Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Article - e007

Assessing how Learner attributes affect learning preference using Explorative Big Data Analysis

A case of four learning institutions in Chikuni Mission of Monze district in Zambia.

Victor Munalula[1]

[1] Senior Lecturer, Information Communication Technology Association of Zambia (ICTAZ)

Received: 10/02/2026 **Revision Received**: 02/02/2026 **Accepted**: 10/03/2026

ABSTRACT

This study explores how different learner attributes affect learning preferences among learners. The study investigates the relationship between attributes such as *gender, age, study duration* and *educational level*, against learner preferred *learning* methods. The study applied an analytical cross-sectional approach using explorative big data machine learning models on a sample of over 350 learners against 19 variables. The study was conducted in 4 learning institutions within the Chikuni Mission of Monze district in the Republic of Zambia. The study's findings indicate that more female learners preferred to learn in cooperative groups with a steadily increasing interest in project learning methods. In contrast, males in primary schools preferred to learn independently. Project methods became popular among males at the secondary school level. The Random Forest Classifier model on a 0.32 train test data split showed a target prediction accuracy of 73%. While *age, level of learning, hours of study* and the *visual domain* were fundamental to predicting learning preference, attributes such as *tribe, number of siblings, and auditory and kinesthetic domains seemed* to contribute less significantly to the target variable. This paper submits that big data and machine learning explorative methods are principal to predicting the learning preferences of learners in classrooms. The study further postulates that creating preferred learning opportunities for learners has great potential to positively affect learning outcomes and create active and performing learners in our schools.

KEYWORDS: Big data, Machine Learning, Learning methods, Learning preference.

1. INTRODUCTION

Learning methodologies are systems of practices and procedures that teachers, educators, mentors and learning guides use to support and enrich the learning journeys of learners (Dale, 2020). Effective teaching and learning are dependent upon understanding the diverse ways learner's process information. Learning style refers to an individual's preferred way to absorb process, comprehend and retain information (Kelli et al, 2011). In recent years, the learning focus has shifted from conventional teacher-centered to learner-centered teaching methods. Therefore, approaches used to teach and support

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

learners must be carefully considered to achieve effective learning processes. While numerous factors influence learning outcomes, individual learner attributes and their corresponding learning preferences have emerged as critical determinants of academic success (Dunn & Griggs, 1998). This study aims to investigate the intricate relationship between learner attributes such as gender, age, duration of study, sleep patterns, educational level, and preferred learning methods. By employing an integrated quantitative approach and leveraging the power of big data and machine learning models, this research seeks to contribute to the development of more personalized and effective learning environments.

Previous research has highlighted the importance of aligning teaching methods with learner's preferred learning to enhance academic achievement (Pashler et al., 2009). However, the complex interplay between learner attributes and learning preferences remains under-explored. This study addresses this gap by examining a broad spectrum of learner characteristics and utilizing advanced data analysis techniques to uncover hidden patterns and relationships.

Through a stratified random sampling of learners from primary, secondary and college level institutions, data was collected via a questionnaire assessing learner's attributes and their respective learning method preferences. The learning methods explored in the study were *Teacher Exposition, Independent Learning, Cooperative Learning (Groups), Project Learning*, and *Assignments*. The selection of learning methods was guided by the participant familiarity to and experience with the methods. By applying classification machine learning algorithms, this study seeks to identify significant predictors of learning method preferences and develop predictive models for optimizing learning experiences.

1.1 Statement of the Problem

Despite the recognition of education as a fundamental human right and the inherent potential of every learner (UNESCO, 2020), the Zambian education system has faced significant challenges in optimizing learning outcomes. Regardless of progress in literacy and numeracy scores, learning outcomes in Zambia remain relatively low. Regional disparities within the country persist in primary school completion rates, with girls facing a higher likelihood of dropping out before reaching senior secondary levels (UNICEF & MOE-Zambia, 2024). Traditional teaching methods have often failed to accommodate the diverse learning styles of students, leading to suboptimal academic performance and a widening achievement gap (Darling-Hammond, 2000). The educational analysis by UNESCO (2024) highlights low learning achievement scores for most of the standardized national, regional, and international assessments and successive public examinations, where **school enrollment does not necessarily translate into learning outcomes,** suggesting that children are drifting through the school system with very low mastery of desired learning competencies. Limited research on the relationship between learner attributes and learning method preferences within the Zambian context hinders the development of targeted pedagogical approaches. Consequently, there is a critical need to investigate

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

how learner attributes such as gender, age, socioeconomic status, and cultural background influence learning preferences among Zambian learners.

This study aims to address this knowledge gap by exploring how learner attributes impact learning method preferences, thereby contributing to the development of more inclusive and effective educational practices that cater to the unique needs of educational practices in Zambia.

1.2 Research Purpose

The current study investigates how different learner attributes affect learning preferences among learners. The research study explores the relationship between personal learner attributes such as gender, age, duration of study and sleep, and educational level among others, against learner-preferred learning methods. By providing valuable insights into the factors shaping learner behaviour, this study contributes to the on-going discourse on personalized learning and educational effectiveness.

1.3 Research Objectives

The following were the underpinning objectives of this particular study;

1. To identify patterns and trends among learner's attributes such as gender, age, study and sleep patterns and educational level, and their effect on learner's learning method preference.
2. To enhance classroom learning experiences by applying machine learning models.

1.4 Research Questions

Ultimately, this research endeavored to answer two (2) fundamental questions:

1. What learning patterns and trends exist between learner's attributes and their learning method preferences?
2. How can machine learning models enhance classroom learning experiences?

1.5 Significance of the study

This study examines how learner attributes affect learner's learning preferences using machine learning models. By identifying significant relationships between learner attributes and learning method preferences, the study aims to contribute to the development of data-driven, personalized learning environments. These attributes were analyzed by applying the decision trees, random forests, and support vector machines learning algorithms. Further, this study serves a significant role in contributing to the understanding of how learner attributes influence learning preferences in the Zambian context, providing insights for educators, policymakers, and curriculum developers to enhance teaching and learning practices.

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

1.6 Motivation for the study

Education is universally recognized as a fundamental human right, essential for personal development, societal progress, and global citizenship (UNESCO, 2020). Every learner possesses unique potential, and unlocking this potential requires tailored approaches that respect individual differences. However, traditional educational approaches often fall short in fully unlocking this potential, as they frequently rely on standardized methods that may not cater to diverse learning methods (Darling-Hammond, 2000).

The researcher's personal experiences within the schooling system highlight the limitations of the one-size-fits-all approaches. The inability to fully engage learners with varied learning preferences has set back optimal learning outcomes. This study is driven by the conviction that understanding how learner attributes influence their learning preferences is crucial for creating inclusive and effective educational environments. By identifying these relationships, we can develop innovative strategies to maximize the learning potential of every student.

This research is thus motivated by the acknowledgement of education as a human right for every child and the unharnessed learning potential of every learner. The researcher's personal schooling experience characterized with excessive limitations of traditional methods and non-inclusive classroom activities of learning also served as motivation for this study.

Ultimately, this research aims to contribute to the realization of education as a powerful tool for human development by ensuring that learning experiences are responsive to the unique needs and learning preferences of individual learners.

1.7 Research Gap

Despite the growing body of research on learning styles and learner attributes, there is a lack of scholarly studies that comprehensively investigate the relationship between these factors using advanced data analysis techniques. Furthermore, the role of contextual factors, such as personal learner attributes, cultural background and socioeconomic status, in shaping learning preferences remains under-explored. This study aims to address these gaps by employing an in depth quantitative approach and leveraging the power of machine learning to uncover hidden patterns, trends and insights in data.

1.8 Study Limitations

Researchers exploring different learning methods and research approaches beyond those investigated in this particular study may report varied findings. Beyond that, studies exploring different learner attributes and those conducted in different locations from the one explored in this research study may

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

equally report varied outcomes. Learner participation at primary school level was restricted to upper level learners due to age while time constraints may have further limited the researcher to fully explore the qualitative aspects of study. Nevertheless, the significance of assessing learner's preference for learning can never be underscored.

2. LITERATURE REVIEW

Recent research has shifted towards examining the factors influencing learning preferences, with learner attributes emerging as a key area of interest. Studies have explored the relationship between gender, age, and learning styles, reporting mixed findings. For instance, MacFarlane in his study suggests that females tend to prefer visual and auditory learning styles, while males lean towards kinesthetic and tactile approaches (MacFarlane, 2003). However, these gender differences are not universally consistent (Pashler et al., 2009). Age-related variations in learning styles have also been investigated, with studies suggesting that older learners may exhibit a preference for reflective and conceptual learning styles. While numerous studies have explored learning styles, the precise interplay between learner attributes and learning preferences remains a complex and multifaceted area.

Even though the influence of demographic factors on learning approaches has received attention, other learner attributes such as sleep, study duration, and socioeconomic status remain under-explored. There is a growing recognition of the importance of sleep for cognitive function and learning, but its relationship to learning preferences is largely unknown (Walker, 2017). Similarly, the impact of study duration and socioeconomic status on learning methods preferences requires further investigation.

Even though traditional research methods have provided valuable insights, the emergence of big data and advanced analytics has opened new avenues for investigating the complex relationship between learner attributes and learning preferences. Machine learning algorithms, such as decision trees, random forests, and support vector machines, have shown strides in identifying patterns and predicting learning preferences based on various attributes (Han, Kamber, & Pei, 2011). Studies employing these techniques have begun to unwind the interplay between learner characteristics and specific preferences in learning, offering the potential for more personalized and effective educational interventions (Chen, Liu, & Zhang, 2020).

However, despite the growing body of research, several gaps persist. The majority of studies have focused on specific learner attributes or learning models, with limited exploration of the combined influence of multiple factors. Additionally, the application of machine learning techniques in this domain is still in its developing stages, with a need for further research to refine methodologies and validate findings (Mayer, 2014).

By adopting an in-depth quantitative approach and machine learning techniques, this study aimed to uncover hidden patterns and relationships between learner attributes and their learning preferences.

While leveraging the power of big data, this research further aligns with the growing trend of using data-driven methods to inform educational practices.

2.1 Machine Learning in Education

The integration of machine learning in educational research has gained momentum in recent years, offering new possibilities for analyzing large datasets and uncovering hidden patterns (Baker & Yacef, 2009). Decision trees, random forests, and support vector machines have been successfully applied to various educational contexts, including student performance prediction, early warning systems, and personalized learning (Romero & Ventura, 2010; Corbett & Anderson, 2003).

While the application of machine learning to learning preferences is still in its early stages, promising studies have demonstrated its potential for identifying learner subgroups based on learning method preferences and predicting academic outcomes, for example; Lin Lin and others, in their sage open article '*A systematic review of Big Data-Driven Education Evaluation*' reviewed focus areas of high order thinking analysis, learning performance prediction, learning emotion recognition, teaching management decision-making, and evaluation mode optimization (Lin Lin et al., 2024).

2.2 Theoretical Framework

This study is grounded in the theoretical foundation of learner's learning preferences and the application of machine learning techniques to educational data. The study adopts a constructivist perspective on learning, positing that learners actively construct knowledge through interaction with their environment (Piaget, 1970). This framework aligns with the notion that learning preferences are shaped by personal experiences and interactions.

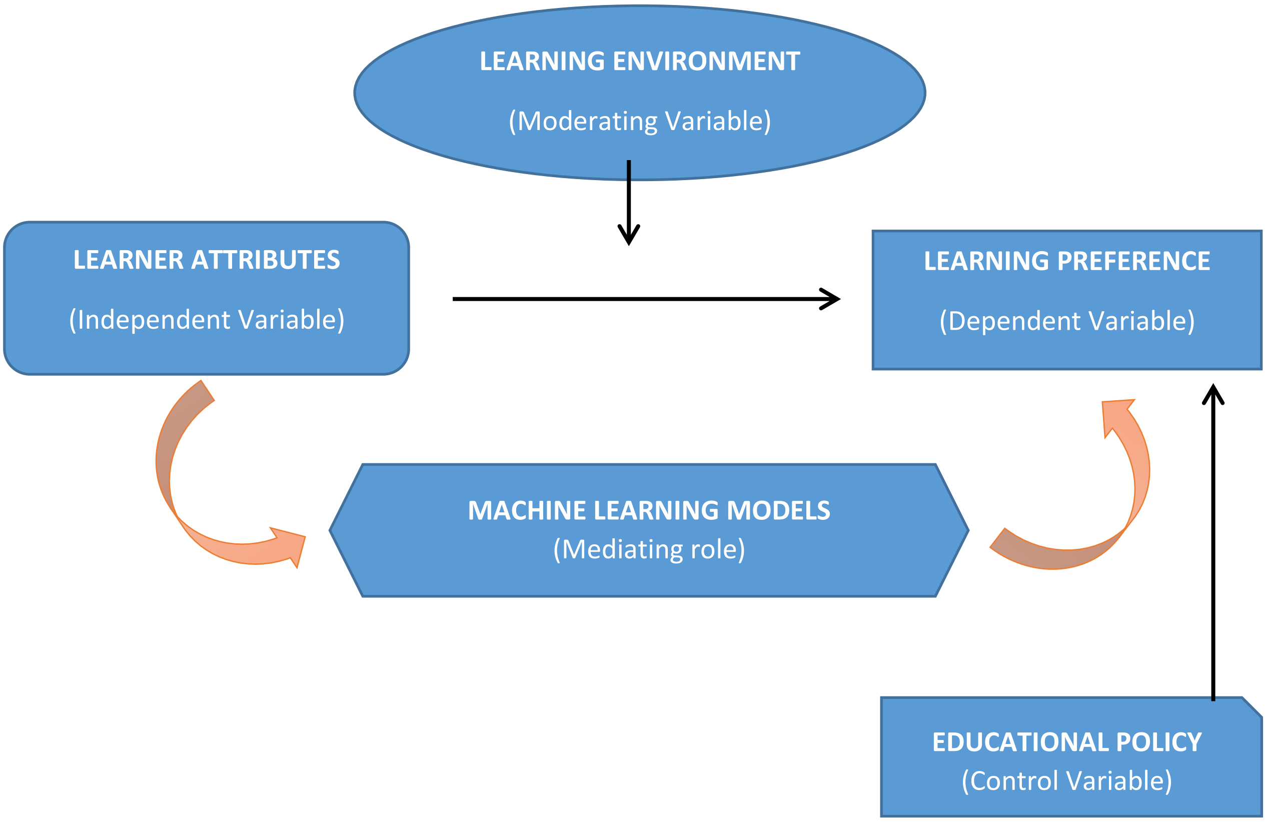
To understand the complex relationship between learner attributes and learning preferences, this study will employ a data-driven approach using machine learning algorithms. This aligns with the growing recognition of the potential of data analytics to inform educational decision-making (Mayer, 2017). These learning algorithms, such as decision trees, random forests, and support vector machines, have demonstrated effectiveness in identifying patterns within large datasets (Han, Kamber, & Pei, 2011). By applying these techniques to a comprehensive dataset of learner attributes and preferred learning methods, this study aims to uncover existing hidden relationships and generate predictive models.

