid-liquid, gas-gas with examples. Crystallization, distillation, precipitation, magnetization, chromatography, sublimation etc. Boiling point for liquids and melting point for solids.
4.0 PERIODIC CHEMISTRY (a) Periodicity of the elements. (b) Different categories of elements in the periodic table. (c) Periodic law: (i) Trends on periodic table; (ii) Periodic gradation of the elements in the third period (Na - Ar).	Electron configurations leading to group and periodic classifications. Metals, semi-metals, non-metals in the periodic table and halogens. Alkali metals, alkaline earth metals and transition metals as metals. Explanation of the periodic law. Periodic properties; atomic size, ionic size, ionization energy, electron affinity and electronegativity. Simple discrepancies should be accounted for in respect to beryllium, boron, oxygen and nitrogen. (1) Progression from: (i) metallic to non-metallic character of element; (ii) ionic to covalent bonding in compounds.

CONTENTS	NOTES
(d) Reactions between acids and metals, their oxides and trioxocarbonates (IV). (e) Periodic gradation of elements in group seven, the halogens: F, Cl, Br and I. (f) Elements of the first transition series. $_{21}\text{Sc} - _{30}\text{Zn}$	(2) Differences and similarities in the properties between the second and the third period elements should be stated. (1) Period three metals (Na, Mg, Al). (2) Period four metals (K, Ca). (3) Chemical equations. (4) pH of solutions of the metallic oxides and trioxocarbonates. Recognition of group variations noting any anomalies. Treatment should include the following: (a) physical states, melting and boiling points; (b) variable oxidation states; (c) redox properties of the elements; (d) displacement reaction of one halogen by another; (e) reaction of the elements with water and alkali (balanced equations required). (1) Their electron configurations, physical properties and chemical reactivity of the elements and their compounds. (2) Physical properties should include: physical states, metallic properties and magnetic properties. (3) Reactivity of the metals with air, water, acids and comparison with s-block elements (Li, Na, Be, Mg).

CONTENT	NOTES
5.0 CHEMICAL BONDS (a) Interatomic bonding (b) (i) Formation of ionic bonds and compounds. (ii) Properties of ionic compounds. (c) Naming of ionic compounds. (d) Formation of covalent bonds and compounds. (e) (i) Properties of covalent compounds.	(4) Other properties of transition metals should include: (a) variable oxidation states; (b) formation of coloured compounds; (c) complex formation; (d) catalytic abilities; (e) paramagnetism; (f) hardness. Meaning of chemical bonding. Lewis dot structure for simple ionic and covalent compounds. Formation of stable compounds from ions. Factors influencing formation: ionization energy; electron affinity and electronegativity difference. Solubility in polar and non-polar solvents, electrical conductivity, hardness and melting point. IUPAC system for simple ionic compounds. Factors influencing covalent bond formation. Electron affinity, ionization energy, atomic size and electronegativity. Solubility in polar and non-polar solvents, melting point, boiling point and electrical conductivity.

(ii) Coordinate (dative) covalent bonding.	Formation and difference between pure covalent and coordinate (dative) covalent bonds.
CONTENT	NOTES
(f) Shapes of molecular compounds.	Linear, planar, tetrahedral and shapes for some compounds e.g. BeCl_2 , BF_3 , CH_4 , NH_3 , CO_2 .
(g) (i) Metallic Bonding	
(ii) Factors influencing its formation.	Factors should include: atomic radius, ionization energy and number of valence electrons. Types of specific packing not required.
(iii) Properties of metals.	Typical properties including heat and electrical conductivity, malleability, lustre, ductility, sonority and hardness.
(h) (i) Inter molecular bonding	Relative physical properties of polar and non-polar compounds.
(ii) Intermolecular forces in covalent compounds.	Description of formation and nature should be treated. Dipole-dipole, induced dipole-dipole, induced dipole-induced dipole forces should be treated under van der Waal's forces.
(iii) Hydrogen bonding	Variation of the melting points and boiling points of noble gases, halogens and alkanes in the homologous series explained in terms of van der Waal's forces; and variation in the boiling points of H_2O , and H_2S explained using Hydrogen bonding.
(iii) van der Waals forces	
(iv) Comparison of all bond types.	

CONTENT	NOTES
6.0 STOICHIOMETRY AND CHEMICAL REACTIONS (a) (i) Symbols, formulae and equations. (ii) chemical symbols (iii) Empirical and molecular formulae. (iv) Chemical equations and IUPAC names of chemical compounds. (v) Laws of chemical combination. (b) Amount of substance.	Symbols of the first thirty elements and other common elements that are not among the first thirty elements. Calculations involving formulae and equations will be required. Mass and volume relationships in chemical reactions and the stoichiometry of such reactions such as: calculation of percentage composition of element. (1) Combustion reactions (including combustion of simple hydrocarbons) (2) Synthesis (3) Displacement or replacement (4) Decomposition (5) Ionic reactions (1) Laws of conservation of mass. (2) Law of constant composition. (3) Law of multiple proportions. Explanation of the laws to balance given equations. (4) Experimental illustration of the law of conservation of mass. (1) Mass and volume measurements. (2) The mole as a unit of measurement; Avogadro's constant, $L = 6.02 \times 10^{23}$ entities mol^{-1}. (3) Molar quantities and their uses. (4) Moles of electrons, atoms, molecules, formula units etc.

CONTENT	NOTES
(c) Mole ratios	Use of mole ratios in determining stoichiometry of chemical reactions. Simple calculations to determine the number of entities, amount of substance, mass, concentration, volume and percentage yield of product.
(d) (i) Solutions	(1) Concept of a solution as made up of solvent and solute. (2) Distinguishing between dilute solution and concentrated solution. (3) Basic, acidic and neutral solutions.
(ii) Concentration terms	Mass (g) or moles (mol) per unit volume. Emphasis on current IUPAC chemical terminology, symbols and conventions. Concentration be expressed as mass concentration, g dm^{-3} , molar concentration, mol dm^{-3} .
(iii) Standard solutions.	(1) Preparation of some primary standards e.g anhydrous Na_2CO_3 , $(\text{COOH})_2 \cdot 2\text{H}_2\text{O}/\text{H}_2\text{C}_2\text{O}_4 \cdot 2\text{H}_2\text{O}$. (2) Meaning of the terms primary standard, secondary standard and standard solution.
(e) Preparation of solutions from liquid solutes by the method of dilution.	Dilution factor

CONTENT	NOTES
7.0 STATES OF MATTER (a) (i) Kinetic theory of matter. (ii) Changes of state of matter. (iii) Diffusion	(1) Postulates of the kinetic theory of matter. (2) Use of the kinetic theory to explain the following processes: melting of solids, boiling of liquids, evaporation of liquids, dissolution of solutes, Brownian motion and diffusion. (1) Changes of state of matter should be explained in terms of movement of particles. It should be emphasized that randomness decreases (and orderliness increases) from gaseous state to liquid state and to solid state and vice versa. (2) Illustrations of changes of state using the different forms of water, iodine, sulphur, naphthalene etc. (3) Brownian motion to be illustrated using any of the following experiments: (a) pollen grains/powdered sulphur in water (viewed under a microscope); (b) smoke in a glass container illuminated by a strong light from the side; (c) a dusty room being swept and viewed from outside under sunlight. (1) Experimental demonstration of diffusion of two gases. (2) Relationship between speed at which different gas particles move and the masses of particles. (3) Experimental demonstration of diffusion of solute particles in liquids.

