International Journal of Informatics and Data Science Research
ISSN 2997-3961 (Online)
Vol. 2, No. 7, Jul 2025,
Available online at: https://scientificbulletin.com/index.php/IJIDSR

Exploring Machine Learning Techniques for Questionnaire Analysis

Hazem Salim Abdullah
Directorate of Municipalities Nineveh Governorate, Mosul, IRAQ

Salim Abdullah Saleh
Retired Assist. Prof. Dr., Tikrit University, Eng. College, Mosul, IRAQ

Mario Maroun
Computer Science Department, Saint Joseph University, USJ, Lebanon

Article information:
Manuscript received: 4 May 2025; **Accepted:** 10 Jun 2025; **Published:** 21 Jul 2025

Abstract: The application of machine learning in questionnaire design and evaluation is examined in this work, with a special emphasis on data quality, specifically Cronbach's alpha. It evaluates the effect of a method for creating various Cronbach's alpha random data (0.8–0.94) on machine learning algorithms. The method minimizes human labor in questionnaire design by generating data with estimated internal consistency through the use of machine learning and natural language processing. To assess how Cronbach's alpha affects the accuracy of machine learning models, the data is analyzed. When dealing with low Cronbach's problems, the ML models RF, NB, LR, SVM, and KNN, respectively, have acceptable and exceptional accuracy (58% - 100%). However, when dealing with high Cronbach's problems, their accuracy drops to 26% - 79%.

Keywords: Machine learning, Artificial Intelligence, Cronbach Alpha, Generated Dataset.

1. INTRODUCTION

AI is a fast evolving field that offers a new approach to data analysis and modelling, particularly in the creation and analysis of questionnaire forms. The main instruments used to collect data for market research and scientific investigations, as well as to evaluate how successfully institutions are carrying out their responsibilities, are questionnaires. facial intelligence (AI) has an advantage in improving the accuracy and efficiency of these tasks [1, 2]. However, their design and analysis are laborious and nontrivial. By supporting questionnaire form creation using natural language processing (NLP), other AI technologies, and machine learning (ML) approaches, art Artificial intelligence (AI) has the potential to improve the clarity of questionnaires, tailor them to the user population, and generate questions based on study objectives [3]. Additionally, it can process the answer using deep learning and text analysis technologies, which make it easier than ever to extract meaning from data something that is challenging to accomplish with conventional methods. The purpose of the study By focusing on AI-related techniques that have been used and how they can help enhance the quality of the data extracted, lessen bias in questionnaires, and speed up analysis processes, this study aims to address the problem of using artificial intelligence for creating and analyzing questionnaires [4].

The curriculum and assessment profoundly influence the lives and careers of youth. School decisions significantly impact students' prospective outcomes and opportunities, but the long-term consequences of public tests and assessments may be even more crucial [5]. Higher education evaluation approaches necessitate a transformation incorporating components of university didactic assessment methodologies, including co-assessment and self-assessment [6].

The systematic gathering and analysis of student feedback is a crucial quality assurance and enhancement activity in higher education teaching and learning. National student feedback surveys, exemplified by the UK's National Student Survey (NSS) [7], have established a benchmark in several nations, with their outcomes used to guide the enhancement of educational interventions and methodologies [8, 9].

Nonetheless, evidence indicates that in the last decade, there has been a negligible rise in overall student satisfaction, attributable to higher education institutions' inability to rectify the adverse elements of students' learning experiences documented in satisfaction feedback reports [10, 11, 12, 13].

Since its start in 1950 [14], AI has seen substantial evolution and applied across many sectors, including healthcare, business, manufacturing, transportation, finance, and education. Artificial intelligence has progressed in healthcare from rule-based expert systems to sophisticated predictive analytics, inventory optimization algorithms, and comprehensive automation technologies [15]. In business and industry, artificial intelligence has evolved from rudimentary production rule systems to sophisticated predictive analytics, inventory optimization algorithms, and comprehensive automation technologies [16]. Artificial intelligence has progressed in transportation from goal-oriented navigation studies to autonomous driving technologies, enhancing convenience for the government and the public by optimizing dynamic routing and managing traffic signals [17].

AI aids academics, researchers, and students with content development, analytical computations, and writing, encompassing thesis preparation and publishing research articles in academic publications. It enhances material quality, graphics, grammar, and spelling, refines the word selection and style of the research paper, and offers suggestions to fortify arguments inside the research papers. AI models may assess draft theses, offer comments on literature deficiencies, determine if research questions and assertions are adequately substantiated by evidence, ensure logical coherence and transitions, and identify sections requiring modification or lacking citations [18].

AI capabilities revolutionize how students receive support across all phases of academic study and writing. Notable AI solutions for writing aid are Grammarly and QuillBot. Miyuki Sasaki’s paper examines the difficulties non-native English speakers face in academia while utilizing AI writing support tools [19]. In contrast, Basic et al. [20] explore the application of ChatGPT in aiding students with argumentative essay composition. Malik et al. [21] examine the viewpoints of Indonesian higher education students on AI writing technology.

In contrast, Imran et al. [22] address the application of AI-based text classifiers for identifying AI-generated essays and managing AI-assisted plagiarism. Salas-Pilco et al. [23] examine the uses of AI and learning analytics in teacher education, emphasizing the prospects for automated assessment and tailored feedback. Nonetheless, ethical considerations and educators' data literacy are essential.

2. THEORITICAL FRAMEWORK

2.1 INRODUCTION TO QUESTIONNAIRE DESIGN AND ANALYSIS USING ARTIFICIAL INTELLIGENCE

By automating processes like data collecting and analysis, artificial intelligence (AI) has drastically changed survey research and questionnaire analysis [24]. It lowers human error, makes user experience more appealing, and creates models that are more accurate [2]. Humans are usually the people who possess the statistical technique, human knowledege, and make subjective judgment in the conventional methods. The use of AI algorithms makes surveys more efficient, more accurate, and better in terms of quality because it is possible to utilize machine learning (ML) and natural language processing (NLP) technologies [25].