The conceptual framework is depicted in Figure 1. The framework illustrates the interplay between learner attributes (independent variables), preferred learning methods (dependent variable), and the mediating role of machine learning algorithms amidst created learning environments as moderating variables and existing educational policies (control variables).

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 1: Conceptual Framework



Conceptual Framework

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 2: below illustrates the procedural outline of the project research process.

Research Procedural Outline

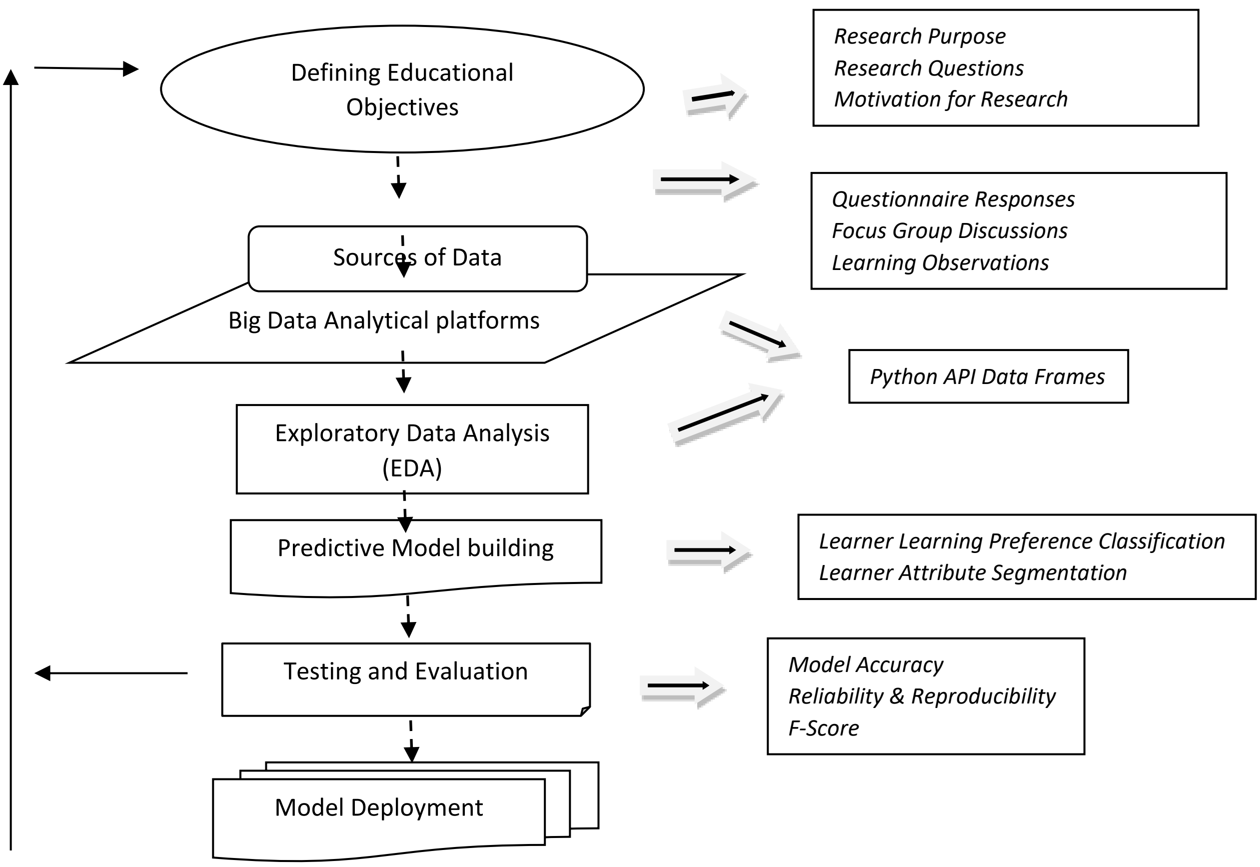


Figure 2: Procedural outline of the research implementation process

3. Research Methodology

The study employed a data-driven approach using machine learning algorithms. An analytical cross-sectional approach was applied in this study on a real data sample of over 350 learner observations against 19 personal attributes using explorative big data algorithms. Three (3) machine learning classification models (the *Decision Tree Classifier, Random Forest Classifier* and the *Support Vector Machines*) were trained on a 0.32 train-test data split with a fixed random state = 0. The dataset was carefully cleaned with missing values replaced by mean and mode scores while non-correlated features were dropped for model optimization. Categorical variables were encoded for numerical analysis. The

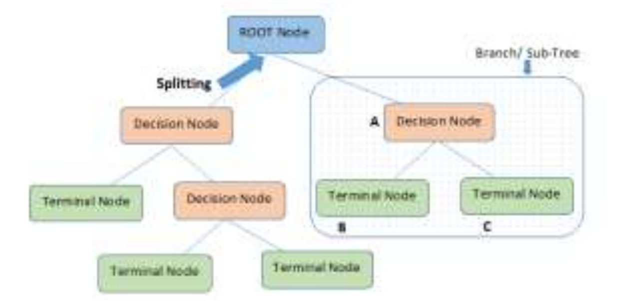
ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

multi-target variable classification was assessed on a one versus one basis. The model performance was ultimately evaluated through *accuracy*, *precision*, *recall* and *F1 scores* on a confusion matrix metric.

3.0.1 The Decision Tree (DT) Classifier

The decision tree builds classification models in the form of a tree structure. It breaks down data into smaller subsets of increasing tree depth (Witten, Frank, & Hall, 2011). The output result of the decision tree classifier is obtained from **decision nodes** and **leaf nodes**. The topmost decision node in the tree represents the best predictor referred to as the **root node**. The diagram below depicts the DT architecture.

Figure 3: The Decision Tree structure and Criterion



(Pathmind, 2024, May 22).

Task	Formula	Description
Classification	$\sum_{i=1}^{C} f_i(1-f_i)$	f_i is the frequency of label i at a node and C is the number of unique labels.
Classification	$\sum_{i=1}^{C} -f_i\log(f_i)$	f_i is the frequency of label i at a node and C is the number of unique labels.

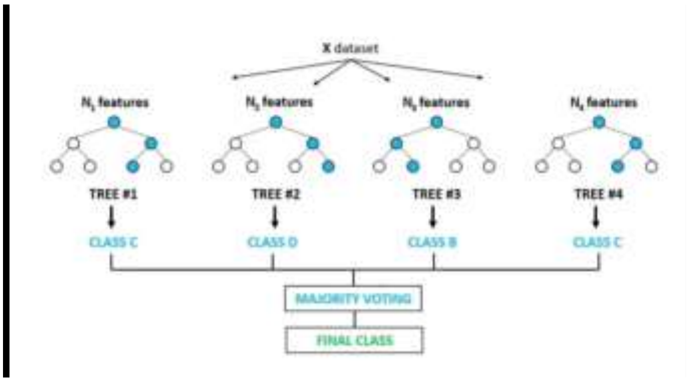
(Medium, 2024, August 04).

3.0.2 The Random Forest (RF) Classifier

Random forests are composed of many decision trees and operate as an ensemble learning method where each tree is built using a random subset of features from the dataset to classify a given population (Breiman, 2001). The decision trees vote on how to classify a given instance of input data and choose the best prediction. **(**Pathmind, 2024, May 22). The diagram below depicts the RF architecture.

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 4: Random Forests Classifier

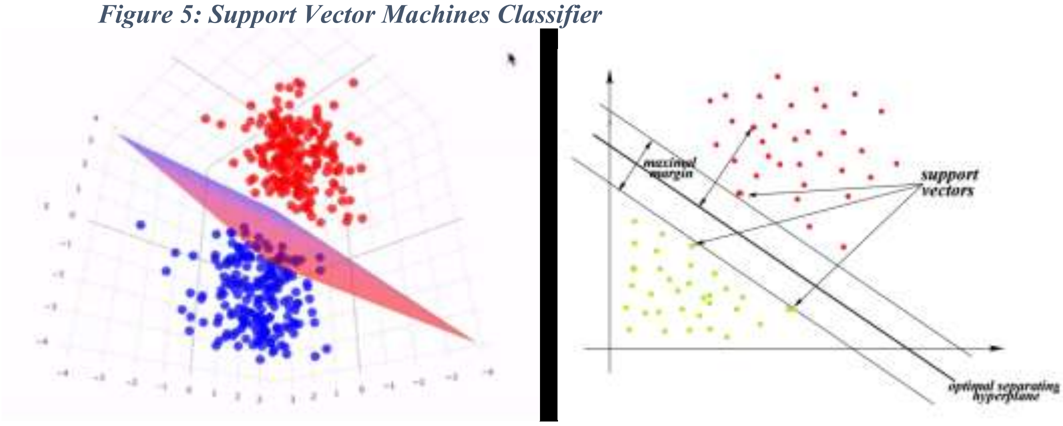


(Medium, 2024, August 04).

3.0.3 The Support Vector Machines (SVM) Classifier

Support Vector Machines in machine learning are used to classify data points by determining an optimal decision boundary that maximizes the separation between different classes (Damasevicius, 2025; Nie et al., 2023). It aims to find the best fit hyper plane with maximum margin between the support vectors. The diagram below depicts the SVM architecture.

Figure 5: Support Vector Machines Classifier



(Medium, 2024, June 05).

3.1 Research Design

This study utilized a quantitative approach through an in-depth big data explorative analysis on questionnaire responses with limited qualitative aspects providing insights on learner's preferences of learning methods. The research was preceded by a large scale in-person survey that collected data on learner attributes and their respective learning preferences. The study applied an analytical cross-sectional approach using predictive machine learning models on a sample of 360 learners against 19 variable attributes. The qualitative aspects incorporated non structured interviews and focus group

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

discussions to delve deeper into the experiences and perceptions of learners regarding learning preferences.

3.2 Study Population

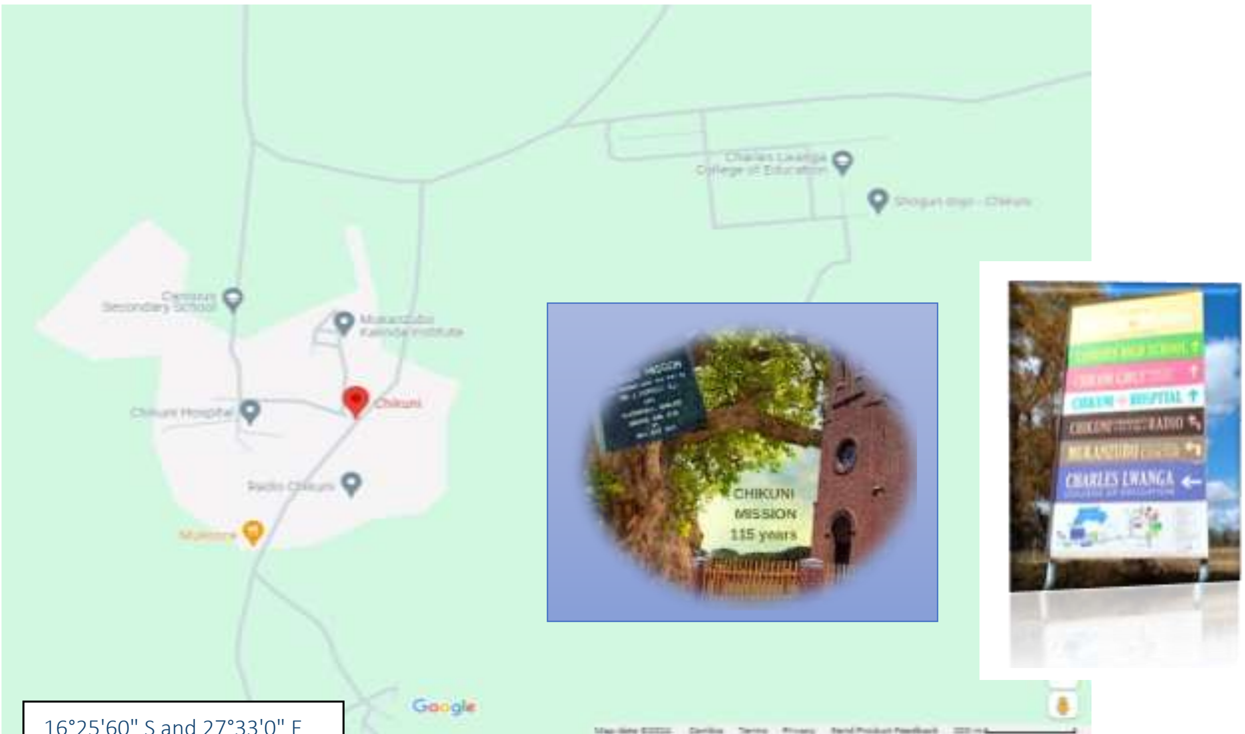
The study comprised a sample of 360 active learners across learning levels from four (4) different learning institutions in rural Monze district. A stratified random sampling technique was applied to ensure representation of different ages, levels of education, enrollment types, geographic locations, and other learner personal attributes. The average population of learners within the mission is approximately 2,380 pupils.