CONTENT	NOTES
(b) Gases: (i) Characteristics and nature of gases; (ii) The gas laws; (iii) Laboratory preparation and properties of some gases. (c) (i) Liquids (ii) Vapour and gases.	Arrangement of particles, density, shape and compressibility. The Gas laws: Charles'; Boyle's; Dalton's law of partial pressure; Graham's law of diffusion, Avogadro's law. The ideal gas equation of state. Qualitative explanation of each of the gas laws using the kinetic model. The use of Kinetic molecular theory to explain changes in gas volumes, pressure, temperature. Mathematical relations of the gas law $PV = nRT$ Ideal and Real gases Factors responsible for the deviation of real gases from ideal situation. (1) Preparation of the following gases: H_2, NH_3 and CO_2. Principles of purification and collection of gases. (2) Physical and chemical properties of the gases. Characteristics and nature of liquids based on the arrangement of particles, shape, volume, compressibility, density and viscosity. (1) Concept of vapour, vapour pressure, saturated vapour pressure, boiling and evaporation. (2) Distinction between vapour and gas. (3) Effect of vapour pressure on boiling points of liquids. (4) Boiling at reduced pressure.

CONTENT	NOTES
(d) Solids: (i) Characteristics and nature; (ii) Types and structures; (iii) Properties of solids. (e) Structures, properties and uses of diamond and graphite. (f) Determination of melting points of covalent solids.	(1) Ionic, metallic, covalent network and molecular solids. Examples in each case. (2) Arrangements of particles ions, molecules and atoms in the solid state. Relate the properties of solids to the type of interatomic and intermolecular bonding in the solids. Identification of the types of chemical bonds in graphite and differences in the physical properties. The uses of diamond and graphite related to the structure. The use of iodine in everyday life. Melting points as indicator of purity of solids e.g. Phenyl methanedioic acid (benzoic acid), ethanedioic acid (oxalic) and ethanamide.
8.0 ENERGY AND ENERGY CHANGES (a) Energy and enthalpy (b) Description, definition and illustrations of energy changes and their effects.	Explanation of the terms energy and enthalpy. Energy changes associated with chemical processes. (1) Exothermic and endothermic processes. (2) Total energy of a system as the sum of various forms of energy e.g. kinetic, potential, electrical, heat, sound etc.

CONTENT	(3) Enthalpy changes involved in the following processes: combustion, dissolution and neutralization. NOTES
9.0 ACIDS, BASES AND SALTS (a) Definitions of acids and bases. (b) Physical and chemical properties of acids and bases. (c) Acids, bases and salts as electrolytes. (d) Classification of acids and bases. (e) Concept of pH	(1) Arrhenius concepts of acids and bases in terms of H_3O^+ and OH^- ions in water. (2) Effects of acids and bases on indicators, metal Zn, Fe and trioxocarbonate (IV) salts and hydrogentrioxocarbonate (IV) salts. Characteristic properties of acids and bases in aqueous solution to include: (a) conductivities, taste, litmus/indicators, feel etc.; (b) balanced chemical equations of all reactions. Electrolytes and non-electrolytes; strong and weak electrolytes. Evidence from conductivity and enthalpy of neutralization. (1) Strength of acids and bases. (2) Classify acids and bases into strong and weak. (3) Extent of dissociation reaction with water and conductivity. (4) Behaviour of weak acids and weak bases in water as example of equilibrium systems. (1) Definition of pH and knowledge of pH scale.

	(2) Measurement of pH of solutions using pH meter, calometric methods or universal indicator. (3) Significance of pH values in everyday life e.g. acid rain, pH of soil, blood, urine.
CONTENT	NOTES
(f) Salts: (i) Laboratory and industrial preparation of salts; (ii) Uses; (iii) Hydrolysis of salt. (g) Deliquescent, efflorescent and hygroscopic compound. (h) Acid-Base indicators	Meaning of salts. Types of salts: normal, acidic, basic, double and complex salts. (1) Description of laboratory and industrial production of salts. (2) Mining of impure sodium chloride and conversion into granulated salt. (3) Preparation of NaOH, Cl₂ and H₂. (1) Explanation of how salts forms acidic, alkaline and neutral aqueous solutions. (2) Behaviour of some salts (e.g NH₄Cl, AlCl₃, Na₂CO₃, CH₃COONa) in water as examples of equilibrium systems. (3) Effects of charge density of some cations and anions on the hydrolysis of their aqueous solution. Examples to be taken from group 1, group 2, group 3 and the d-block element. Use of hygroscopic compounds as drying agent should be emphasized. (1) Qualitative description of how acid-base indicator works. (2) Indicators as weak organic acids or bases (organic dyes).

(i) Acid-Base titration CONTENT	(3) Colour of indicator at any pH dependent on relative amounts of acid and forms. (4) Working pH ranges of methyl orange and phenolphthalein. (1) Knowledge and correct use of relevant apparatus. (2) Knowledge of how acid-bases indicators work in titrations. NOTES
10.0 SOLUBILITY OF SUBSTANCES (a) General principles	(3) Acid-base titration experiments involving HCl, HNO₃, H₂SO₄ and NaOH, KOH, Ca(OH)₂, CO₃²⁻, HCO₃⁻. (4) Titration involving weak acids versus strong bases, strong acids versus weak bases and strong acids versus strong bases using the appropriate indicators and their applications in quantitative determination; e.g. concentrations, mole ratio, purity, water of crystallization and composition. (1) Meaning of Solubility. (2) Saturated and unsaturated solutions. (3) Saturated solution as an equilibrium system. (4) Solubility expressed in terms of: mol dm⁻³ and g dm⁻³ of solution/solvent. (5) Solubility curves and their uses. (6) Effect of temperature on solubility of a substance. (7) Relationship between solubility and crystallization. (8) Crystallization/recrystallization as a method of purification.