2.2 Techniques for Developing Questionnaires Using Artificial Intelligence

Techniques for Artificial Intelligence in Questionnaire Creation

Several artificial intelligence techniques are used while designing surveys, chief among them being:

- Natural language processing is a method that makes the writing of clear and understandable questions quite easy, and at the same time the method is used to find out how good people's skill of understanding is in relation to the questions asked[3].
- Machine Learning() refers to the process of Predicting the right questions to a particular topic by looking at the past data, ML is very helpful in making personalized surveys [2].
- Deep Learning (Deep Neural Network): It can perform a quick check of the data it has received in relation to the accuracy of the response patterns and at the same time undertake the analysis of the response patterns [1].

2.3 ARTIFICIAL INTELLIGENCE IN DATA ANALYSIS

Artificial intelligence is capable of handling the following tasks in the analysis stage post data collection:

Citing the work of [4] the authors list the example of participant responses on the basis of data classification methods (SVM and Logistic Regression) (this is data categorization and evaluation).

- By applying sentiment analysis, it is possible to uncover patterns in unstructured text as well as open-ended responses [2].
- The usage of complex AI algorithms that can minimize the impact of uneven data is one solution to the problem of bias in data analysis [3].
- Deep Learning in the context of analysis is a method that emphasizes the fact that such relationships exist [1].

2.4 The Benefits of Artificial Intelligence for Surveys

Artificial intelligence offers several benefits which are as follows:

- Conserving time and energy: Artificial intelligence enables faster creation and analysis of surveys compared to traditional methods [1].
- Improving accuracy and decreasing mistakes: Intelligent models improve data quality while reducing errors caused by human intervention [4].

The strength of scientific research is enhanced by sophisticated data analysis techniques that use AI to identify concealed connections among survey variables [2].

2.5 CHALLENGES AND RISKS

Notwithstanding its numerous advantages, AI in questionnaire analysis has many drawbacks, including:

- Data bias: Inaccurate results might result from unbalanced data, necessitating model modification and better training parameters [3].
- Data privacy: The sensitive data gathered for questionnaire analysis needs protection according to established privacy regulations [1].
- Difficulty in understanding outcomes: The opaque nature of deep neural networks and other AI models creates challenges for interpreting their decision-making processes [2].

3. RESEARCH METHODOLOGY

The application of artificial intelligence in the development and assessment of questionnaire forms is investigated in this work using analytical and experimental methods. To assess their efficiency and accuracy, it makes use of modern AI techniques. For machine learning models to function well, data quality—in particular, Cronbach's alpha—is important. In this paper, a technique for producing different Cronbach's alpha random data is presented, and its effect on the performance of machine learning algorithms is tested

3.1 DESIGNING THE QUESTIONNAIRE USING ARTIFICIAL INTELLIGENCE

AI is revolutionizing questionnaire design by improving question generation, structure, and personalization. A model will be developed using natural language processing and machine learning to generate data with calculated internal consistency. The data will be based on a five-point Likert scale, representing hypothetical responses to hypothetical questions. A set of random variables will be created with high correlation using a multivariate Gaussian distribution. The covariance matrix will be adjusted to ensure the calculated Cronbach's alpha coefficient. This approach removes bias and adapts surveys dynamically, reducing the need for intensive human effort in traditional survey design [25]. The Python code in Figure 1 illustrates these steps.

```
import numpy as np
import pandas as pd
def
generate_high_cronbach_data(n_samples=1000,
n_features=5, correlation=0.8):
    mean = np.zeros(n_features)
    cov_matrix=np.full((n_features,
n_features), correlation)
    np.fill_diagonal(cov_matrix, 1)
    data=
np.random.multivariate_normal(mean,
cov_matrix, size=n_samples)
    df=pd.DataFrame(data,
columns=[f'Feature_{i+1}'for i in
range(n_features)])
    return df
data = generate_high_cronbach_data()
def cronbach_alpha(df):
    k = df.shape[1]
    variances = df.var(axis=0, ddof=1)
    total_variance =
df.sum(axis=1).var(ddof=1)
    alpha = (k / (k - 1)) * (1 - (variances.sum()
/ total_variance))
    return alpha
alpha_value = cronbach_alpha(data)
print(f' cronbach_alpha: {alpha_value:.4f}')
```

FIGURE 1. - the Python code for Random Number generation

3.2 DATA PROCESSING USING AI AND MACHINE LEARNING ALGORITHMS

Data processing is a crucial step in AI and machine learning, ensuring the cleaning, structuring, and transformation of raw data for effective model training. Machine learning algorithms automate this process to enhance efficiency and accuracy [25]. Techniques like imputation, normalization, and outlier detection are commonly used [24], while tokenization and stemming are required for text data [26]. Feature engineering improves model performance by selecting relevant data attributes, while algorithms like Principal Component Analysis and Support Vector Machines help reduce dimensionality while preserving meaningful information [27].

Following its creation and consistency check, the data is examined using a variety of AI and Machine Learning methods, such as:

- ✓ Logistic Regression (LR)
- ✓ Decision Tree (DT)
- ✓ Random Forest (RF)
- ✓ Support Model Machine (SVM)
- ✓ Naive Bayes (NB)

The generated data is divided into two sets (80% for training) and (20% for testing) the model, and then the performance of the models is evaluated using metrics such as accuracy, recall, precision and F1-

Score.