3.2.1 Research Site

This research study was undertaken in four (4) different learning institutions within the Chikuni Mission of rural Monze district, namely; Chikuni Girl's secondary, St. Canisius secondary, Chikuni primary schools and Charles Lwanga College of Education.

Chikuni mission is approximately 28.6 kilometers south east of Monze town and 11 kilometers east of Chisekesi town in the southern province of the republic of Zambia. Figure 6 below depicts a map of the research site.

Figure 6: Chikuni Mission Map



16°25'60" S and 27°33'0" E
(Degrees Minutes Seconds)

(Google, 2024, May 27).

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

3.3 Data Collection Methods and Instruments

A variety of learner data variables were collected through a structured questionnaire and focus group guides.

3.3.1 Questionnaire:

A structured questionnaire was developed to gather learner demographic information such as age, gender, and socioeconomic status, and respective learning method preferences. Descriptors of key terminologies were clearly explained to participants, particularly primary school learners. The questionnaire incorporated the VARK (Visual, Auditory, Reading and Writing and Kinesthetic) domains.

3.3.2 Focus Group Guide:

Semi-structured focus group guides were explored on learner's perceptions of their learning preferences, exploring factors influencing their choices, and the impact of learning approaches on learning environments.

3.4 Data Collection Procedures

3.4.1 Questionnaire Administration:

The questionnaire was administered through paper-based surveys to a stratified sample of primary school, secondary school and college level learners. Questionnaire administration and discussions were conducted in conducive environments to encourage free and open discourse.

3.4.2 Data Cleaning and Preparation:

The collected data was carefully cleaned, encoded and prepared for exploration, mining and analysis.

3.5 Ethical Considerations

This research study was conducted in adherence to professional and ethical research considerations and requirements. The research project followed a high ethical standard roadmap throughout the entire implementation process; from data collection, application of methodologies to findings. All figures, tables and results analyzed in this study are organic outputs attributable to this particular study, and all outsourced pieces of information have been rightly recognized. Approval to conduct the study was duly obtained from the administrative authorities in the participating institutions before commencement.

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Participant confidentiality was strictly maintained, and informed consent was obtained from all the participants. All data collected in this research remains confidential and exclusively for the purpose of informing the study.

4. Results and Analysis

While machine learning algorithms particularly the *decision trees*, *random forests*, and *support vector machines* classifiers were employed to build predictive models for learning method preferences, correlation feature analysis was implored to examine the relationships between learner attributes and learning preferences. Emerging patterns and trends were identified and carefully assessed. Descriptive statistics was used to summarize the demographic characteristics of the sampled learners.

4.1 Analysis by Institution

Four learning institutions were assessed namely; Chikuni primary school, Chikuni girls secondary school, St. Canisius boys secondary school and Charles Lwanga College of education.

4.1.1 Chikuni Primary School

The sampled learners at the primary school comprised of 56.7% females and 43.3% males with a mean age of 14 years. All of the sampled learners at this level were enrolled in day school and 69.1% of the learners were residing with their biological parents while only 30.8% were in the custody of other guardians.

The primary school learner's numeric variable description is summarized in table 1 below.

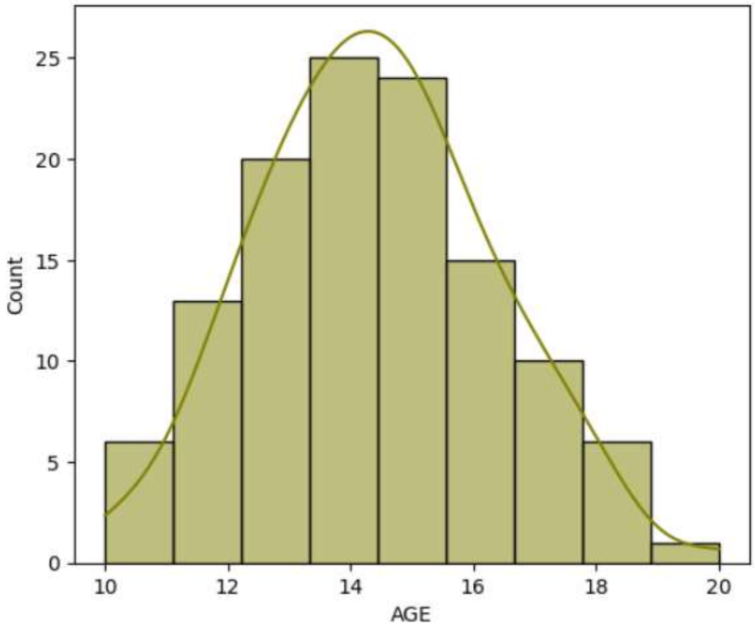
Table 1: Numeric Variable Description Summary 1

	AGE	NO. IN HOUSEHOLD	NO. OF SIBLINGS	HOURS OF STUDY	HOURS OF SLEEP
count	120.00000	120.000000	120.000000	120.000000	120.000000
mean	14.40000	6.741667	5.191667	2.175000	8.041667
std	1.89382	2.739367	3.141738	1.089773	1.349733
min	10.00000	2.000000	0.000000	1.000000	4.000000
25%	13.00000	5.000000	3.000000	1.000000	7.000000
50%	14.00000	6.000000	5.000000	2.000000	8.000000
75%	16.00000	8.000000	7.000000	3.000000	9.000000
max	20.00000	20.000000	17.000000	5.000000	11.000000

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 7(a) and 7(b) below show the age and parental care distribution of the primary school learners.



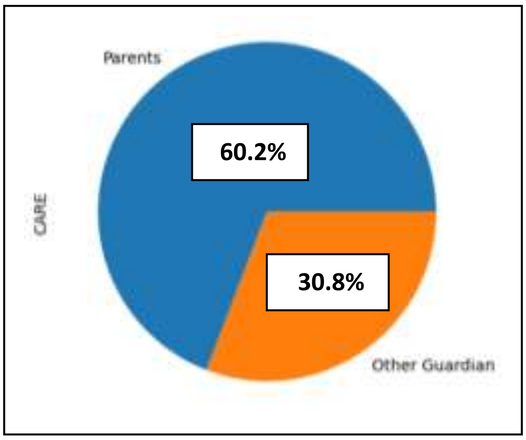


Figure 7: (a) Primary Age Distribution. *(b) Parental Care Distribution.*

An assessment of the learner's learning methods preference at primary school showed that more learners preferred to learn in cooperative groups representing 41.7% while independent and project methods stood at 26.7% and 20.0% respectively. While 10.0% of learners preferred assignments, lecture methods were preferred less than 2% of the time. Figure 8 below shows the distribution of learner's learning preferences.

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

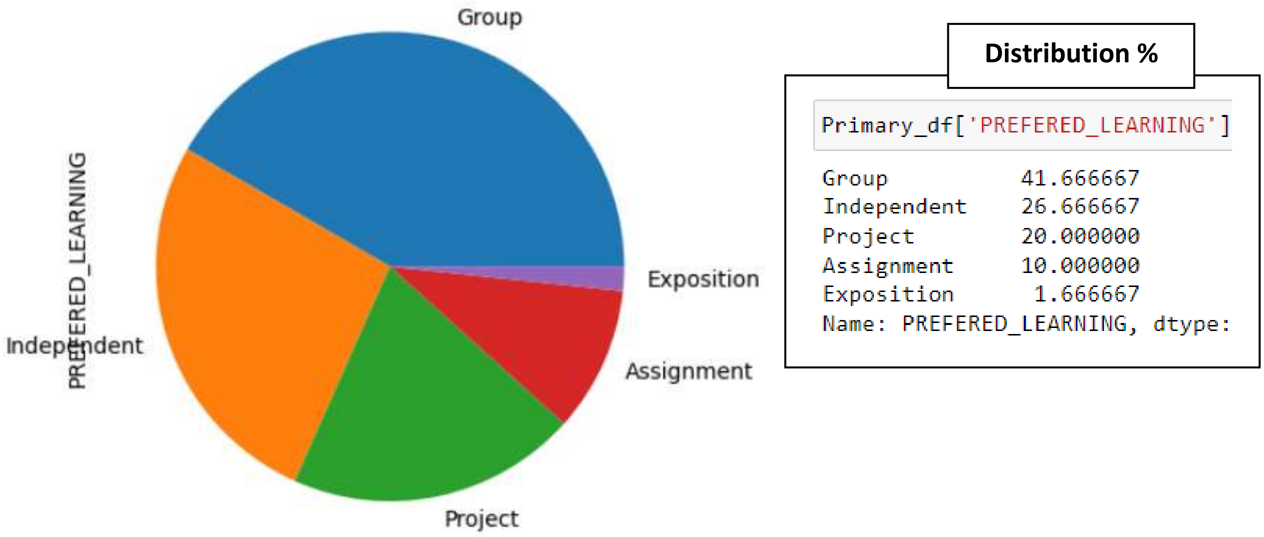


Figure 8: Distribution of learner's Learning Preferences at Chikuni primary school

4.1.2 Chikuni Girls Secondary School

A majority of the sampled learners from the girl's secondary school were enrolled under day school learning representing 88.9% while only 11.1% of the learners were in boarding school. The mean age of these learners was 17 years with a majority at 72.3% from rural areas and only 27.7% from urban residencies. Learners residing with their biological parents stood at 75.2% while 24.8% were in the custody of other guardians.

The learners' numeric variable description is summarized in table 2 below.

Table 2: Numeric Variable Description Summary 2

	AGE	NO. IN HOUSEHOLD	NO. OF SIBLINGS	HOURS OF STUDY	HOURS OF SLEEP
count	101.000000	101.000000	101.000000	101.000000	101.000000
mean	16.930693	7.128713	5.277228	3.019802	6.465347
std	1.133644	2.784469	3.541522	1.348927	1.513700
min	14.000000	2.000000	0.000000	1.000000	1.000000
25%	16.000000	5.000000	3.000000	2.000000	6.000000
50%	17.000000	7.000000	4.000000	3.000000	6.000000
75%	18.000000	8.000000	7.000000	4.000000	8.000000
max	19.000000	20.000000	25.000000	8.000000	10.000000

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 9(a) and 9(b) below show the learner enrollment and age distributions.

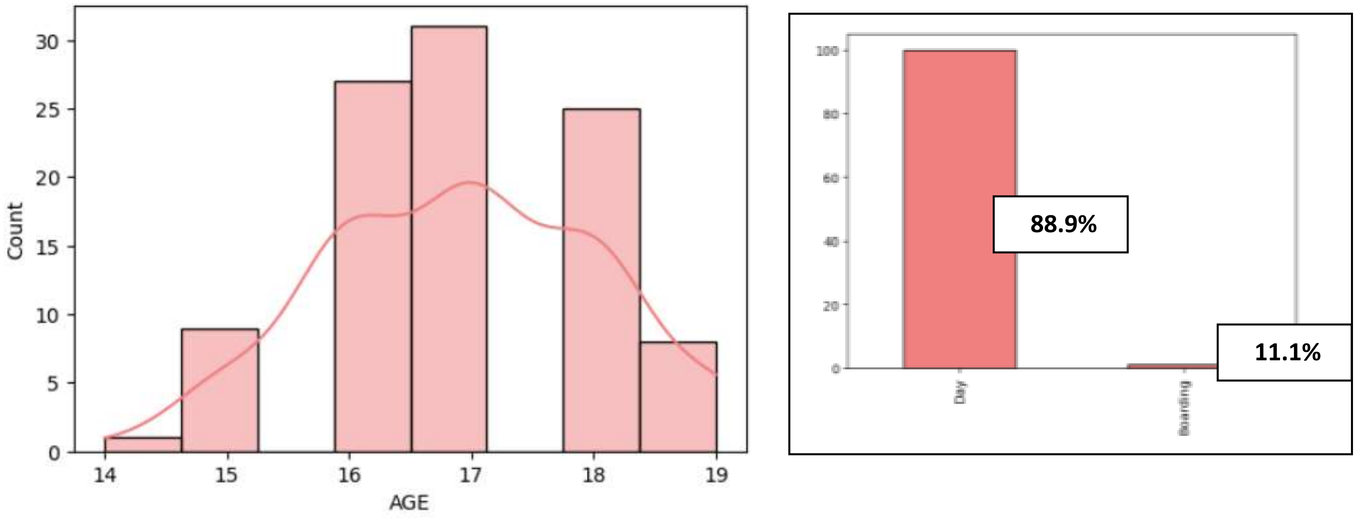


Figure 9: (a) Age Distribution *(b) Learner Enrollment*

Figure 10(a) and 10(b) below show the parental care status and town description distributions.