(b) Practical application of solubility.	(9) Knowledge of soluble and insoluble salts of stated cations and anions. (10) Calculations on solubility. Generalization about solubility of salts and their applications to qualitative analysis. e.g. Pb^{2+}, Ca^{2+}, Al^{3+}, Cu^{2+}, Fe^{2+}, Fe^{3+}, Cl^-, Br^-, I^-, SO_4^{2-}, S^{2-}, and CO_3^{2-}, Zn^{2+}, NH_4^+, SO_3^{2-} Explanation of solubility rules.
CONTENT	NOTES
11.0 CHEMICAL KINETICS AND EQUILIBRIUM SYSTEM (a) Rate of reactions: (i) Factors affecting rates; (ii) Theories of reaction rates;	(1) Definition of reaction rate. (2) Observable physical and changes: colour, mass, temperature, pH, formation of precipitate etc. (1) Physical states, concentration/ pressure of reactants, temperature, catalysts, light, particle size and nature of reactants. (2) Appropriate experimental demonstration for each factor is required. (1) Collision and transition state theories to be treated qualitatively only. (2) Factors influencing collisions: temperature and concentration. (3) Effective collision. (4) Activation energy. (5) Energy profile showing activation energy and enthalpy change. Drawing of graphs and charts.

(iii) Analysis and interpretation of graphs. (b) Equilibrium: (i) General Principle;	Explanation of reversible and irreversible reactions. Reversible reaction i.e. dynamic equilibrium. Equilibrium constant K must be treated qualitatively. It must be stressed that K for a system is constant at constant temperature. Simple experiment to demonstrate reversible reactions.
CONTENT	NOTES
(ii) Le Chatelier's principle. 12.0 REDOX REACTIONS (a) Oxidation and reduction process. (b) Oxidizing and reducing agents. (c) Redox equations (d) Electrochemical cells: (i) Standard electrode potential; (ii) Drawing of cell diagram and writing cell notation.	Prediction of the effects of external influence of concentration, temperature, pressure and volume changes on equilibrium systems. (1) Oxidation and reduction in terms of: (a) addition and removal of oxygen and hydrogen; (b) loss and gain of electrons; (c) change in oxidation numbers/states. (2) Determination of oxidation numbers/states. (1) Description of oxidizing and reducing agents in terms of: (a) addition and removal of oxygen and hydrogen; (b) loss and gain of electrons; (c) change in oxidation numbers/state. Balancing redox equations by:

CONTENT	NOTES
(iii) e.m.f of cells; (iv) Application of Electrochemical cells. (e) Electrolysis: (i) Electrolytic cells; (ii) Principles of electrolysis; (iii) Factors influencing discharge of species; (iv) Faraday's laws; (v) Practical application;	(a) ion, electron or change in oxidation number/states; (b) half reactions and overall reaction. Definition/Explanation (1) Standard hydrogen electrode: meaning of standard electrode potential (E°) and its measurement. (2) Only metal/metal ion systems should be used. (1) Electrochemical cells as a combination of two half-cells. (2) The meaning of magnitude and sign of the e.m.f. (1) Distinction between primary and secondary cells (2) Daniell cell, lead acid battery cell, dry cells, fuel cells and their use as generators of electrical energy from chemical reactions. Definition. Comparison of electrolytic and electrochemical cells; weak and strong electrolyte. Mechanism of electrolysis. Limit electrolytes to molten PbBr_2 and NaCl, dilute NaCl solution, concentrated NaCl solution, $\text{CuSO}_{4(\text{aq})}$, dilute H_2SO_4, $\text{NaOH}_{(\text{aq})}$ and $\text{CaCl}_{2(\text{aq})}$ (using platinum or graphite and copper electrodes).

CONTENT	NOTES
(vi) Corrosion of metals. 13.0 CHEMISTRY OF CARBON COMPOUNDS (a) Classification (b) Functional group (b) Separation and purification of organic compounds. (c) Petroleum/crude oil	Simple calculations based on the relation $1F = 96,500 C$ and mole ratios to determine mass, volume of gases, number of entities, charges etc. using half and overall reactions. Electroplating, extraction and purification of metals. (1) Corrosion treated as a redox process. (2) Rusting of iron and its economic costs. (3) Prevention based on relative magnitude of electrode potentials and preventive methods like galvanizing, sacrificial/cathodic protection and non-redox methods (painting, greasing/oiling etc.). Broad classification into straight chain, branched chain, aromatic and alicyclic compounds. Systematic nomenclature of compounds with the following functional groups: alkanes, alkenes, alkynes, hydroxyl compounds (aliphatic and aromatic), alkanoic acids, alkyl alkanoates (esters and salts) and amines. Methods to be discussed should include: distillation; crystallization; drying and chromatography.

CONTENT	NOTES
(d) Determination of empirical and molecular formulae and molecular structures of organic compounds. (e) General properties of organic compounds: (i) Homologous series; (ii) Isomerism. (f) Alkanes: (i) Sources, properties; (ii) Uses. (g) Alkenes: (i) Sources and properties;	(1) Composition and classification. (2) Fractional distillation and major products. (3) Cracking and reforming. (4) Petro-chemicals: sources; uses e.g. as starting materials of organic synthesis. (5) Quality of petrol, meaning of octane number and its importance to the petroleum industry. (1) Gradation in physical properties. (2) Effects on the physical properties by introduction of active groups into the inert alkane. (1) Examples should be limited to compounds having maximum of five carbon atoms. (2) Differences between structural and geometric/stereo isomerism. (1) Laboratory and industrial preparations and other sources. (2) Nomenclature and structure. (3) Reactivity: (a) combustion; (b) substitution reactions;

	(c) cracking of large alkane molecules. As fuels, as starting materials for synthesis. Uses of haloalkanes and pollution effects. (1) Laboratory preparation. (2) Nomenclature and structure.
CONTENT	NOTES
(ii) Uses; (iii) Laboratory detection. (h) Alkynes: (i) Sources, characteristic properties and uses; (ii) Chemical reactions. (i) Benzene: (i) Structure and physical properties; (ii) Chemical properties.	(3) Addition reactions with halogens hydrogen, bromine water, hydrogen halides and acidified water. (4) Oxidation: hydroxylation with aqueous KMnO_4. (5) Polymerization. Use of reaction with Br_2/water, Br_2/CCl_4 and $\text{KMnO}_{4(\text{aq})}$ as means of characterizing alkenes. (1) Nomenclature and structure. (2) Industrial production of ethyne. (3) Uses of ethyne. (4) Distinguishing test between terminal and non-terminal alkynes. (5) Test to distinguish between alkane, alkene and alkyne. Chemical reactions: halogenation, combustion, hydration and hydrogenation. Resonance in benzene. Stability leading to substitution reactions.