3.3 EVALUATING THE ACCURACY AND EFFECTIVENCESS OF THE USED MODELS

To evaluate the performance of artificial intelligence techniques in designing and analyzing questionnaires, several criteria will be used, such as:

- Normal distribution is a crucial assumption in statistical analysis and machine learning, ensuring data behaves reliably and enhancing model performance. Techniques like parametric hypothesis testing, t-tests, ANOVA, and linear regression use normality to ensure data reliability [28, 29]. **Q-Q plots** are used to determine if a **dataset is normally distributed**, but non-normal features may be present if points differ significantly from the diagonal line. This examination is essential for applying statistical models relying on normal distribution (see Figure 3 G, an N).
- When evaluating the internal consistency of scales, **Cronbach's Alpha** is an essential metric. According to [30], scores below 0.7 imply poor consistency, whereas values near 1 indicate strong dependability. It is frequently used in the social sciences to guarantee that questionnaires and surveys yield accurate findings.

$$\boldsymbol{Cronbach's\ Alpha\ (\alpha)} = \frac{\boldsymbol{K}}{\boldsymbol{K-1}} \times \left(\boldsymbol{1} - \frac{\sum \boldsymbol{S_i^2}}{\boldsymbol{S_t^2}}\right)\ \boldsymbol{(1)}$$

K= Number of items (questions) in the scale, $\boldsymbol{S_i^2}$ = Variance of each individual item, and $\boldsymbol{S_t^2}$ = Total variance of the test (sum of all item variances).

- When the original (actual) label is compared to the percentage of accurately anticipated instances, accuracy is the result. Predictions are made with greater accuracy the more accurate the information. Researchers aim to increase the model's accuracy in order to detect common or uncommon computer network problems. The ratio of correct predictions to the overall size of the dataset determines accuracy; it is at its peak at level 1.

Accuracy = (TP + TN) / (TP + FP + TN + FN) (2).

TP denotes the count of true positive instances, TN signifies the count of true negative cases, FP represents false positive cases, and FN indicates false negative cases [31].

- Recall, also referred to as sensitivity, is the proportion of violent episodes that are appropriately categorized. Recall is expressed as the percentage of correct positive predictions among all positive occurrences [31]. Another name for the same is "true positive rate" (TPR). The ideal sensitivity value is 1.

Recall = TP/(TP + FN) (3).

- The ratio of correctly predicted assaults executed is referred to as precision. The procedure involves dividing the overall count of positive forecasts by the number of accurate positive predictions [31]. It is also termed the positive predictive value (PPV). The optimal precision is one.

Precision = TP / (TP + FP) (4).

- A higher recall and precision number denotes superior performance. To combine the benefits of accuracy and recall into a single score, the F1-Score is employed. This is how the accuracy and recall harmonic means are calculated:

F1-Score = 2TP / (2TP + FP + FN) (5).

3.4 DISCUSSION OF RESULTS AND HYPOTHESIS VALIDATION

The study will examine the effects of questionnaires with high and low Cronbach's alpha values on the effectiveness of AI algorithms. To ascertain if intelligent models improve data quality while achieving more efficiency and accuracy and reducing bias, the study will compare AI outcomes with those obtained using conventional approaches [2].

3.5 QUESTIONNAIRE AND ML MODEL IMPLIMENTATION

Using Python 3.7 code, a questionnaire representing a five-point Likert scale with good Cronbach's is created and run in order to test the machine learning algorithms Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Support Model Machine (SVM), and Naive Bayes (NB). Windows 11, an i5 CPU, and 16 GB of RAM make up the computer used for the inquiry. To guarantee that bias and variance are balanced, the resultant dataset is divided into training and testing 80:20 ratios. The 20% test set provides a sufficient sample for generalization performance, even when the 80% training set efficiently trains each model.. Each model is evaluated using equations (1) through (5).

4. RESULTS AND DISCUSSION

4.1 THE RELATINSHIP BETWEEN CRONBACH AND DATASET SIZE (STUDENTS AND QUESTIONS VALUE)

Table 1 displays a part of the dataset as an example generated by a five-point Likert scale with a high Cronbach's (0.82). For fictitious surveys with many respondents, Table 2 demonstrates that Cronbach's alpha values rise as the number of items or feature values increases, decreasing random oscillations and boosting internal consistency. It enhances internal consistency and data dependability by enabling a more comprehensive concept assessment. However, Table 2 and Figure 2 show that Cronbach's Alpha is typically lower when there are insufficient questions or students because of erratic statistical estimations. The estimation improves with more questions or students, which lowers random mistakes.

- ✓ Adding more questions raises Cronbach's Alpha and enhances internal consistency.
- ✓ More students lead to more stable estimates, which lower random variation and raise Cronbach's Alpha.
- ✓ Nevertheless, Cronbach's Alpha may suffer if irrelevant or inconsistent questions are included.

Table 1. - As a sample, part of a questionnaire constructed using a five-point Likert scale with a high Cronbach's (0.82).

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
5	2	2	4	5	5	1	3	5	4
5	1	4	4	3	3	5	3	3	4
4	2	1	4	5	4	5	1	3	5
3	3	5	5	4	3	4	2	3	5
3	1	1	3	4	3	4	3	3	1
3	3	2	4	3	3	2	4	3	1
5	3	2	4	1	4	5	3	5	5
4	4	3	4	2	3	3	5	3	3

Table 2. - Cronbach's alpha values obtained through the respondent's questionnaire

	Q No.	100 Resp.	160 Resp.	200 Resp.	300 Resp.	500 Resp.	600 Resp.	1000 Resp.
Features	46	Cronbach' s not verified	0.80	0.80	0.82	0.87	0.89	0.90
	64		0.73	0.82	0.86	0.89	0.90	0.92
	100		0.72	0.85	0.89	0.91	0.91	0.94