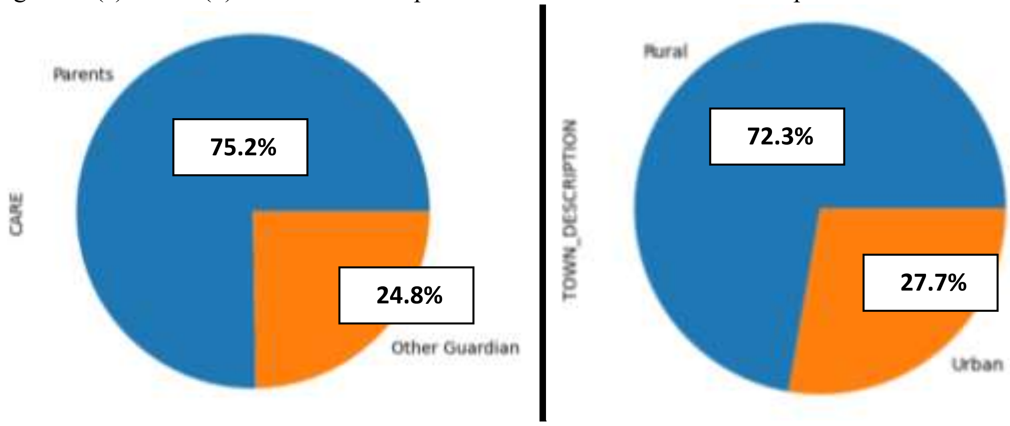
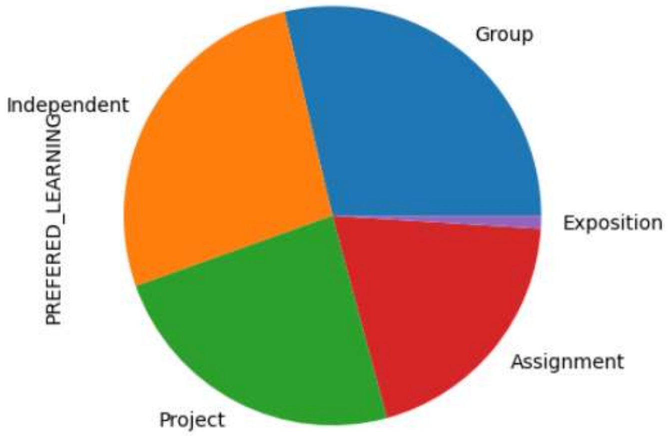


Figure 10: (a) Parental Care Distribution. *(b): Town Description.*

An assessment of the learner's learning preference at the girl's secondary school showed that more learners preferred to learn in focus groups representing 28.7% while independent and project methods stood at 26.7% and 23.8% respectively. While 19.8% of the learners preferred assignments, lecture methods were almost non-preferred at less than 1%. Figure 11 below shows the distribution of Chikuni girl's secondary learner's learning preferences.

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66



Distribution %

```
Group          28.712871
Independent    26.732673
Project        23.762376
Assignment     19.801980
Exposition      0.990099
Name: PREFERED_LEARNING,
```

Figure 11: Distribution of learner's Learning Preferences at Chikuni girl's secondary

4.1.3 St. Canisius Boys Secondary School

Unlike much of the learners at the girl's secondary school, a majority of the sampled learners from the boy's secondary school were enrolled in boarding school representing 65.5% while 34.5% of the learners were day schooling. The mean age of the boy's secondary learners was 17 years with a majority of learners at 95.2% residing with their biological parents. Only less than 5% of learners were in the custody of other guardians while 80.8% were from urban residencies and only 19.2% from rural homes.

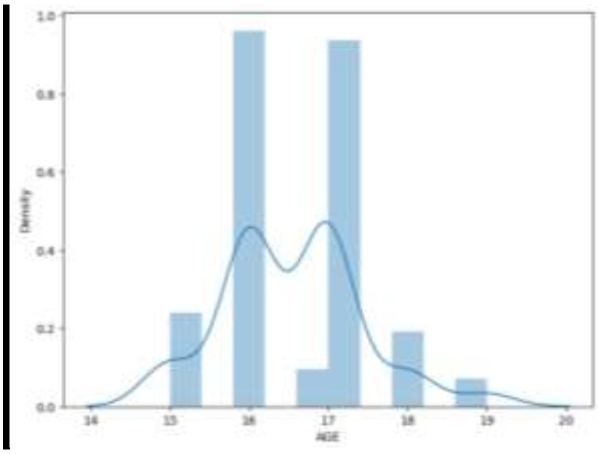
The learner's numeric variable description is summarized in table 3 below.

Table 3: Numeric Variable Description Summary 3

	AGE	NO. IN HOUSEHOLD	NO. OF SIBLINGS	HOURS OF STUDY	HOURS OF SLEEP
count	104.000000	104.000000	104.000000	104.000000	104.000000
mean	16.545632	6.288462	3.240385	4.413462	7.567308
std	0.875350	1.831086	1.579573	1.084852	0.889687
min	15.000000	2.000000	0.000000	2.000000	5.000000
25%	16.000000	5.000000	2.000000	4.000000	7.000000
50%	16.686441	6.000000	3.000000	4.000000	8.000000
75%	17.000000	7.000000	4.000000	5.000000	8.000000
max	19.000000	13.000000	9.000000	9.000000	10.000000

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)
ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 12(a) and 12(b) below show the learner's enrollment and age distribution.



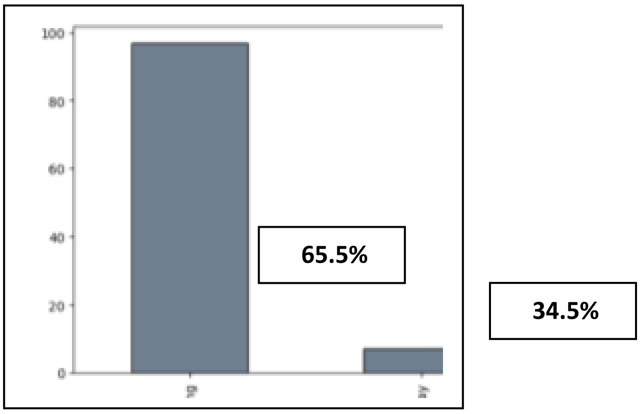
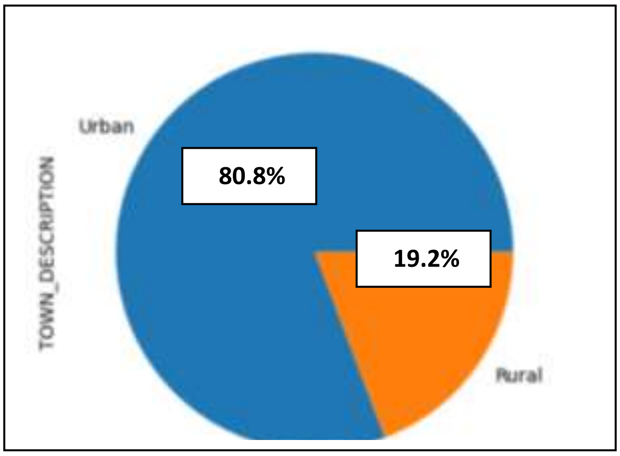


Figure 12: (a) Age distribution. *(b): Learner Enrollment*

Figure 13(a) and 13(b) below show the parental care status and town description distribution of the sampled boy's secondary school learners.



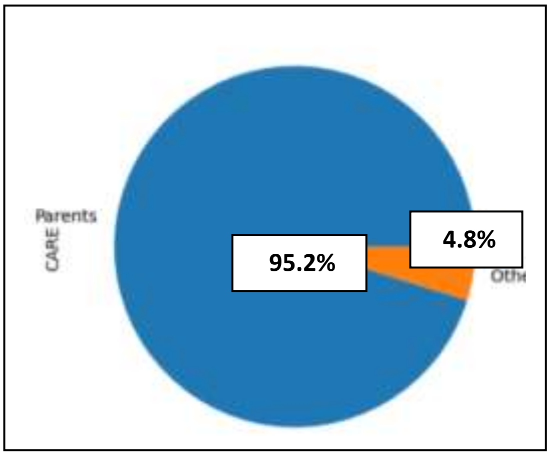
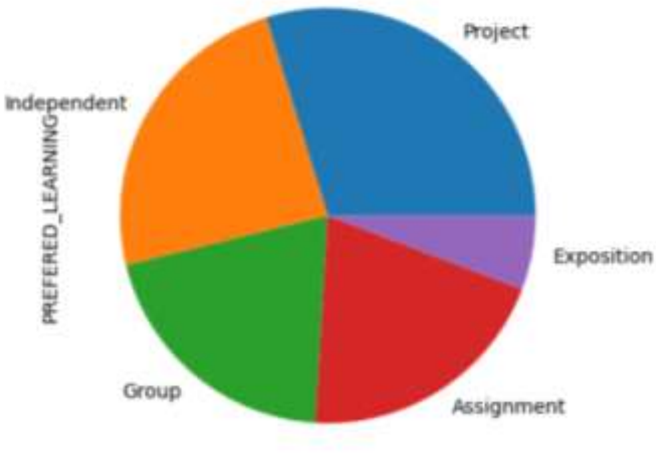


Figure 13: (a) Town Description Distribution *(b) Parental Care Status*

An assessment of the learning preference of the learners from the boy's secondary school showed that more learners preferred project learning methods at 29.8%. Independent learning methods stood at 24.0% while cooperative focus group and assignment methods were equally preferred at 20.2%. Exposition methods lagged at less than 6% in preference.

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 14 below shows the distribution of learner's learning preferences from the boy's secondary school.



Distribution %

```
Project        29.807692
Independent    24.038462
Group          20.192308
Assignment     20.192308
Exposition      5.769231
Name: PREFERED_LEARNING, dtype:
```

Figure 14: Distribution of learner's Learning Preferences at St. Canisius boy's secondary school

4.1.4 Charles Lwanga College of Education

The sampled learners at the college comprised of 57.1% females and 42.9% males with a mean age of 24 years. All of the sampled learners at this level were enrolled in boarding school with 51.4% from rural homes and 48.6% from urban areas. While 54.3% of the learners were from homes taken care of by biological parents, only 45.7% were in the custody of other guardians.

The college learner's numeric variable description is summarized in table 4 below.

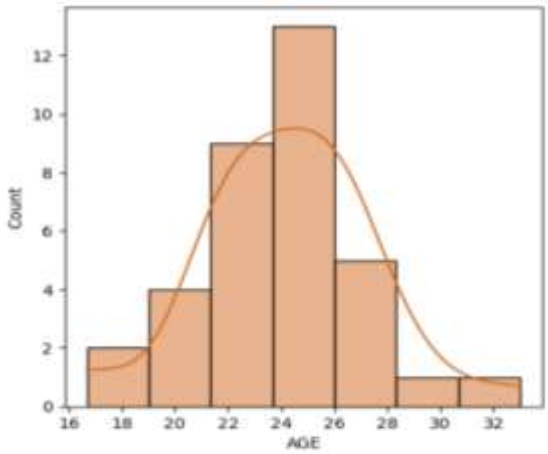
Table 4: Numeric Variable Description Summary 4

	AGE	NO. IN HOUSEHOLD	NO. OF SIBLINGS	HOURS OF STUDY	HOURS OF SLEEP
count	35.000000	35.000000	35.000000	35.000000	35.000000
mean	24.239225	6.885714	5.171429	3.114286	6.371429
std	3.280841	3.103806	2.307095	1.231246	1.139807
min	16.686441	3.000000	0.000000	1.000000	5.000000
25%	22.000000	5.000000	4.000000	2.000000	5.500000
50%	24.000000	6.000000	5.000000	3.000000	6.000000
75%	26.000000	8.500000	7.000000	4.000000	7.000000
max	33.000000	15.000000	9.000000	6.000000	9.000000

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 15(a) and 15(b) below show the age and gender distributions for the college learners.



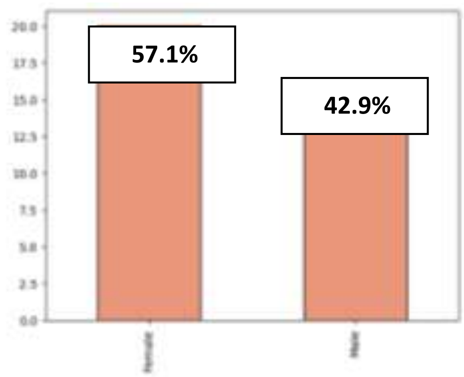
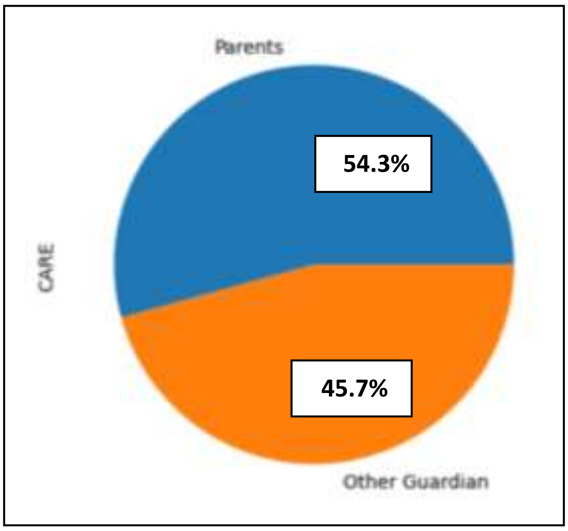


Figure 15: (a) Age Distribution *(b) Gender Distribution*

Figure 16(a) and 16(b) below show the parental care status and town description distributions of the college learners.