CONTENT	NOTES
(J) Alkanols: (i) Sources, nomenclature and structure; (ii) Classification; (iii) Physical properties; (iv) Chemical properties; (v) Laboratory test; (vi) Uses. (k) Alkanoic acids: (i) Sources, nomenclature and structure; (ii) Physical properties;	(1) Addition reactions: hydrogenation and halogenation (mechanism not required). (2) Compare reactions with those of alkenes. (1) Laboratory preparation including hydration of alkenes. (2) Industrial and local production of ethanol including alcoholic beverages, (3) Harmful impurities and methods of purification should be mentioned. (4) Recognition of the structure of mono-, di- and triols. Primary, secondary and tertiary alkanols. Boiling point, solubility in water. Including hydrogen bonding effect. (1) Reaction with: (a) Na; (b) alkanoic acids (esterification); (c) conc. H_2SO_4. (2) Oxidation by: (a) $\text{KMnO}_{4(\text{aq})}$; (b) $\text{K}_2\text{Cr}_2\text{O}_{7(\text{aq})}$; (c) I_2 in $\text{NaOH}_{(\text{aq})}$. Laboratory test for ethanol.

CONTENT	NOTES
(iii) Chemical properties; (iv) Laboratory test; (iv) Uses. (l) Alkanoates as drivatives of alkanoic acids: (i) Sources, nomenclature, preparation and structure; (ii) Physical properties; (iii) Chemical properties; (iv) Uses. 14.0 CHEMISTRY, INDUSTRY AND THE ENVIRONMENT (a) Chemical industry	Methanoic acid –insect bite. Ethanoic acid – vinegar. Recognition of mono and dioic acid. Boiling point, solubility in water. Including hydrogen bonding effect. Acid properties only i.e. reactions with H_2O, NaOH, NH_3, NaHCO_3, Zn and Mg. Reaction with NaHCO_3, Na_2CO_3. Uses of ethanoic and phenyl methanoic (benzoic) acids as examples of aliphatic and aromatic acids respectively. Preparation of alkyl alkanoates (esters) from alkanoic acids. Solubility, boiling and melting point. Hydrolysis of alkyl alkanoates (mechanism not required). Uses of alkanoates to include production of soap, flavouring agent, plasticizers, as solvents and in perfumes.

CONTENT	NOTES
(b) Pollution: air, water and soil pollution; (c) Biotechnology. 15.0 BASIC BIOCHEMISTRY AND SYNTHETIC POLYMERS (a) Proteins: (i) Sources and properties; (ii) Uses of protein. (b) Amino acids	(1) Natural resources in candidate's own country. (2) Chemical industries in candidate's own country and their corresponding raw materials. (3) Distinction between fine and heavy chemicals. (4) Factors that determine location of chemical industries. (5) Effect of industries on the community. (1) Sources, effects and control. (2) Greenhouse effect and depletion of the ozone layer. (3) Biodegradable and non-biodegradable pollutants. Food processing, fermentation including production of gari, bread and alcoholic beverages e.g. Local gin. Proteins as polymers of amino acids molecules linked by peptide or amide linkage. Physical properties e.g. solubility Chemical properties to include: (a) hydrolysis of proteins; (b) laboratory test using Ninhydrin/Biuret reagent/Millons reagent.

CONTENT	NOTES
(c) Fats/oils: (i) Sources and properties; (ii) General structure of fats/oils; (iii) Preparation of soap; (iv) Uses of fats/oils. (d) Carbohydrates: (i) Sources and nomenclature; (ii) Properties;	(1) Nomenclature and general structure of amino acids. (2) Difunctional nature of amino acids. As alkyl alkanoates (esters). From animals and plants. Physical properties such as solubility. Chemical properties: (a) acidic and alkaline hydrolysis; (b) hydrogenation; (c) test for fats and oil. As mono-, di-, and tri- esters of propane-1,2,3-triol (glycerol). (1) Preparation of soap (saponification) from fats and oils. (2) Comparison of soap less detergents and their action on soft and hard water. (1) Classes of carbohydrates as: (a) monosaccharides; (b) disaccharides; (c) polysaccharides. (2) Name and components of various classes of carbohydrates.

CONTENT	NOTES
(iii) Carbohydrate as examples of polymer; (iv) Uses. (e) Synthetic polymers: (i) Properties; (ii) Uses of polymers.	(1) Physical properties such as solubility of sugars. (2) Chemical properties- Hydrolysis of disaccharides into monosaccharides. (3) Test for reducing sugars using sugar strips, Fehling's or Benedicts solution or Tollen's reagent. (1) Starch as a polymer made up of glucose units. (2) Condensation of monosaccharides to form disaccharides and polysaccharides. (1) Definition of terms: monomers, polymers and polymerization. (2) Addition and condensation polymerization. (3) Classification and preparation based on the monomers and comonomers. (1) Thermoplastics and thermosets. (2) Modification of properties of polymers. (3) Plastics and resins. (4) Chemical test on plastics using: (a) heat; (b) acids; (c) alkalis.

SECTION B

(For candidates in Ghana only)

CONTENTS	NOTES
1.0 STRUCTURE OF THE ATOM (a) Elementary treatment of mass spectrometer. (b) (i) Nuclear chemistry (ii) Types and nature of radiations: alpha, beta particles and gamma radiation. (iii) Radioactivity: induced/stimulated. (iv) Nuclear reactions: fission and fusion in nuclear reactions. (v) Effects and application of radioactivity	(1) Qualitative knowledge of the mass spectrometer: principles and operations of the mass spectrometer; and its use to detect isotopes, determination of Relative atomic and molecular masses only. (2) Wave nature of electrons. (3) Quantum numbers and their importance. Meaning of terms: Nucleons, nuclide. Charges, relative mass and penetrating power of radiations. Meaning of radioactivity. Difference between spontaneous nuclear reactions (radioactivity) and induced nuclear reactions. Natural and artificial radioactivity. Detection of radiation by Geiger-Muller counter. Distinction between ordinary chemical reactions and nuclear reactions. Generations of electricity; atomic bombs. Balanced equations of nuclear reactions (1) Carbon dating (qualitative treatment only). (2) Use of radioactivity in agriculture, medicine and industries. (3) Hazards associated with nuclear radiations. Factors affecting stability of nuclides: Binding energy, neutron-proton ratio, and half life. Calculations involving half-life