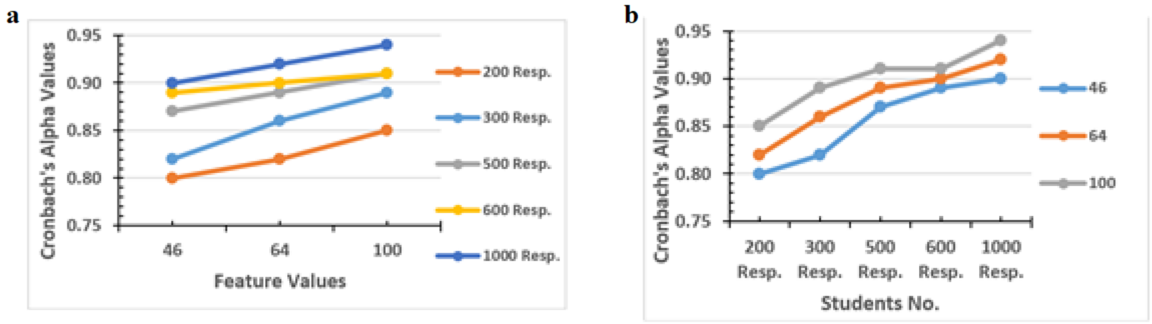
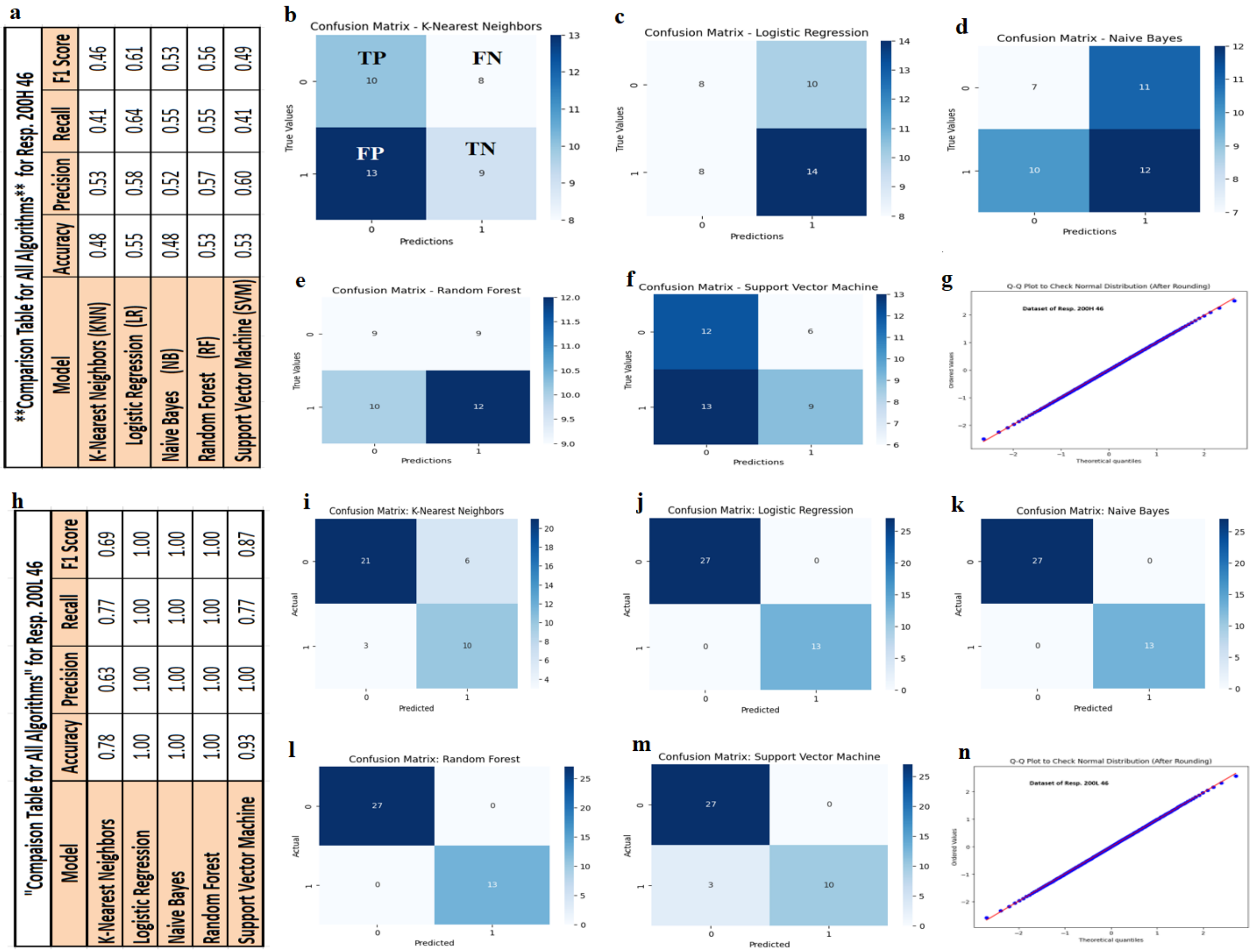


FIGURE 2. - The Relationship between Cronbach and; (a) Feature Values (Questions value), (b) Sample Size (Students value)

4.2 Generated Dataset and ML Models performance

- Figure 3 displays Confusion matrices and performance values (%) for ML Models using datasets Resp.200H 46 and Resp.200L 46 with their Q-Q plots as examples. Table 3 summarizes the performance of used ML models in Processing Low or High Cronbach Problems for all hypothetical generated datasets.
- The accuracy of machine learning techniques categorized by the three compelling features (46, 64, and 100) of the hypothetical problems under low and high Cronbach's constraint is shown in Tables 4, 5 and 6.