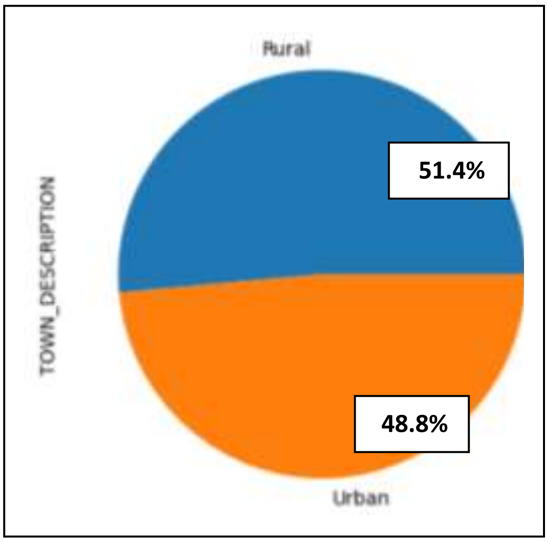


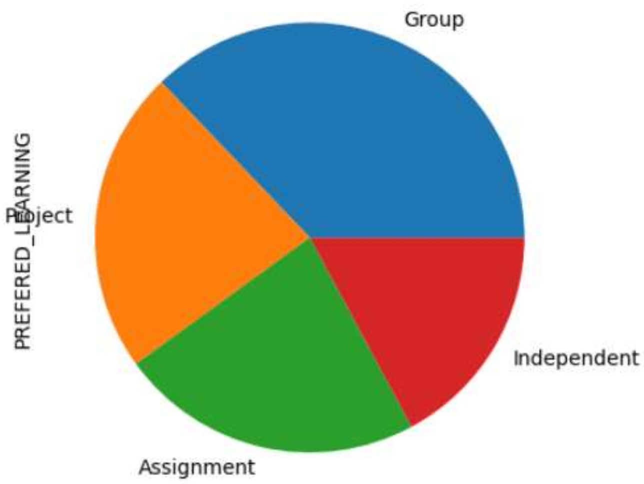
Figure 16: (a) Parental Care Status *(b) Town Description*

An assessment of college learner's learning preference methods showed that more learners preferred to learn in focus groups representing 37.1%. Project and assignment methods were equally preferred at 22.9%. Independent methods were preferred at 17.1% and none of the learners preferred lecture methods.

Figure 17 below shows the distribution of the learner's learning preferences at Charles Lwanga College of Education.

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66



Distribution %

```
Group          37.14285
Project        22.85714
Assignment     22.85714
Independent    17.14285
Name: PREFERED_LEARNING
```

Figure 17: Distribution of learner's Learning Preferences at Charles Lwanga College of Education

4.2 General Cross-Variable Analysis

A total of 360 learners were assessed of which 189 were females and 171 were males representing 52.5% and 47.5% respectively. The mean age was 17 years. The majority of the sampled learners were enrolled in day school representing 63.1% with more in primary and secondary day school and residing in rural townships. While 56.9% represented secondary school learners, 33.3% represented primary school pupils, and only 9.7% representing college students. 76.9% of the learners were residing with their biological parents while 23.1% were in the custody of other guardians.

The general learner's numeric variable description is summarized in table 5 below.

Table 5: Numeric Variable Description Summary 5

	AGE	NO. IN HOUSEHOLD	NO. OF SIBLINGS	HOURS OF STUDY	HOURS OF SLEEP
count	360.000000	360.000000	360.000000	360.000000	360.000000
mean	16.686441	6.733333	4.650000	3.150000	7.300000
std	3.180807	2.573921	2.965869	1.472023	1.441139
min	10.000000	2.000000	0.000000	1.000000	1.000000
25%	15.000000	5.000000	3.000000	2.000000	6.000000
50%	16.000000	6.000000	4.000000	3.000000	7.500000
75%	17.000000	8.000000	6.000000	4.000000	8.000000
max	33.000000	20.000000	25.000000	9.000000	11.000000

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 18 below visualizes independent variables and target variable correlations through a correlation matrix and heat map. The analysis revealed that hours of study were positively correlated to age, learning level, number in household and preferred learning.

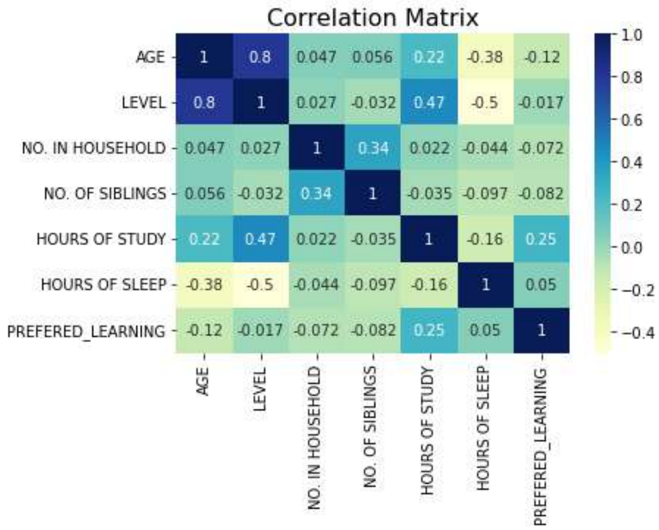
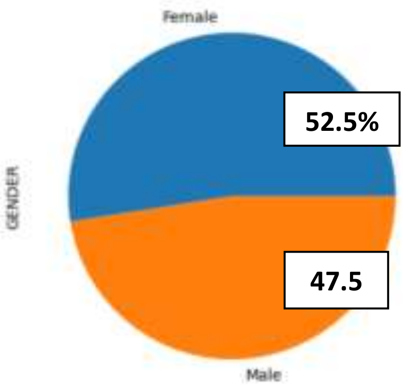


Figure 18: Independent and Target variables correlation matrix

Figure 19(a) and 19(b) below shows the general gender and student enrollment distributions.



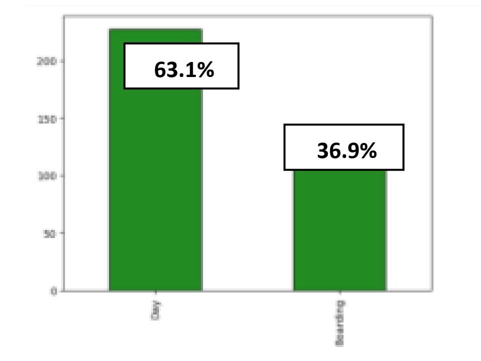
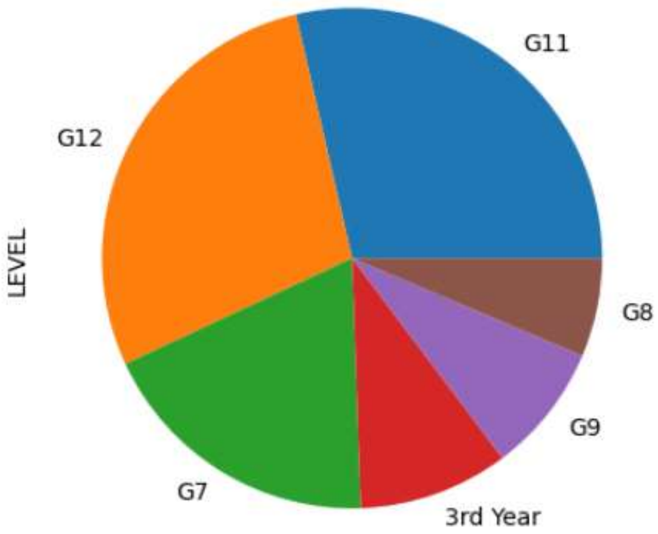


Figure 19: (a) Gender Distribution *(b) Enrollment Distribution*

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)
ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 20 shows the distribution of students by learning level. While Grade11 learners carried the most frequency at 28.6%, grade 8 learners were least represented at 6.4%.



Distribution %

G11	28.611111
G12	28.333333
G7	18.611111
3rd Year	9.722222
G9	8.333333
G8	6.388889

Figure 20: Distribution of learner's Learning Level

Figure 21(a) and 21(b) show the distribution of student's parental care status and town description respectively.

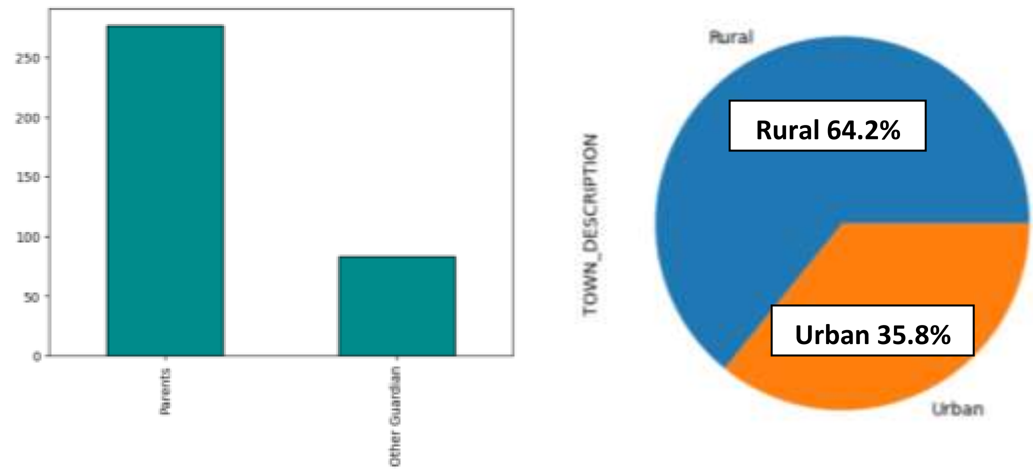


Figure 21: (a) Parental Care Status **(b) Town Description**

A cross variable analysis was conducted on the age of learners against their respective study and sleep hours. Figure 22 shows the general learner age distribution while figure 23(a) and 23(b) below show an analysis of the age of learners against their study and sleep durations. The analysis revealed that hours of sleep steadily reduced with increasing age while hours of study were peak in the age range of 17 years to 24 years.

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

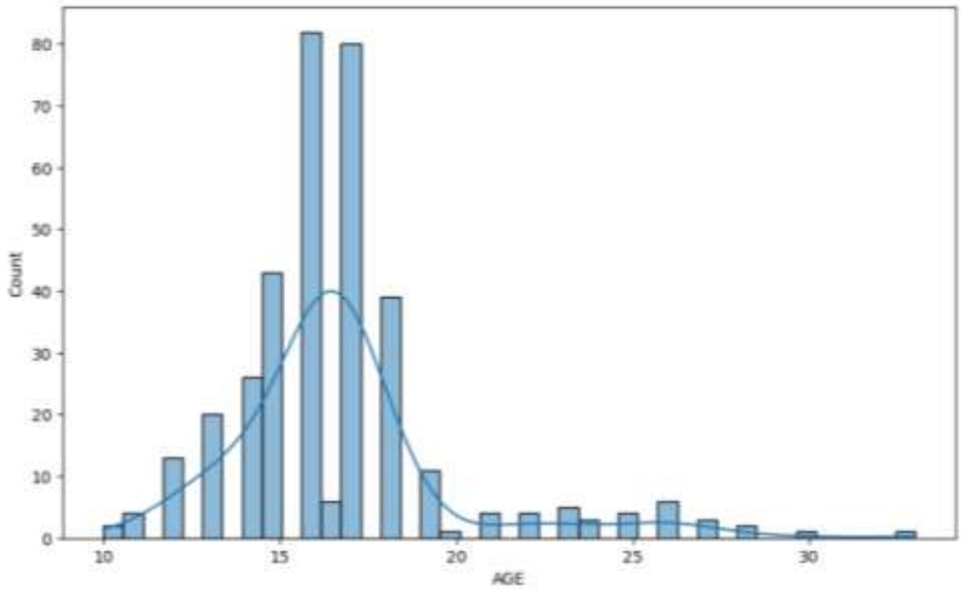
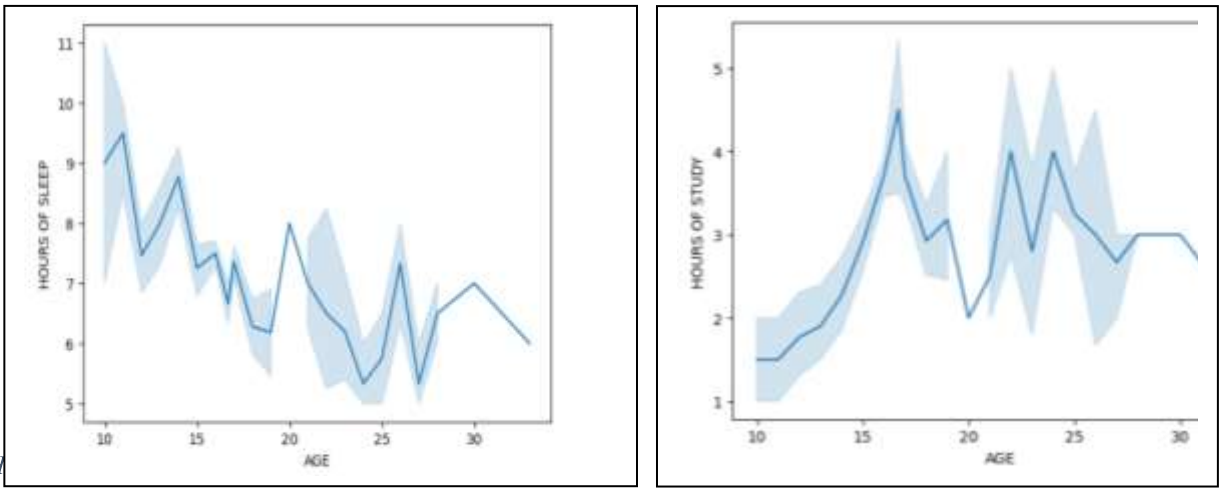


Figure 22: Learner's Age Distribution



H

The violin plot visualization in figure 24 below compares learner's hours of study against their respective hours of sleep. The mean hours of study and hours of sleep were 3 hours and 7 hours respectively.