2.0 PERIODIC CHEMISTRY (a) Reactions between acids and metals their oxides and trioxocarbonates (IV).	(1) Period three metals (Na, Mg, Al) (2) Period four metals (K, Ca) (3) Chemical equations (4) pH of solutions of the metallic oxides and trioxocarbonates.
CONTENTS	NOTES
(b) Acidic properties of oxides of non-metals. (c) Physical and chemical properties of period 3 elements and their compounds. (d) Silicon (e) Periodic gradation of elements in group seven i.e. the halogens. (f) Bonding in complex compounds. (g) Shapes of complex compounds.	(1) Oxides of carbon, nitrogen, sulphur, phosphorus and chlorine. (2) pH of aqueous solutions of the oxides. (3) Chemical equations. (1) Comparison of the physical and chemical properties of period three elements. (2) Comparison of the physical and chemical properties of (hydrides, oxides, hydroxides and chlorides) compounds. (3) Thermal stability of CO_3^{2-} and NO_3^- of Li, Na, K, Mg and Ca. (4) Experiment to compare thermal stability of $\text{Na}_2\text{CO}_3/\text{LiCO}_3/\text{CuSO}_4$. (1) Structures for SiO_2 and CO_2 account for the differences between physical and chemical properties of the two oxides. (2) Uses of silicon and its compounds e.g. ceramics, glass, silica gel and microchips. (1) Inter- atomic bond energies. (2) Hydrides and their acid strength comparison of the K_a values of the hydrogen halides. (3) Variable oxidation states of the halogens. Definition of ligands and central ions Examples of ligands (1) Formation of coordination compounds. (2) Nomenclature of complex ions and compounds (Cl^- , F^- , I^- , NO_3^- , NH_3 , H_2O , SO_4^{2-}).

(h) Elements of the first transition series. 3.0. CHEMICAL BONDS (a) Formation of Ionic bonds: (i) Factors that influence ionic bond formation;	Tetrahedral, square planar, octahedral e.g. $(\text{Fe}(\text{CN})_6)^{3-}$, $[\text{Cu}(\text{NH}_3)_4]^{2+}$, $[\text{Ag}(\text{NH}_3)_2]^+$ $[\text{Cu}(\text{CN})_4]^{2-}$ Reactivity of the metals with air, water, acids and comparison with s-block elements (Li, Na, Be, Mg). Factors should include lattice energy.
CONTENTS	NOTES
(ii) Covalent character in ionic bond; (iii) Polar covalent bonds. (b)(i) Hybridization of atomic orbitals. (ii) Formation of hybrid orbitals. (iii) Formation of sigma (σ) and pi (π) bonds. 4.0 SOLUTIONS (a) Preparation of solutions from liquid solutes by the method of dilution.	(1) Ionic character (polarity) in covalent bonds based on electronegativity difference between the species involved. (2) Effects of covalent and ionic character in ionic and covalent bonds on the solubility, thermal stability and boiling points of ionic and covalent compounds. Definition of Hybridization. (1) Description of sp, sp^2, sp^3 hybrid orbitals. (2) Shapes of sp, sp^2, sp^3 and sp^3d^2 hybrid orbitals. Treatment should be limited to the following molecules only. CH_4, H_2O, NH_3, BCl_3, C_2H_2, BeCl_2, C_2H_4 and SF_6. Description of sigma and pi bonds. Using C_2H_2 and C_6H_6. (1) Outline of steps involved in the preparation of solutions from liquid solutes. (2) Determination of concentration of liquid solutes (stock solution) given the density, w/v, w/w), specific gravity, relative molecular mass, molar mass, and % purity.

5.0 ENERGY AND ENERGY CHANGES (a) Energy changes in physical and isolated systems. (b) Hess's Law of heat summation and Born-Haber cycle.	(3) Primary standard, secondary standard and standardized solution. (1) Definition and understanding of the meaning of the energy terms: systems, surroundings, open and closed. (2) Enthalpy change involved in the following processes: combustion, atomization, sublimation, hydration/solvation and dissolution. Explanation of Hess's law and its application in the development of the Born-Haber cycle. (1) Use of different cycles to illustrate Hess's law.
CONTENTS	NOTES
(c) Bond Energy 6.0 ACIDS, BASES AND SALTS (a) Definitions of acids and bases. (b) pH, pOH and pK_w	(2) Simple calculations using chemical equations, energy cycles or diagrams with given energy changes. Explanation of bond energy and bond dissociation energy. (1) Bond energy as an average value. Differences in bond energy and bond dissociation energy. (2) Bond energy in molecules and its use in assessment of bond strength, energy content and enthalpy of reaction. (3) Calculations using summation of bond energies in reactants and products as a measure of enthalpy of reaction. (1) Bronsted – Lowry and Lewis concept of acids and bases. (2) Conjugate acid-base pair concept in terms of equilibrium.

(c) Partial ionization of weak acids and weak bases. (d) Buffer Solutions	(1) Ionic product constant of water $K_w = [H^+_{(aq)}][OH_{(aq)}] = 1.0 \times 10^{-14} \text{ mol}^2\text{dm}^{-6}$. (2) pH and pOH as a measure of acidity and alkalinity respectively $\text{pH} = -\log[H_3O^+]$. (3) Knowledge of pH scale. (4) Calculation of $[H^+]$, $[OH^-]$ and the corresponding pH and pOH of given solutions. Explanation of pKa and pKb of weak acids and bases. (1) Behaviour of weak acids and weak bases in water as example of equilibrium systems. (2) Calculations involving Ka, pKa and Kb, pKb. (3) Ka, pKa and Kb, pKb as measurements of acid and basic strengths respectively. (1) Qualitative definition of buffers. (2) Examples of buffers from the laboratory. (3) Preparation of buffer solutions.
CONTENTS	NOTES
(e) Acid base titrations 7.0 SOLUBILITY OF SUBSTANCES (a) Solubility and solubility product. (c) Crystallization and recrystallization.	Double indicator titrations (continuous and Discontinuous) and back titration. Calculations involving concentration, composition and % purity. Graphs for acid-based titrations. Nature of graphs of strong acid and strong base, strong acid and weak base and strong base and weak acid. (1) Explanation of solubility products (K_{sp}) of sparingly soluble ionic compounds. (2) Calculations involving solubility and solubility products. (3) Factors affecting solubility.