Comparison Table for All Algorithms for Resp. 200H 46

Model	Accuracy	Precision	Recall	F1 Score
K-Nearest Neighbors (KNN)	0.48	0.53	0.41	0.46
Logistic Regression (LR)	0.55	0.58	0.64	0.61
Naive Bayes (NB)	0.48	0.52	0.55	0.53
Random Forest (RF)	0.53	0.57	0.55	0.56
Support Vector Machine (SVM)	0.53	0.60	0.41	0.49

"Compaison Table for All Algorithms" for Resp. 200L 46

Model	Accuracy	Precision	Recall	F1 Score
K-Nearest Neighbors	0.78	0.63	0.77	0.69
Logistic Regression	1.00	1.00	1.00	1.00
Naive Bayes	1.00	1.00	1.00	1.00
Random Forest	1.00	1.00	1.00	1.00
Support Vector Machine	0.93	1.00	0.77	0.87

FIGURE 3. -Confusion matrices and performance values (%) for ML Models using datasets Resp.200H 46 and Resp.200L 46 with their Q-Q plots as examples.

4.3 IMPACT OF CRONBACH'S ALPHA VALUES ON ML MODELS ACCURACY

- Figure 4 illustrates the impact of Cronbach's alpha values of Table 6 on ML Models accuracy.
- This indicates that Cronbach's alpha limits the machine learning model's capacity to resolve the issue. A high Cronbach's alpha, which indicates good internal consistency, may lead to over similarity and redundancy, which hinder the machine learning model's ability to learn. The accuracy and generalization potential of the model can be improved by reducing feature redundancy. Various independent traits are required to identify trends and produce accurate forecasts.
- The RF, NB, LR, SVM, and KNN models have good accuracy when handling low or high Cronbach's difficulties. The ranking of the efficiency of machine learning models in handling complex Cronbach's problems is due to the following difference in the structure of these models:

✓ Random Forest (RF) is a powerful ensemble learning model that combines multiple decision trees to handle complex and diverse datasets. Averaging predictions across trees reduces variance and improves stability.

✓ Naïve Bayes (NB) is efficient for dealing with probabilistic patterns in data, especially when there is a significant variation in difficulty levels.

✓ Logistic Regression (LR) is a linear model that analyzes the relationship between features and the target variable. It performs well when the decision boundary between classes is approximately linear.

✓ SVM, a non-parametric model, works by finding the "maximum margin" hyperplane that separates classes, effectively handling high variation in difficulty levels.

✓ K-Nearest Neighbors (KNN) is a non-parametric model that classifies data points based on their distance from neighbors. This flexibility allows it to handle datasets with varying difficulty levels. KNN can still perform well if an appropriate K value is chosen.

TABLE 3. –Performance of ML Models in Processing Cronbach Problems (a) Low, (b) High

Model	Dataset Size (Resp. X Quest.)		(a) Low Cronbach					Dataset Size (Resp. X Quest.)		(b) High Cronbach			
			Acc.	Prec.	Rec.	F1 Sc.				Acc.	Prec.	Rec.	F1 Sc.
K-Nearest Neighbors (KNN)	Resp. 200L	46	0.78	0.63	0.77	0.69		Resp. 200H	46	0.48	0.53	0.41	0.46
		64	0.68	0.50	0.54	0.52			64	0.55	0.52	0.68	0.59
		100	**0.58**	**0.38**	**0.20**	**0.26**			100	0.68	0.79	0.70	0.75
	Resp. 500L	46	0.67	0.64	0.53	0.58		Resp. 500H	46	0.51	0.49	0.38	0.42
		64	0.71	0.79	0.50	0.61			64	0.51	0.57	0.48	0.52
		100	0.72	0.43	0.54	0.48			100	0.50	0.47	0.51	0.49
	Resp. 1000L	46	0.75	0.69	0.64	0.67		Resp. 1000H	46	0.61	0.60	0.58	0.59
		64	0.75	0.66	0.62	0.64			64	0.54	0.52	0.48	0.50
		100	0.71	0.68	0.51	0.58			100	0.53	0.45	0.44	0.45
Logistic Regression (LR)	Resp. 200L	46	1.00	1.00	1.00	1.00		Resp. 200H	46	0.55	0.58	0.64	0.61
		64	0.83	0.69	0.85	0.76			64	0.58	0.54	0.74	0.62
		100	0.75	0.69	0.60	0.64			100	0.53	0.65	0.63	0.64
	Resp. 500L	46	1.00	1.00	1.00	1.00		Resp. 500H	46	0.54	0.52	0.54	0.53
		64	0.94	0.92	0.96	0.94			64	0.59	0.65	0.57	0.61
		100	0.96	0.88	0.96	0.92			100	0.67	0.68	0.57	0.62
	Resp. 1000L	46	1.00	1.00	1.00	1.00		Resp. 1000H	46	0.67	0.68	0.61	0.64
		64	1.00	1.00	1.00	1.00			64	0.59	0.59	0.51	0.54
		100	1.00	1.00	1.00	1.00			100	0.55	0.47	0.43	0.45
Naive Bayes (NB)	Resp. 200L	46	1.00	1.00	1.00	1.00		Resp. 200H	46	0.48	0.52	0.55	0.53
		64	1.00	1.00	1.00	1.00			64	0.53	0.50	0.63	0.56
		100	0.90	0.92	0.80	0.86			100	0.60	0.68	0.78	0.72
	Res. 500L	46	1.00	1.00	1.00	1.00		Resp. 500H	46	0.58	0.58	0.44	0.50
		64	0.99	1.00	0.98	0.99			64	0.54	0.59	0.61	0.60