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

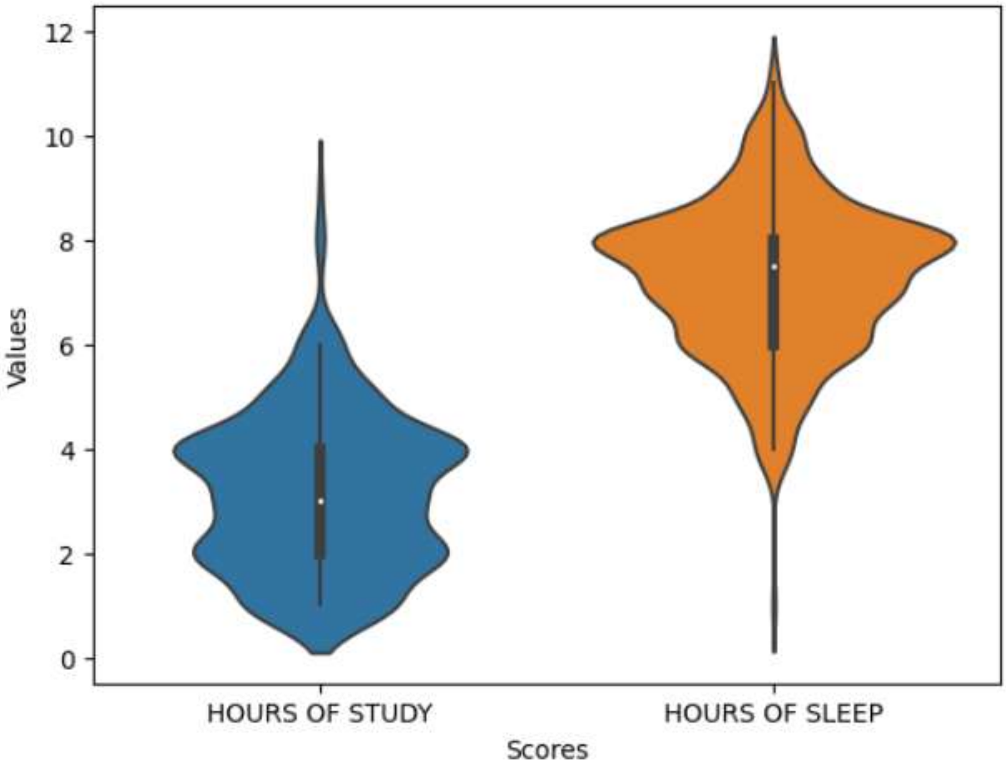
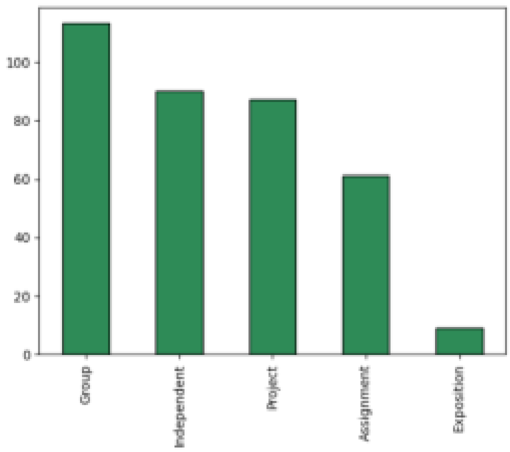


Figure 24: Learner's 'Hours of Study' and 'Hours of Sleep' Violin plot

An assessment of learners learning preference showed that more learners preferred to learn in cooperative groups representing 31.4% while independent and project methods stood at 25.0% and 24.2% respectively. 16.9% of the learners preferred assignments and only 2.5% preferred exposition methods. Figure 25 below shows the distribution of the student learning preference methods while figure 26 shows a cross variable review of learner's learning preference against learner age.

Learner's Learning Preference Distribution



Distribution %

Group	31.388889
Independent	25.000000
Project	24.166667
Assignment	16.944444
Exposition	2.500000
Name: PREFERED_LEARNING,	

Figure 25: Distribution of learners Learning Preference methods

Figure 26 below explores a cross variable analysis of learner's learning preference against age.

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)
ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

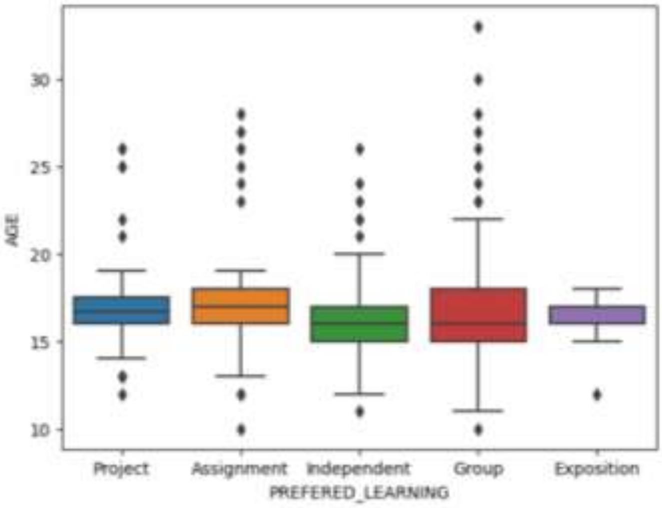


Figure 26: Learner's Learning Preference against Age Analysis plot

4.3 Analysis by Gender

A specific analysis segregated by the gender attribute of the learners was explored to understand learner's learning preference progression.

4.3.1 Female Learner's learning preference progression.

Of all the sampled learners, 189 were female representing 52.5% with a mean age of 17 years. The majority of the sampled female learners were enrolled in day school representing 88.8% with a greater representation in secondary day school and 80.4% residing in rural townships. While 21.2% represented female learners at primary school, 10.6% were from college. Learners residing with their biological parents were represented by 68.9% while 31.2% were in the custody of other guardians.

The female learner's numeric variable description is summarized in table 6 below.

Table 6: Numeric Variable Description Summary 6

	AGE	NO. IN HOUSEHOLD	NO. OF SIBLINGS	HOURS OF STUDY	HOURS OF SLEEP
count	189.000000	189.000000	189.000000	189.000000	189.000000
mean	16.666667	7.063492	5.243386	2.687831	7.068783
std	3.310203	2.755303	3.208039	1.293564	1.669670
min	10.000000	2.000000	0.000000	1.000000	1.000000
25%	15.000000	5.000000	3.000000	2.000000	6.000000
50%	16.000000	7.000000	5.000000	2.000000	7.000000
75%	18.000000	8.000000	7.000000	4.000000	8.000000
max	33.000000	20.000000	25.000000	8.000000	11.000000

Figure 27(a) and 27(b) below show the age and enrollment level distribution for female learners.

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

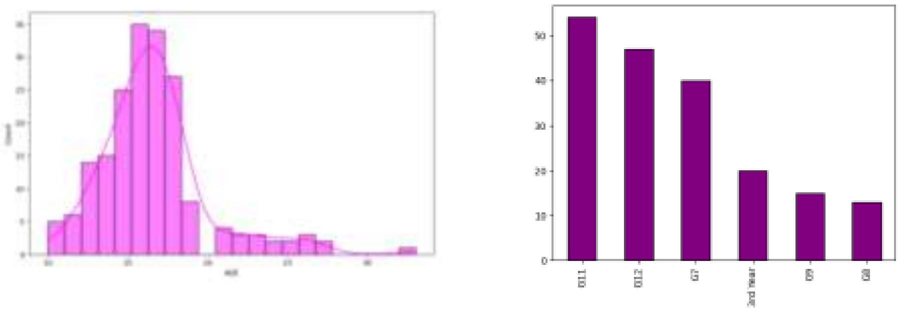
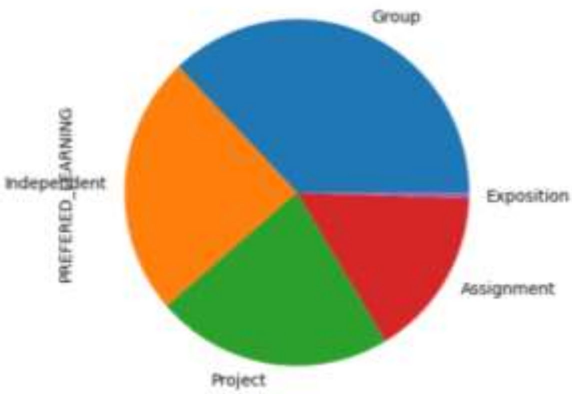


Figure 27: (a) Female Learner's Age Distribution (b): Female Learner's Enrollment Level

An assessment of the learning preferences of female learners showed that more learners preferred to learn in cooperative groups representing 37.0% while independent and project methods stood at 24.3% and 22.2% respectively. 15.8% of learners preferred assignments and less than 1% preferred exposition methods. Figure 28 and figure 29 below shows the female overall learner's learning preferences.



Distribution %

```
females_df['PREFERED_LEARNING']

Group          37.037037
Independent    24.338624
Project        22.222222
Assignment     15.873016
Exposition      0.529101
Name: PREFERED_LEARNING, dtype:
```

Figure 28: Distribution of Female learner's Learning Preference

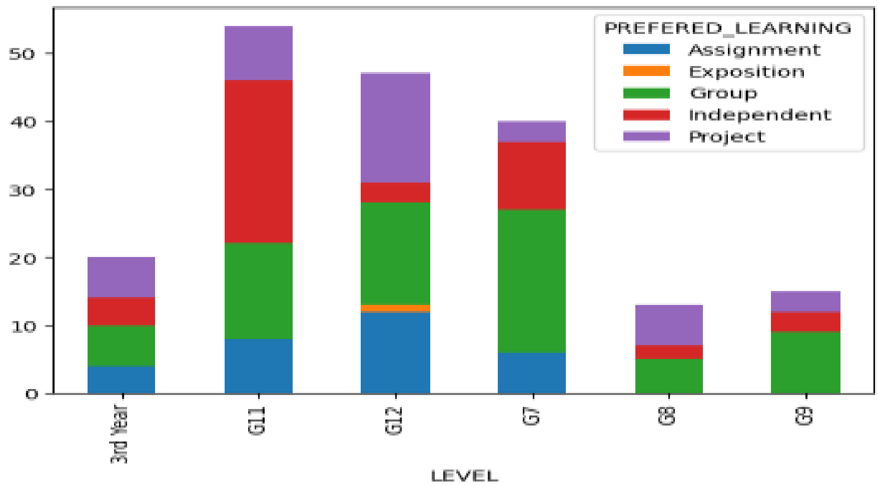


Figure 29: Female learner's Learning Preference by Learning Level

4.3.1.1 ***Primary School Female Learner's Learning Preference***

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

The mean age for the sampled female learners at primary school was 14 years. The average hours of study and sleep for the learners were 2 hours and 8 hours respectively. The learners preferred group methods at 51.5%. Figure 30(a) and 30(b) below shows the age distribution and preferred learning methods for the primary female learners.

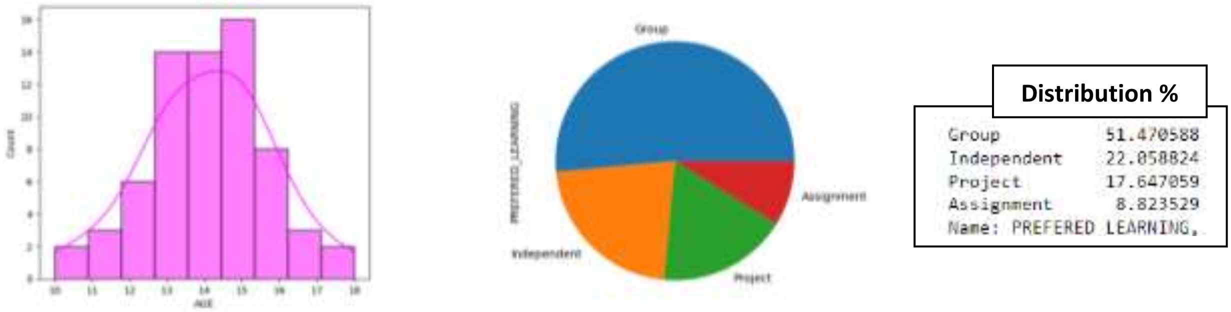


Figure 30: (a) Primary school Female Learner's Age Distribution. (b) Primary school Female learner's Learning Preference

4.3.1.2 ***Secondary School Female Learner's Learning Preference***

The mean age for the sampled female learners at secondary school was 17 years. The average hours of study and sleep for the learners were at 3 hours and 6 hours respectively. The learners preferred group methods at 28.7%. Figure 31(a) and 31(b) below shows the age distribution and preferred learning methods for the secondary female learners.