9.0 CHEMISTRY OF CARBON COMPOUNDS (a) Separation and Purification. (b) Determination of empirical and molecular formulae. (c) Reactivity of Organic Compounds. (d) Alkanes (e) (i) Reactions of benzene. (ii) Comparison or reactions of benzene and alkenes. CONTENT	Other methods should include solvent extraction and melting point determinations. Outline of steps in: (a) Detection of N, S and the halogens. (b) Estimation of C, H and O. (1) Inductive effect and Mesomeric effect. (2) Resonance illustrated with benzene molecule. (3) Explanation of the terms: nucleophiles, electrophiles, free radicals and ions. homolytic fission, heterolytic fission. Halogenation – free radical mechanism. Mono substituted reactions of benzene: toluene, phenol, aniline, benzoic acid and nitrobenzene. (IUPAC and trivial names) Differences between the reactivity of benzene and alkenes towards certain reagents. Uses of hexachlorocyclobenzene and benzene hexachloride (BHC). NOTES
10.0 CHEMICAL INDUSTRY AND ENVIRONMENT (a) (i) Sources of raw materials (ii) Mining of mineral as ore. (iii) Extraction of metals Mineral deposits in Ghana.	Location of mineral deposits and their nature. (1) Metals – gold, bauxite, manganese and iron. (2) Precious stone – diamond. (3) Industrial mining of limestone CaCO_3, clay Kaolin, solar salt (4) Processing of Au, Al, Fe as main products (5) Uses of the metals

(b) Cement and its uses	(1) Sources of raw materials for cement production. (2) Processes involved in the production of cement. (3) Uses of cement. (4) Environmental impact.
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SECTION C

(For candidates in Nigeria, Sierra-Leone, Liberia and The Gambia)

CONTENT	NOTES
1.0 NON METALS AND THEIR COMPOUNDS (a) Carbon: (i) Allotropes of carbon; (ii) Coal: I. Types; II. Destructive distillation of coal and uses of the products. (iii) Coke: I. Classification and uses; II. Manufacture of synthetic gas and uses. (iv) Oxides of carbon I. Carbon (IV) oxides;	(1) Graphite, diamond and amorphous Carbon; (2) Structures, properties and uses. (3) The uses of the allotropes should be correlated with their properties and structures. (4) Combustion of allotropes. Different types should include anthracite, peat and lignite. Water gas and producer gas. (1) Laboratory preparation. (2) Properties and uses.

II. Carbon (II) oxides; III. Trioxocarbonate (IV) salt.	(3) Test for carbon (IV) oxides. Properties and uses only. (1) Properties: solubility, action of heat, reaction with dilute acid. (2) Uses.
CONTENT	NOTES
(b) Oxygen: (i) Laboratory and industrial preparation; (ii) Properties and uses; (iii) Binary compounds of oxygen: acidic, basic, amphoteric and neutral oxides. (c) Hydrogen: (i) Laboratory preparations; (ii) Properties and uses. (d) Water and solution: (i) Composition of water; (ii) Water as a solvent; (iii) Hardness of water, causes and methods of removing it; (iv) Treatment of water for town supply. (e) Halogens: (i) Chlorine:	Test for oxygen will be required. Test for hydrogen will be required. Test for water will be required. Reference should be made to the electrolysis of acidified water. (1) Advantages and disadvantages of hard water and soft water. (2) Experiments to compare the degrees of hardness in different samples of water. Redox properties of the elements; displacement reaction of one halogen by another.

I. Laboratory preparation; II. Properties and reactions. (f) Hydrogen chloride gas: (i) Laboratory preparation; (ii) Properties and uses; CONTENT	Properties should include: (a) variable oxidation states; (b) reaction with water and alkali (balanced equation required). (1) Test for HCl gas. (2) Fountain experiment. NOTES
(iii) Uses of halogen compounds. (g) Nitrogen: (i) Preparation and properties; (ii) Uses of nitrogen; (iii) Compounds of nitrogen: I. Ammonia; II. Trioxonitrate (V) acid; III. Trioxonitrate (V) salts. (h) Sulphur: (i) Allotropes and uses; (ii) Compound of sulphur; (iii) Trioxosulphate (IV) acids and its salts;	Uses should include silver halide in photography and sodium oxochlorate (I) as a bleaching agent. Both laboratory and industrial preparations from liquefied air are required. (1) Laboratory and industrial preparations. (2) Properties and uses. (3) Test for ammonia. (4) Fountain experiment. (1) Laboratory preparation. (2) Properties and uses. (1) Action of heat will be required. (2) Test for trioxonitrate (V) ions.

(iv) Tetraoxosulphate (VI) acid: industrial preparation, reactions and uses. (i) The noble gases: properties and uses. 2.0 METALS AND THEIR COMPOUNDS (a) Extraction of metals: (i) Aluminium; (ii) Iron; (iii) Tin. (b) Alloys. CONTENT	Contact process should be discussed. (1) Raw materials, processing, main products and by-products. (2) Uses of metals. Common alloys of Cu, Al, Pb, Fe, Sn and their uses. NOTES
(c) Properties and uses of sodium and its compounds. (d) Properties and uses of calcium and its compounds. (e) Reactivity of iron and aluminium with air, water and acids. (f) Properties and uses of copper and its compounds.	Compounds must be limited to NaCl, NaOH, Na₂CO₃, NaNO₃, Na₂SO₄ and NaClO. The compounds must be limited to CaCO₃, CaO, CaSO₄, CaCl₂, and Ca(OH)₂ The compounds must be limited to CuSO₄, CuO and CuCl₂.

PRACTICALS

(a) GENERAL SKILLS AND PRINCIPLES

Candidates will be expected to be familiar with the following skills and principles:

- (i) Measurement of mass and volume;
- (ii) Preparation and dilution of standard solutions;
- (iii) Filtration, recrystallisation and melting point determination;

- (iv) Measurement of heats of neutralization and solutions;
- (v) Determination of pH value of various solutions by colorimetry;
- (vi) Determination of rates of reaction from concentration versus time curves;
- (vii) Determination of equilibrium constants for simple system.

(b) QUANTITATIVE ANALYSIS

Acid-base titrations

The use of standard solutions of acids and alkalis and the indicators; methyl orange, methyl red and phenolphthalein to determine the following:

- (i) The concentrations of acid and alkaline solutions;
- (ii) The molar masses of acids and bases and water of crystallization.
- (iii) The solubility of acids and bases;
- (iv) The percentage purity of acids and bases;
- (v) Analysis of $\text{Na}_2\text{CO}_3/\text{NaHCO}_3$ mixture by double indicator methods (Ghanaians only).
- (vi) Stoichiometry of reactions.

Redox titrations

Titration of the following systems to solve analytical problems:

- (i) Acidic MnO_4^- with Fe^{2+} ;
- (ii) Acidic MnO_4^- with $\text{C}_2\text{O}_4^{2-}$;
- (iii) I_2 in KI versus $\text{S}_2\text{O}_3^{2-}$.