		100	1.00	1.00	1.00	1.00			**100**	0.59	0.59	0.40	0.48
	Resp. 1000L	**46**	1.00	1.00	1.00	1.00		**Resp. 1000H**	**46**	0.63	0.64	0.56	0.59
		64	1.00	1.00	1.00	1.00			**64**	0.52	0.51	**0.26**	0.34
		100	1.00	1.00	1.00	1.00			**100**	0.56	0.47	0.33	0.39
Random Forest (RF)	**Resp. 200L**	**46**	1.00	1.00	1.00	1.00		**Resp. 200H**	**46**	0.53	0.57	0.55	0.56
		64	1.00	1.00	1.00	1.00			**64**	0.65	0.61	0.74	0.67
		100	0.98	1.00	0.93	0.97			**100**	0.53	0.65	0.63	0.64
	Resp. 500L	**46**	1.00	1.00	1.00	1.00		**Resp. 500H**	**46**	0.52	0.50	0.38	0.43
		64	1.00	1.00	1.00	1.00			**64**	0.56	0.62	0.55	0.58
		100	1.00	1.00	1.00	1.00			**100**	0.59	0.56	0.60	0.58
	Resp. 1000L	**46**	1.00	1.00	1.00	1.00		**Resp. 1000H**	**46**	0.64	0.65	0.55	0.60
		64	1.00	1.00	1.00	1.00			**64**	0.52	0.51	0.42	0.46
		100	1.00	1.00	1.00	1.00			**100**	0.57	0.49	0.49	0.49
Support Vector Machine (SVM)	**Resp. 200L**	**46**	0.93	1.00	0.77	0.87		**Resp. 200H**	**46**	0.53	0.60	0.41	0.49
		64	0.90	0.85	0.85	0.85			**64**	0.55	0.52	0.68	0.59
		100	0.68	0.60	0.40	0.48			**100**	0.60	0.72	0.67	0.69
	Resp. 500L	**46**	0.96	0.95	0.95	0.95		**Resp. 500H**	**46**	0.54	0.53	0.44	0.48
		64	0.92	0.90	0.93	0.91			**64**	0.49	0.55	0.46	0.50
		100	0.90	0.73	0.92	0.81			**100**	0.60	0.58	0.53	0.56
	Resp. 1000L	**46**	0.97	0.94	0.97	0.96		**Resp. 1000H**	**46**	0.64	0.65	0.56	0.60
		64	0.98	0.97	0.96	0.96			**64**	0.56	0.54	0.53	0.53
		100	0.97	0.94	0.97	0.96			**100**	0.54	0.46	0.43	0.44

TABLE 4. - Machine learning model's accuracy in processing high Cronbach's alpha datasets

High Cronbach Alpha		**0.80**	**0.82**	**0.85**	**0.82**	**0.86**	**0.89**	**0.87**	**0.89**	**0.92**	**0.89**	**0.90**	**0.91**	**0.90**	**0.92**	**0.94**
Generated Dataset (Resp. * Questions)		**200 *46**	**200 *64**	**200 *100**	**300 *46**	**300 *64**	**300 *100**	**500 *46**	**500 *64**	**500 *100**	**600 *46**	**600 *64**	**600 *100**	**1000 *46**	**1000 *64**	**1000 *100**
Machine Learning Models and Accuracy %	**KNN**	0.48	0.55	0.68	0.62	0.72	0.55	0.51	0.51	0.5	0.53	0.55	0.50	0.61	0.54	0.53
	LR	0.55	0.58	0.53	0.63	0.72	0.58	0.54	0.59	0.67	0.63	0.55	0.61	0.67	0.59	0.55
	NB	0.48	0.53	0.60	0.62	0.60	0.50	0.58	0.54	0.59	0.57	0.59	0.56	0.63	0.52	0.56
	RF	0.53	0.65	0.53	0.65	0.72	0.55	0.52	0.56	0.59	0.53	0.51	0.50	0.64	0.52	0.57
	SVM	0.53	0.55	0.60	0.65	0.72	0.52	0.54	0.49	0.6	0.61	0.58	0.57	0.64	0.56	0.54

TABLE 5. - Machine learning model's accuracy in processing Low Cronbach's alpha datasets

Low Cronbach Alpha (Less than 50%)																
Traditional Generated Dataset (Resp. * Questions)		**200 *46**	**200 *64**	**200 *100**	**300 *46**	**300 *64**	**300 *100**	**500 *46**	**500 *64**	**500 *100**	**600 *46**	**600 *64**	**600 *100**	**1000 *46**	**1000 *64**	**1000 *100**
Machine Learning Models and	**KNN**	0.78	0.68	0.58	0.65	0.77	0.70	0.67	0.71	0.72	0.80	0.69	0.68	0.75	0.75	0.71
	LR	1.00	0.83	0.75	0.87	0.93	0.93	1.00	0.94	0.96	1.00	0.98	0.95	1.00	1.00	1.00
	NB	1.00	1.00	0.90	1.00	0.98	0.97	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	RF	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	SVM	0.93	0.90	0.68	0.83	0.92	0.83	0.96	0.92	0.90	0.95	0.97	0.93	0.97	0.98	0.97

TABLE 6. -Accuracy of the ML Models categorized by Features, and (a) High Cronbach Values, (b) Low Cronbach Values

(a)		**Resp. 200H**					**Resp. 300H**					**Resp. 500H**					**Resp. 600H**					**Resp. 1000H**				
		KNN	**LR**	**NB**	**RF**	**SVM**	**KNN**	**LR**	**NB**	**RF**	**SVM**	**KNN**	**LR**	**NB**	**RF**	**SVM**	**KNN**	**LR**	**NB**	**RF**	**SVM**	**KNN**	**LR**	**NB**	**RF**	**SVM**
Feature	**46**	0.48	0.55	0.48	0.53	0.53	0.62	0.63	0.62	0.65	0.65	0.51	0.54	0.58	0.52	0.54	0.53	0.63	0.57	0.53	0.61	0.61	0.67	0.63	0.64	0.64
	64	0.55	0.58	0.53	0.65	0.55	0.72	0.72	0.6	0.72	0.72	0.51	0.59	0.54	0.56	0.49	0.55	0.55	0.59	0.51	0.58	0.54	0.59	0.52	0.52	0.56
	100	0.68	0.53	0.6	0.53	0.6	0.55	0.58	0.5	0.55	0.52	0.5	0.67	0.59	0.59	0.6	0.5	0.61	0.56	0.5	0.57	0.53	0.55	0.56	0.57	0.54