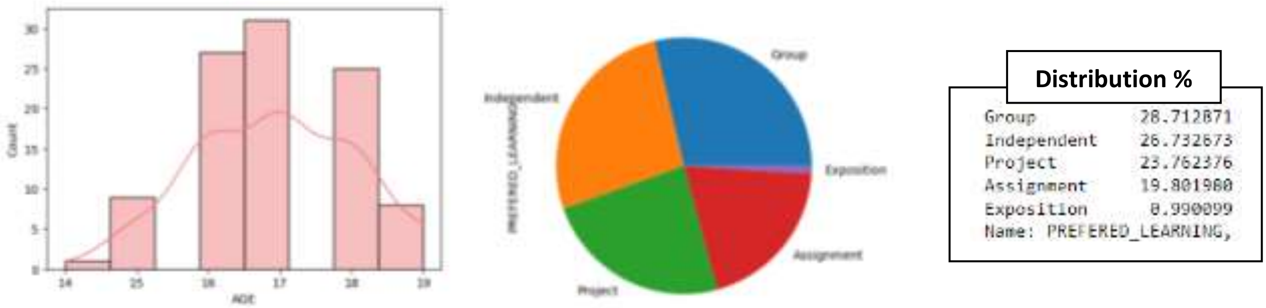


Figure 31: (a) Secondary school Female Learner's Age Distribution. (b) Secondary school Female learner's Learning Preference.

4.3.1.3 ***College Female Learner's Learning Preference***

The mean age for the sampled female learners at college level was 20 years. The average hours of study and sleep for the learners were at 3 hours and 6 hours respectively. The learners preferred project methods at 31.2%. Figure 32(a) and 32(b) below shows the age distribution and preferred learning methods for the college female learners.

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)
ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Figure 32: (a) College Female Learner's Age Distribution. (b) College Female learner's Learning Preference

4.3.2 Male Learner's learning preference progression.

Of all the sampled learners, 171 were male representing 47.5% with a mean age of 17 years. The majority of the sampled male learners were enrolled in boarding school representing 65.5% with a greater representation in secondary day school. More learners at 53.8% were coming from urban homes with 86.0% taken care by their biological parents and 31.2% in the custody of other guardians. While 15.8% represented primary school male learners, 8.8% were college students.

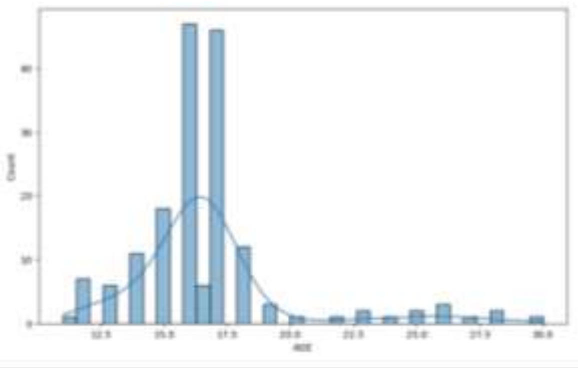
The male learner's numeric variable description is summarized in table 7 below.

Table 7: Numeric Variable Description Summary 7

	AGE	NO. IN HOUSEHOLD	NO. OF SIBLINGS	HOURS OF STUDY	HOURS OF SLEEP
count	171.000000	171.000000	171.000000	171.000000	171.000000
mean	16.708296	6.368421	3.994152	3.660819	7.555556
std	3.040936	2.310831	2.523996	1.491796	1.085255
min	11.000000	2.000000	0.000000	1.000000	5.000000
25%	15.500000	5.000000	2.500000	3.000000	7.000000
50%	16.000000	6.000000	4.000000	4.000000	8.000000
75%	17.000000	7.000000	5.000000	4.000000	8.000000
max	30.000000	20.000000	17.000000	9.000000	10.000000

Figure 33(a) and 33(b) below show the age and enrollment level distribution for the male learners.

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)
ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66



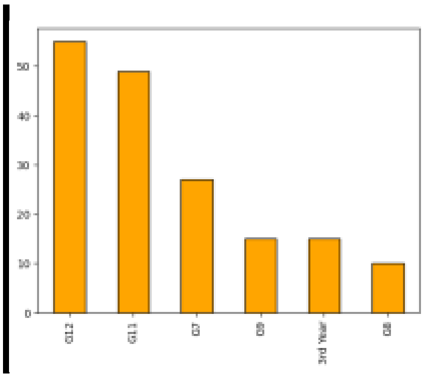
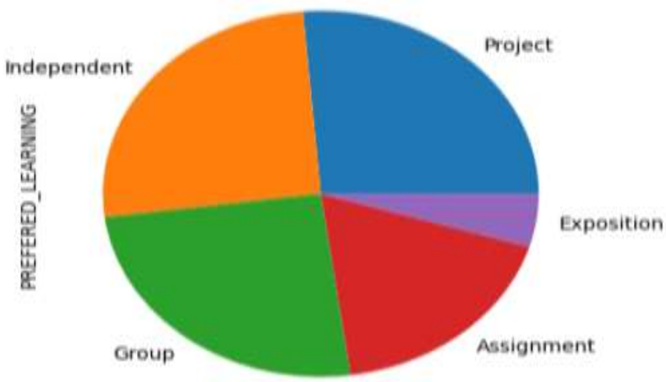


Figure 33: (a) Male Learner's Age Distribution. *b) Male Learner's Enrollment Level*

An assessment of the learning preference of male learners showed that more learners preferred to learn using project methods representing 26.3% while independent and cooperative group methods were preferred at 25.7% and 25.1% respectively. 18.1% of learners preferred assignments and less than 5% preferred exposition methods. Figure 34 and figure 35 below show the male overall learner's learning preference.



Distribution %

```
males_df['PREFERED_LEARNING']

Project        26.315789
Independent    25.730994
Group          25.146199
Assignment     18.128655
Exposition      4.678363
Name: PREFERED LEARNING, dtyp
```

Figure 34: Distribution of Male learner's Learning Preference

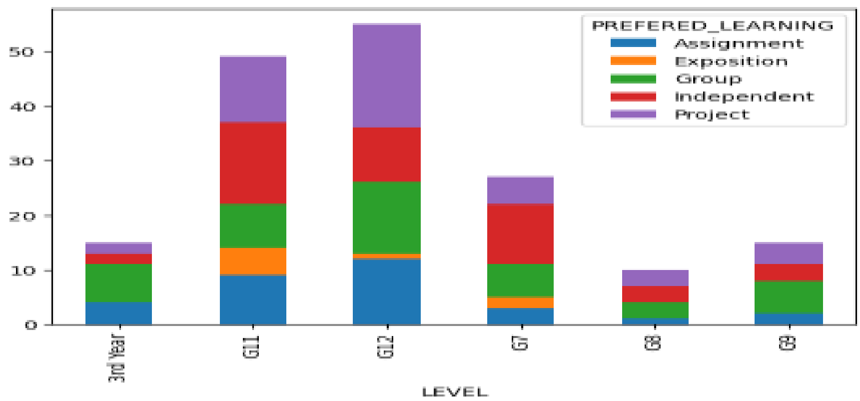


Figure 35: Male learner's Learning Preference by Learning Level

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

4.3.2.1 *Primary School Male learner's Learning Preference*

The mean age for the male learners in primary school was 15 years. The average hours of study and sleep for the learners were 2 hours and 8 hours respectively. The learners preferred independent methods at 32.7%. Figure 36(a) and 36(b) below shows the age distribution and preferred learning methods for the primary school male learners.

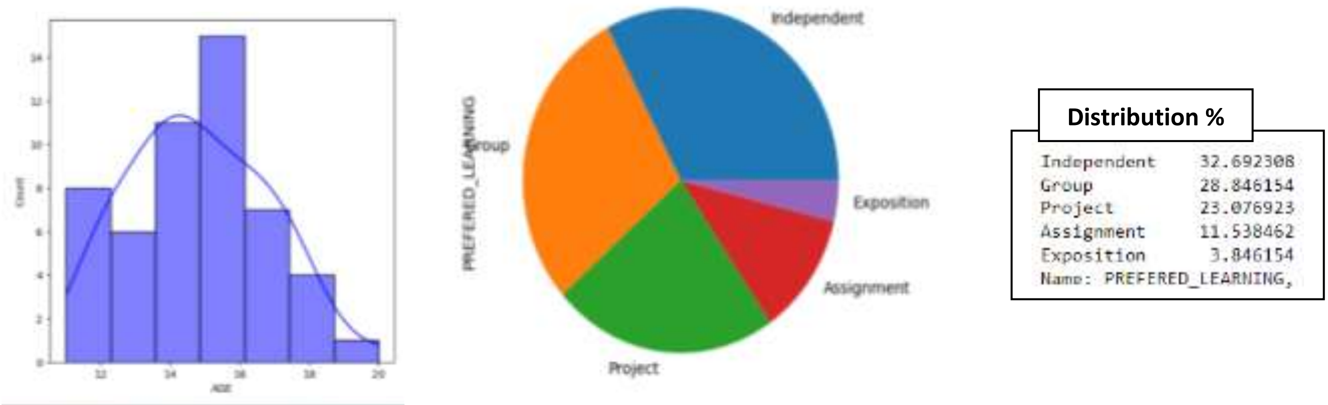


Figure 36: (a) Primary school Male learner's Age Distribution. (b) Primary school Male learner's Learning Preference

4.3.2.2 *Secondary School Male learner's Learning Preference*

The mean age for the male learners at secondary school was 17 years. The average hours of study and sleep for secondary the learners were at 4 hours and 7 hours respectively. The learners preferred project methods at 29.8%. Figure 37(a) and 37(b) below show the age distribution and preferred learning methods for the secondary male learners.

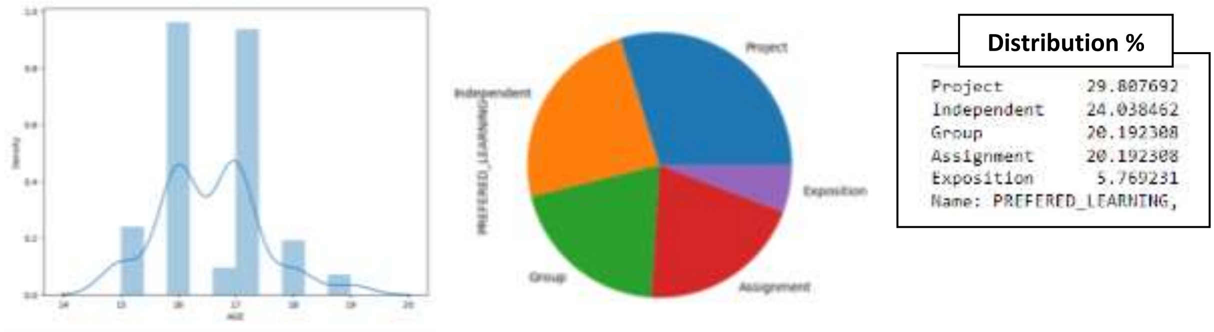


Figure 37: (a) Secondary school Male Learner's Age Distribution. (b) Secondary school Male learner's Learning Preference

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

4.3.2.3 *College Male learner's Learning Preference*

The mean age for the sampled male learners at college level was 24 years. The average hours of study and sleep for the learners were 3 hours and 6 hours respectively. The learners preferred to learn in cooperative groups represented by 32.7%.

Figure 38 and figure 39 below shows the age distribution and preferred learning methods for the college male learners.

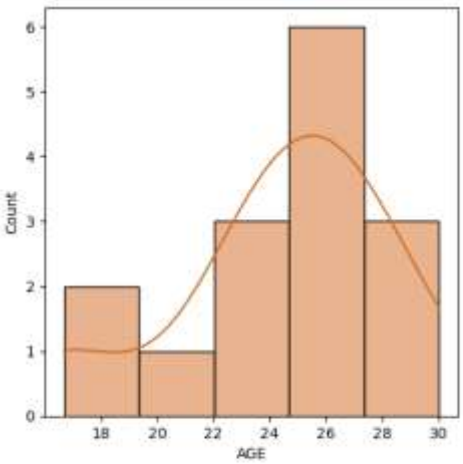
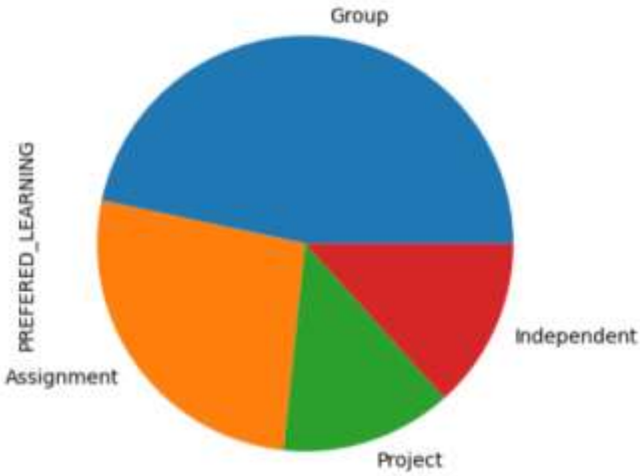


Figure 38: College Male Learner's Age Distribution



Distribution %

```
Group          46.66666
Assignment     26.66666
Project        13.33333
Independent    13.33333
Name: PREFERED_LEARNING
```

Figure 39: College Male learner's Learning Preference methods

Interdisciplinary Journal of AI, Machine Learning & Data Science (IJAIMLDS)

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

4.5 Results

4.5.1 Research Question 1: Findings

Figure 40 below depicts the machine learning feature significance output of varying learner attributes to their respective learning method preferences. *Age*, *duration of Study*, *Level of learning* and the *Visual Domain* showed more significance to predicting the target variable (*preferred learning method*).