(d) QUALITATIVE ANALYSIS

No formal scheme of analysis is required.

- (i) Characteristic tests of the following cations with dilute $\text{NaOH}_{(\text{aq})}$ and $\text{NH}_3_{(\text{aq})}$; NH_4^+ ; Ca^{2+} ; Pb^{2+} ; Cu^{2+} ; Fe^{2+} ; Fe^{3+} ; Al^{3+} ; and Zn^{2+} .
- (ii) Confirmatory tests for the above cations.
- (iii) Characteristic reaction of dilute HCl on solids or aqueous solutions and conc. H_2SO_4 on solid samples of the following: Cl^- ; SO_3^{2-} ; CO_3^{2-} ; NO_3^- and SO_4^{2-} .
- (iv) Confirmatory tests for the above anions
- (v) Comparative study of the halogens; displacement reactions.

- (vi) Characteristic tests for the following gases: H_2 ; NH_3 ; CO_2 ; HCl and SO_2 .
- (vii) Characteristic test tube reactions of the functional groups in the following simple organic compounds: Alkenes; alkanols; alkanoic acids, sugars (using Fehling's and Benedict's solutions only); starch (iodine test only) and proteins (using the Ninhydrin test, Xanthoproteic test, Biuret test and Millon's test only).

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Chemistry Performance Test (CPT)
Table of Specification

Topic	Recall	Understand	Application	Analysis
Introduction to Chemistry	No 8	-	-	-
Structure of the Atom	No 1	No 9	-	-
Standard Separation Techniques	-	No 12	-	-
Periodic Chemistry	-	No 13, 14	-	-
Chemical Bonds	-	No 6, 15	-	-
Stoichiometry and Chemical Reaction	-	-	-	No 19
States of Matter	-	-	No 7	-
Energy and Energy changes	No 16	-	-	-
Acids, Bases & Salts	-	No 4	No 10	No 18, 20
Solubility of Substances	-	-	No 17	-
Chemical Kinetics and Equilibrium Systems	No 1	-	-	-
Redox Reactions	-	No 3	No 2	-
Chemistry of Carbon Compounds	-	No 5	-	-
Chemical Industry and the Environment	-	-	-	-
Qualitative and Quantitative Analysis	-	-	-	-
Total	4	9	4	3
Total (%)	20%	45%	20%	15%

Chemistry Performance Test (CPT)

Please read the following instructions before responding to the questions.

1. Read the questions before ticking the (☒) correct answers.
2. You will be given a number, write your number on the top of this question paper.
3. Answer **ALL** questions.
4. Do **not** start until you are told to do so.
5. **All** questions carry equal marks.
6. Tick (☒) the box if you are male ☐ or female ☐

Duration: 30 mins.

1. The electron configuration $1S^22S^22P_x^2$ contravenes the
 - A. Pauli's exclusion principle.
 - B. Aufbau's principle.
 - C. Octet rule.
 - D. Hund's rule.
2. The oxidation number of chromium in $Na_2Cr_2O_7$ is
 - A. +2.
 - B. +6.
 - C. +7.
 - D. +12.
3. The product formed when concentrated sodium chloride solution is electrolyzed using carbon electrodes is
 - A. chloride water.
 - B. hydrochloric acid.
 - C. sodium hydroxide.
 - D. sodium oxochlorate (I).
4. An acidic salt has
 - A. double anions in its aqueous solution.
 - B. a single cation in its aqueous solution.
 - C. hydrogen ions in its aqueous solution.
 - D. hydrogen atoms in its aqueous solution.

5. When substance **X** was added to a solution of bromine water, the solution became colourless. **X** is **likely** to be
- propane.
 - propanoic acid.
 - propyne.
 - propanol.
6. When *s* and *p* block elements react, the bond formed is
- electrovalent.
 - covalent.
 - metallic.
 - dative-covalent.
7. The volume of $22_{(g)}$ of $\text{CO}_{2(g)}$ at stp is equivalent to [C=12.0, O=16.0, Molar volume at stp = 22.4 dm^3]
- 22.0 dm^3 .
 - 22.4 dm^3 .
 - 11.2 dm^3 .
 - 5.6 dm^3 .
8. The branch of science that deals with the nature and properties of substances and how one substance can be converted to another is known as
- Biology.
 - Chemistry.
 - Geography.
 - Physics.
9. The atomic number of an isotope of hydrogen is equal to its mass number because it
- has a totally filled valence shell.
 - has a high charge to mass ratio.
 - does not contain neutrons.
 - exhibits isotopy.
10. Which of the following solutions contains the **least** amount in moles of HCl?
- 250 cm^3 of 4.0 mol dm^{-3}
 - 125 cm^3 of 6.0 mol dm^{-3}
 - 750 cm^3 of 1.5 mol dm^{-3}
 - 500 cm^3 of 2.0 mol dm^{-3}

11. Factors that could affect the speed of chemical reactions do **not** include
- A. pressure.
 - B. temperature.
 - C. volume of gas.
 - D. change in mass.
12. Which of the following methods can be used to separate blood cells from plasma?
- A. Centrifugation
 - B. Filtration
 - C. Chromatography
 - D. Distillation
13. Group VII elements in their combined states are called
- A. cations.
 - B. anions.
 - C. halogens.
 - D. halides.
14. Arrange the following halogens in order of increasing reactivity:
bromine, iodine, chlorine
- A. bromine, chlorine, iodine
 - B. iodine. Bromine, chlorine
 - C. chlorine, bromine, iodine
 - D. iodine. Chlorine, bromine
15. Which of the following formulae is that of a molecular solid?
- A. $\text{Cu}_{(s)}$
 - B. $\text{KF}_{(g)}$
 - C. $\text{NaCl}_{(g)}$
 - D. $\text{C}_6\text{H}_{12}\text{O}_6_{(s)}$
16. The amount of heat energy produced by a system is known as
- A. enthalpy.
 - B. entropy.
 - C. exothermic.
 - D. endothermic.