(b)		Resp. 200L					Resp. 300L					Resp. 500L					Resp. 600L					Resp. 1000L				
		KNN	LR	NB	RF	SVM	KNN	LR	NB	RF	SVM	KNN	LR	NB	RF	SVM	KNN	LR	NB	RF	SVM	KNN	LR	NB	RF	SVM
Feature	46	0.78	1.00	1.00	1.00	0.93	0.65	0.87	1.00	1.00	0.83	0.67	1.00	1.00	1.00	0.96	0.80	1.00	1.00	1.00	0.95	0.75	1.00	1.00	1.00	0.97
	64	0.68	0.83	1.00	1.00	0.90	0.77	0.93	0.98	1.00	0.92	0.71	0.94	0.99	1.00	0.92	0.69	0.98	1.00	1.00	0.97	0.75	1.00	1.00	1.00	0.98
	100	0.58	0.75	0.90	0.98	0.68	0.70	0.93	0.97	1.00	0.83	0.72	0.96	1.00	1.00	0.90	0.68	0.95	1.00	1.00	0.93	0.71	1.00	1.00	1.00	0.97

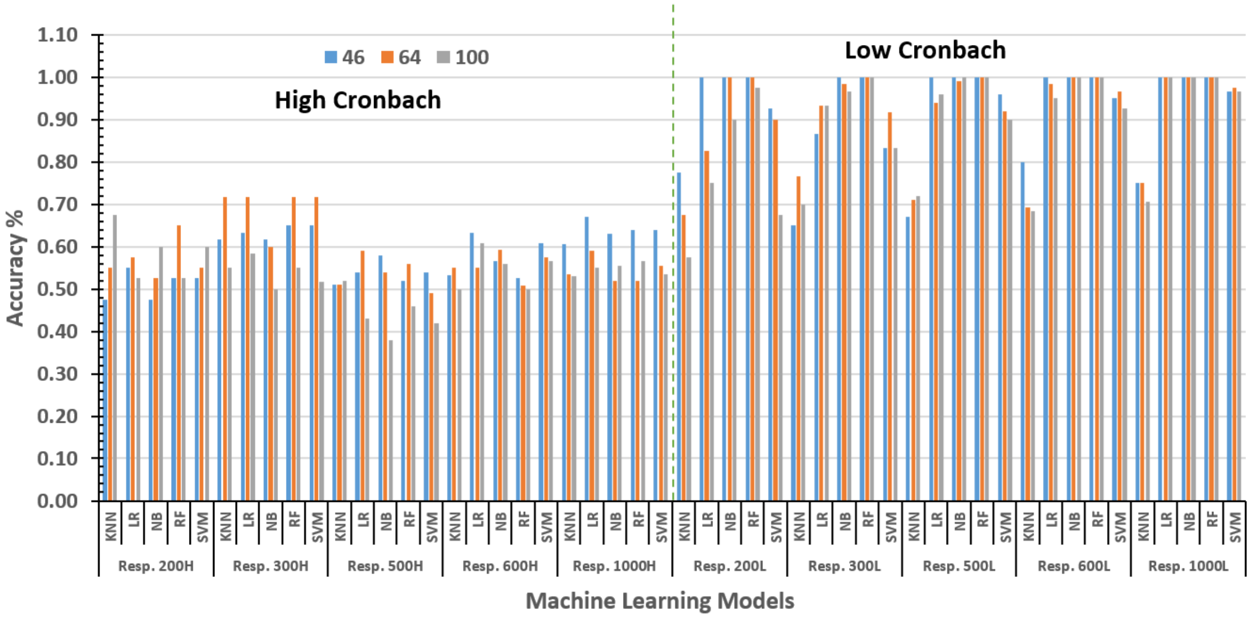


FIGURE 4. - Impact of Cronbach's Alpha Values on ML Models Accuracy

4.4 The impact of artificial intelligence on data quality and analysis

- The study reveals that AI algorithms improve participant answer interpretation accuracy, reduce human bias, and reveal hidden patterns, aligning with research suggesting AI algorithms are superior in identifying participant trends.

4.5 Reducing bias and improving accuracy

- Experiments show that AI algorithms can identify associations between variables more accurately, potentially reducing bias in data analysis, supporting the claims of researchers that AI could enhance the accuracy of Big Data processing.

4.6 Challenges associated with interpreting AI results

- The study revealed that the use of AI in questionnaire analysis faces challenges due to the need for precise interpretation of findings to ensure their validity and acceptability in scientific studies.

4.7 Linking the results to the research objectives

- The study reveals that AI improves questionnaire accuracy, accelerates processing, and reduces conclusion bias, enabling more intelligent and dynamic surveys. However, transparent interpretative models are needed to understand AI's findings.

5. CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

This study investigates the use of machine learning and natural language processing methods to the creation and analysis of questionnaires. Based on the results, study dependability is increased as AI dramatically lowers human error, increases the accuracy of data processing, and minimizes data bias.

Further study in this field is necessary, nevertheless, as issues like the difficulty of comprehending AI models call for the creation of more transparent analytical tools.