Feature Importance

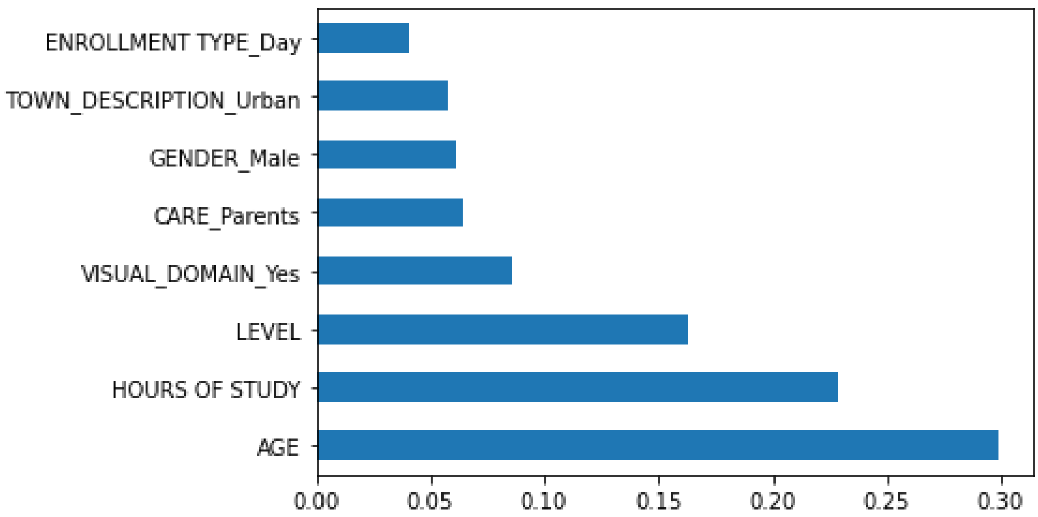


Figure 40: Independent variable feature importance

Table 8 below summarizes the results for the patterns in learning domains of learners to their respective learning preferences across learning levels by gender.

Table 8: Learner's learning preferences results summary

Learner Description	Level of Learning	Mean Age (Years)	Prominent Learning Domain	Prominent Learning Domain (%)	Preferred Learning	Preferred Learning (%)
Female	Primary	14	VISUAL	75.0	Focus Group	**51.5**
	Secondary	17	VISUAL	67.3	Focus Group	**28.7**
	College	20	AUDITORY	70.0	Project	**31.3**
Male	Primary	15	VISUAL	82.7	Independent	**32.7**
	Secondary	17	KINESTHETIC	68.5	Project	**29.8**
	College	24	VISUAL	53.3	Focus Group	**46.7**

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

4.5.2 Research Question 2: Findings

The summary outputs for the respective machine learning classification models applied are tabulated as shown below in table 9, table 10 and table 11 respectively.

Table 9: The Decision Tree Classifier results summary

	Precision	Recall	F1-Score
Accuracy			0.56
Macro Average	0.56	0.54	0.52
Weighted Average	0.56	0.56	0.53

Table 10: The Random Forest Classifier results summary

	Precision	Recall	F1-Score
Accuracy			0.73
Macro Average	0.75	0.72	0.71
Weighted Average	0.74	0.73	0.72

Table 11: The Support Vector Machine Classifier results summary

	Precision	Recall	F1-Score
Accuracy			0.54
Macro Average	0.50	0.27	0.35
Weighted Average	1.00	0.54	0.70

The learning models showed that the *Random Forest* classifier had a much higher performance in predicting learners *learning method preferences* with an *accuracy* output of 73% (as could be observed on the *F1-score* in *Table 10* above).

5. Discussion and Conclusion

5.1 Discussion

The findings of the study indicate that learner attributes of *Age*, *duration of Study*, *Level of learning* and the *Visual Domain* have more significance to predicting the learner's learning method preference (as could be observed through figure 40 in the results). The results further show that primary and secondary school female learners preferred to learn in cooperative groups with the Visual domain as the prominent learning sphere, while female learners at college preferred to learn through projects with the auditory domain being prominent (as tabulated in table 8 in the results section). Males at the primary school level preferred to learn independently with an inclination to the Visual domain while

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

males at secondary school preferred project methods with the kinesthetic domain being profound. Meanwhile college level males preferred cooperative groups with a prominence in the visual domain.

Generally, more female learners preferred to learn in cooperative groups across all learning levels representing 37% with a steadily increasing interest in project learning methods. The research study shows that while more young males at primary school level preferred to learn independently, project methods became more popular among males at secondary school level representing 27%. Further investigation in the study revealed that more female students at the college level preferred project methods while cooperative methods and assignments became popular among college male students. Broadly lecture methods were unpopular, with less than 2% preference across all learning levels. Learner attributes such as tribe, parental care, and the auditory and kinesthetic domains seemed not to contribute significantly to the target variable. The findings further show that the age of learners was negatively correlated to the duration of sleep while learners around the mean age of 17 years showed the highest number of study hours.

The experimental evaluation of the classification machine learning models showed that the *Random Forest* classifier had a much higher performance output for predicting target class labels (*learning method preference*) at an *accuracy F1-score* of 73% (as tabulated in Table 10 in the Results section). The *accuracy metric* of the learning model provides the ratio of the correctly predicted instances to the total number of all instances. The *precision metric* measures the proportion of true positive (TP) instances to the total number of all predicted positive instances while the *recall metric* measures the proportion of actual positive variables correctly predicted by the algorithm (Naveed et al., 2024; Salama et al., 2025). The *F1-score* provides the harmonic mean of the precision and recall values.

The specific mathematical formulas for accuracy, precision and recall scores are outlined below;

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN},$$

$$Precision = \frac{TP}{TP+FP},$$

$$Recall = \frac{TP}{TP+FN},$$

Where;

TP = True Positive, FP = False Positive, TN = True Negative and FN = False Negative, (Google Developers, 2024).

Independent variable features were carefully assessed before determining features. Feature selection is a significant process for many machine learning algorithms. It is essentially a process of removing less useful features which would normally introduce unnecessary noise that could affect the effective

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

modeling process (El Touati et al., 2024). A random forest feature importance was applied to assess for feature importance in classifying the target variable. Instances which could potentially lead to an over fitted model were excluded from the independent variable set. This is important for the optimization, fit and reliability of our predictive models (Montesinos et al., 2022).

5.2 Conclusion and Recommendations

Differentiated learning carefully coupled with a good understanding of learner preferred learning methods would greatly improve individual learner performance and enhance learning atmospheres. Failing to create learning opportunities for learners in their respective learning preferences has great potential to negatively affect their learning outcomes and create passive and non-performing learners in our school settings.

This paper recommends that machine learning explorative models can be useful to a larger extent to assess and predict the learning preferences of learners in classrooms.

Research Objective 1: Recommendations

This research paper proposes the following recommendations towards the fulfillment of the research objective number 1.

1. More female learners are encouraged to explore a diverse of learning preferences, particularly primary school girls towards project based learning.

2. Learners across learning levels are encouraged to have more effective study duration times.

Research Objective 2: Recommendations

This research paper proposes strongly the following recommendations towards the fulfillment of the research objective number 2.

1. Teachers, trainers and educators are strongly encouraged to effectively utilize a variety of teaching and learning methods, approaches and strategies with clearly thought out teaching activities that reflects the learning preference and interest of learners.

2. Teachers, trainers and educators are encouraged to enhance learning experiences by familiarizing themselves to trending learning models and artificial intelligence tools and processes that could enhance classroom experience and service delivery.

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

Acknowledgements

The successful completion of this research would not have been possible without the invaluable support and cooperation of many individuals and institutions.

I would like to express my sincere gratitude to the administrations, staff, and learners of the four participating institutions; Canisius Secondary School, Chikuni Girls' Secondary School, Chikuni Primary School, and Charles Lwanga College of Education. The openness, cooperation, and willingness from the participants made the data collection process smooth and meaningful.

I am especially grateful to the selected learners who generously shared their time, experiences, and insights, which formed the foundation of this study.

I also extend my appreciation to the educators and administrators who facilitated access, coordinated schedules, and provided essential institutional support throughout the research process.

Conflict of Interest Statement

I wish to state that this study was conducted without any financial sponsorship or external funding, and there are no financial conflicts of interest influencing the study process or findings. The integrity and independence of this work was maintained throughout the research process. However, it is worth to note that the researcher is serving as a senior lecturer at Charles Lwanga College of Education. The researcher further has no direct or indirect relationship with the journal editors or any employee of the Interdisciplinary Journal of AI, Machine Learning and Data Science (IJAIMLDS).

References

1. Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5-32. https://doi.org/10.1023/A:1010933404324
2. Chen, X., Liu, Y., & Zhang, H. (2020). Predicting students' learning styles using machine learning techniques: A case study. *IEEE Access, 8*, 123456-123478.
3. Coffield, F., Moseley, D., Hall, E., & Ecclestone, K. (2004). *Learning styles and pedagogy*. Routledge.
4. Damasevicius R. (2025). Recent trends and progress in support vector machines. In *Recent Trends and Progress in Support Vector Machines*. IntechOpen. https://doi.org/10.5772/intechopen.1005410
5. Darling-Hammond, L. (2000). *The impact of teacher quality on student achievement*. Educational Researcher, 29(2), 3-14.
6. Dunn, R., & Dunn, K. (1992). Teaching students through their learning styles: Matching instruction and student needs. Allyn & Bacon.

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

7. Dunn, R., & Griggs, S. A. (1998). Learning style and academic performance: Does it matter? *Journal of Educational Psychology, 90*(4), 737-746.
8. El Touati, Y., Ben Slimane, J., & Saidani, T. (2024). Adaptive method for feature selection in the machine learning context. Engineering, Technology & Applied Science Research, 14(3), 14295–14300. https://doi.org/10.48084/etasr.7401
9. Google (2024, May 27). Google Maps – Chikuni, Hamavwa. https://www.google.com/maps/@-16.4209454,27.5021824,13z?entry=ttu&g_ep=EgoyMDI2MDMwOC4wIKXMDSoASAFQAw%3D%3D
10. Google Developers. (2024). Classification: Accuracy, precision, recall, and related metrics. Google Machine Learning Crash Course. https://developers.google.com/machine-learning/crash-course/classification/accuracy-precision-recall
11. Han, J., Kamber, M., & Pei, J. (2011). Data mining: Concepts and techniques. Morgan Kaufmann.
12. Hattie, J. (2009). Visible learning: A synthesis of over 800 meta-analyses relating to achievement. Routledge.
13. Kolb, D. A. (1984). Experiential learning: Experience as the source of learning and development. Prentice-Hall.
14. Lin Lin et al (2024). A systematic review of Big Data Driven Education Evaluation.
15. MacFarlane, A. (2003). Learning styles: An overview of theories, models, and measures.
16. Mayer, R. E. (2017). Learning and instruction. Pearson.
17. Medium (2024, August 04). Decision Tree Classification (numerical example). https://medium.com/@balajicena1995/decision-tree-classification-numerical-example-23d26386f03f
18. Medium (2024, August 04). Machine Learning Algorithms(9)-Ensemble techniques (Bagging-Random Forest Classifier and Regression). https://medium.com/towardsdev/machine-learning-algorithms-9-ensemble-techniques-bagging-random-forest-classifier-and-5d3747c7a953
19. Medium (2024, June 05). Support Vector Machine (SVM): An Intuitive Explanation. https://medium.com/low-code-for-advanced-data-science/support-vector-machines-svm-an-intuitive-explanation-b084d6238106
20. Montesinos Lopez, O. A., Montesinos Lopez, A., & Crossa, J. (2022). Overfitting, model tuning, and evaluation of prediction performance. In Multivariate statistical machine learning methods for genomic prediction (pp. 109–139). Springer. https://doi.org/10.1007/978-3-030-89010-0_4
21. Naveed, M. A., et al. (2024). Performance evaluation metrics for machine learning models. International Journal of Engineering & Science Research, 14(2), 1627–1643.
22. Nie, F., Hao, Z., & Wang, R. (2023). Multi-class support vector machine with maximizing minimum margin. *arXiv*. https://arxiv.org/abs/2312.06578

ISSN: 3139-3527 | January-March-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/zadvbn66

23. Pashler, H., McDaniel, M., Rohrer, D., & Bjork, R. A. (2009). Learning and memory: Issues, perspectives, and controversies. Oxford University Press.
24. Pathmind (2024, May 22). *A Beginner's Guide to Important Topics in AI, Machine Learning, and Deep Learning*. wiki.pathmind.com/random-forest
25. Routledge. Fleming, N. (2001). VARK: A guide to learning styles. Neil Fleming.
26. Sharon Kim et al (2019). *Improving 21st century teaching skills: The key to effective 21st century learners.* Vol. 14(1)99-117. DOI: 10.1177/1745499919829214. SAGE.
27. UNESCO (2026, March 10). Zambia: Education Country Brief. https://www.iicba.unesco.org/en/zambia?utm_source=chatgpt.com
28. UNESCO. (2020). *Education for all 2030: The global monitoring report*. UNESCO.
29. UNICEF (2024, August 06). Innocenti-DMS-Zambia-Report. UNICEF. https://www.unicef.org/innocenti/media/7891/file
30. Walker, M. P. (2017). Why we sleep: Unlocking the power of sleep and dreams. Scribner.
31. Witten, I. H., Frank, E., & Hall, M. A. (2011). *Data Mining: Practical Machine Learning Tools and Techniques* (3rd ed.). Morgan Kaufmann.