17. What is the solubility of a salt if 0.4 g of it is obtained on evaporating 200 cm^3 of its saturated solution to dryness?
- A. 0.08 gdm^{-3}
 - B. 2.00 gdm^{-3}
 - C. 8.00 gdm^{-3} .
 - D. 80.00 gdm^{-3} .
18. A white precipitate was formed when $\text{BaCl}_{2(\text{aq})}$ was added to an aqueous solution of a salt **X**. The precipitate dissolved in dilute HCl with rapid effervescence. Salt **X** is likely to contain
- A. SO_4^{2-} ions.
 - B. SO_3^{2-} ions.
 - C. NO_3^- ions.
 - D. CO_3^{2-} ions.
19. Analysis of hydrocarbon shows that it contains 0.93 g of carbon per gram of the compound. The mole ratio of carbon to hydrogen in the compound is [H=1.0, C=12.0]
- A. 1:1.
 - B. 1:2.
 - C. 2:1.
 - D. 2:3.
20. Which of the following acid-base titrations is phenolphthalein **not** suitable to determine end-point?
- A. HCl against NaOH
 - B. H_2SO_4 against KOH
 - C. CH_3COOH against $\text{NH}_{3(\text{aq})}$
 - D. CH_3COOH against $\text{NaOH}_{(\text{aq})}$

STEPS IN THE ADMINISTRATION OF RESEARCH QUESTIONNAIRES TO SS2 CHEMISTRY STUDENTS AND TEACHERS IN BOTH PUBLIC AND PRIVATE SCHOOLS

Dear colleagues, please these guidelines will facilitate the process of administration of the questionnaires to both SS 2 chemistry students and their teachers.

Step 1: The school to be visited were informed ahead of time as the practice for trial test so they can get their SS 2 students prepared for the exercise.

Step 2: On arrival at the school, a senior teacher was assigned to coordinate the administration and collection of the questionnaires. The exact number of teachers and students was used as the basis for allocation of the questionnaires.

Step 3: Students were mandated to write their examination numbers on the questionnaires which were generated for them. i.e. 001, 002, 003, -----

Step 4: A unique code was generated for each school. For instance, City College Academy, Abeokuta took a code of CCAA. All the SS 2 Chemistry students and their teachers in a school wrote the unique code for the school after generation of the code and was written on all the questionnaires with their examination numbers. This code allowed the researcher to attach the students' responses to the responses of their teachers.

Step 5: Students' responses and teachers' responses for a particular school were tied together using a rubber band or rope. This enhanced the sorting of data after collection on a school basis.

Step 6: The name of the school, the Local Government Area where the school is located, with the number of students and teachers that participated in the exercise were written on a sheet of paper and tied with the collected questionnaires. Please note that all the information in the questionnaires is important, including an achievement test which is attached with the students' questionnaires.

Step 7: For more information, please call the researcher.

Thank you for your assistance.

I wish all of us journey mercies.

Thank you.



Lead City University (LCU)

Motto: Knowledge for Self-reliance

Administrative Building, Lagos - Ibadan Expressway, Toll Gate Area, Ibadan,
Oyo State, Nigeria Tel: 08033794249 Email: ase@lcu.edu.ng

Dr. Oluyomi Susan Pitan

B.Sc., (Ed.), Dip. M.Ed., Ph.D. Ibadan

Head, Department of Arts & Social Science Education

Department of Arts & Social Science Education

www.lcu.edu.ng

31st January 2025

Dear Sir/Ma

LETTER OF INTRODUCTION FOR FIELD WORK

The Bearer of this letter, ADETORO OLUYEMI ABIADE is a Postgraduate student (PhD) of Measurement and Evaluation in the Department of Arts and Social Science Education, Lead City University, Ibadan. He is currently carrying out a research on "Predictive Modelling of Teachers Workload, Classroom Management Skills and Students Factors on Academic Achievement of Chemistry Students." To achieve this, he needs to administer Questionnaire to Senior Secondary Two (ss2) Chemistry Students and Teachers.

I, therefore write on his behalf that you kindly accord him all the necessary support that he needs in the collection of data for his research.

We promise that all information given will be used solely for research purpose.

Thank you

Yours Faithfully,

Dr Oluyomi Susan Pitan

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Lead







Bio-data

Name: Oluyemi Abiade ADETORO

Address: Fimosokan Landlords & Landladies Asociation, Ajia Road, Ibadan, Oyo State, Nigeria

Email: toromi2020@yahoo.com

Telephone No: 09084431603

Date of Birth: 2nd May, 1981

State of Origin: Oyo

Hometown: Ibadan

Local Government of Origin: Ibadan Southeast

Place of Birth: Ibadan

Nationality: Nigerian

Next of Kin: Omolara Esther Adetoro

Address: Fimosokan Community, Ajia Road, Ibadan, Oyo State, Nigeria

Academic Qualifications and Institutions Attended with Dates

Institution	Qualification Obtained	Date
Lead City University, Ibadan	PhD in Educational Evaluation & Measurement	2022-2026
University of Ibadan	MEd in Educational Evaluation	2010-2011
Obafemi Awolowo University, Ife	BSc (Ed) in Chemistry Education	2004-2006
Adeyemi College of Education, Ondo	NCE in Biology/Chemistry	1999-2004
Alilak Grammar School, Ondo	West African Senior School Certificate Examinations (WASSCE)	2001

Work Experience:

Diocesan College, Ondo	Chemistry Teacher	2007 – 2008
Community Secondary School, Amachalla, Igbo-Eze North LGA, Enugu State	Chemistry Teacher (NYSC) Chemistry Teacher	2008 – 2009
Bishop Akinyele Grammar School, Oke-Are, Ibadan	Chemistry/Biology Teacher	2009-2010
Loyola College, Ibadan	Chemistry Teacher	2010-2015
The West African Examinations Council Lagos	Chemistry Subject Officer	2015-Date

Conference and Workshop Attended with Dates

- i. Conference of Association for Educational Assessment (AEA), The Hague,
Netherlands 2025

- | | |
|--|------|
| ii. Workshop on Items Psychometrics, The Hague, Netherlands | 2025 |
| iii. The Postgraduate College Lead City University
Multidisciplinary International Conference, Ibadan | 2025 |
| iv. International Conference of Educational Assessment &
Research Network in Africa (EARNiA), Nigeria | 2025 |
| v. 5 th Continental African Curriculum Association (ACA) Conference,
Abuja | 2025 |
| vi. 65 th National Conference of the Science Teachers Association
of Nigeria, STAN, Abuja | 2024 |
| vii. Workshop on Modern Test Development, WAEC, Lagos | 2023 |
| viii Workshop on the use of R-Programming Language in data analysis,
Lagos | 2023 |
| ix. National Conference of the Science Teachers Association of
Nigeria, STAN, Kano | 2019 |
| x. 60 th National Conference of the Science Teachers Association of
Nigeria, STAN, Port-Harcourt | 2017 |

University Compliance Certificate

This is to certify that this thesis by Oluyemi Abiade ADETORO with matriculation number LCU/PG/004006 in the Departments of Arts and Social Sciences Education, Faculty of Arts and Education, Lead City University, Ibadan, Nigeria is in full compliance with the approved university formats.

Name

Signature & Date

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