5.2 RECOMMENDATIONS

The research findings suggest the following recommendations:

- Improving the design of questionnaires with artificial intelligence: Artificial intelligence technologies should be used to create intelligent interactive questionnaires which will enhance data collection and analysis accuracy.
- Improving comprehension of AI results: Artificial intelligence models enhance the validity of study findings by streamlining data analysis outcomes.
- Using sophisticated data analysis methods: Deep learning algorithms represent a recommended solution for enhancing the accuracy of analysis while reducing errors and gaining better insight into decision-making processes.
- Minimizing bias in data: AI models require training with diverse balanced data sets to prevent bias.
- Increasing the security and privacy of data processing: All AI methods used for survey data analysis need to adhere to ethical and legal standards to protect personal information of respondents.
- Carrying out more research on the beneficial applications of AI in science: Future research needs to assess how traditional methods alongside artificial intelligence techniques perform in creating and examining questionnaires across multiple research fields.

5.3 IN CONCLUSION

Artificial intelligence (AI) improves both questionnaire data collection methods and processing to achieve higher accuracy in results. Its optimal application in scientific research needs further development due to challenges in understanding data and ensuring privacy protection.

FUNDING

None

ACKNOWLEDGEMENT

None

CONFLICTS OF INTEREST

The author declares no conflict of interest.

REFERENCES

1. U. Sivarajah, M. M. Kamal, Z. Irani, and V. Weerakkody, "Critical analysis of Big Data challenges and analytical methods," J. Bus. Res., vol. 70, pp. 263–286, 2017.
2. X. Yang and Y. Wu, "AI-powered survey generation and analysis: A systematic review," Artif. Intell. Rev., vol. 55, no. 3, pp. 2519–2542, 2022.
3. Y. Liu and G. Salvendy, "Design and evaluation of automation in questionnaires," Int. J. Hum.-Comput. Interact., vol. 25, no. 6, pp. 474–491, 2009.
4. A. Joshi, S. Kale, S. Chandel, and D. K. Pal, "Likert scale: Explored and explained," Br. J. Appl. Sci. Technol., vol. 7, no. 4, p. 396, 2015.
5. J. L. G. Ortega and A. R. Fuentes, "The accuracy of students' evaluations: Study of their evaluative competences," REDU Rev. Docencia Univ., vol. 15, no. 2, pp. 349–366, 2017.
6. A. R. Fuentes and J. G. Ortega, "An analytical perspective of the reliability of multi-evaluation in higher education," Mathematics, vol. 9, p. 1223, 2021.

7. Higher Education Funding Council for England (HEFCE), "National Student Survey Results 2016," 2016. [Online]. Available: http://www.hefce.ac.uk/lt/nss/results/2016/. [Accessed: Aug. 20, 2021].
8. R. Harrison et al., "Evaluating and enhancing quality in higher education teaching practice: A meta review," Stud. High. Educ., vol. 47, pp. 80–96, 2022.
9. S. Paek and N. Kim, "Analysis of worldwide research trends on the impact of artificial intelligence in education," Sustainability, vol. 13, p. 7941, 2021.
10. M. Shah and C. S. Nair, "The changing nature of teaching and unit evaluations in Australian universities," Qual. Assur. Educ., vol. 20, no. 3, pp. 274–288, 2012.
11. National Student Survey (NSS), "National Student Survey Results 2015," 2015. [Online]. Available: http://www.hefce.ac.uk/lt/nss/results/2015/. [Accessed: Aug. 20, 2021].
12. C. S. Nair, D. Pawley, and P. Mertova, "Quality in action: Closing the loop," Qual. Assur. Educ., vol. 18, no. 2, pp. 144–155, 2010.
13. R. Symons, "Listening to the student voice at the University of Sydney: Closing the loop in the quality enhancement and improvement cycle," in Proc. Aust. Assoc. Inst. Res. Forum, Coffs Harbour, Australia, 2006.
14. A. M. Turing, "Computing machinery and intelligence," Mind, vol. 59, no. 236, pp. 433–460, 1950.
15. F. Jiang et al., "Artificial intelligence in healthcare: past, present and future," Stroke Vasc. Neurol., vol. 2, no. 4, pp. 230–243, 2017.
16. A. Kaplan and M. Haenlein, "Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence," Bus. Horiz., vol. 62, no. 1, pp. 15–25, 2019.
17. C. Badue et al., "Self-driving cars: A survey," Expert Syst. Appl., vol. 165, p. 113816, 2021.
18. L. K. Allen, R. Eagleson, A. de Ribaupierre, and C. Odgers, "Multi-level support using artificial intelligence (AI) for students in higher education: The next generation of teaching, and precursors to success in the twenty-first century workforce," Int. J. Innov. Online Educ., vol. 4, no. 3, 2020.
19. M. Sasaki, "AI tools as affordances and contradictions for EFL writers: Emic perspectives and L1 use as a resource," J. Second Lang. Writ., vol. 62, p. 101068, 2023.
20. Ž. Bašić, A. Banovac, I. Kružić, and I. Jerković, "ChatGPT-3.5 as writing assistance in students' essays," Humanit. Soc. Sci. Commun., vol. 10, no. 1, p. 750, 2023.
21. A. R. Malik et al., "Exploring artificial intelligence in academic essay: Higher education student's perspective," Int. J. Educ. Res. Open, vol. 5, p. 100296, 2023.
22. M. Imran and N. Almusharraf, "Analyzing the role of ChatGPT as a writing assistant at higher education level: A systematic review of the literature," Contemp. Educ. Technol., vol. 15, no. 4, p. ep464, 2023.
23. S. Z. Salas-Pilco, K. Xiao, and X. Hu, "Correction: Salas-Pilco et al. Artificial Intelligence and Learning Analytics in Teacher Education: A Systematic Review," Educ. Sci., vol. 13, no. 9, p. 897, 2023.
24. J. A. Krosnick, "Questionnaire design," in The Palgrave Handbook of Survey Research, Springer, 2018, pp. 439–455.
25. D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet allocation," J. Mach. Learn. Res., vol. 3, pp. 993–1022, 2003.
26. S. Wang and C. D. Manning, "Baselines and bigrams: Simple, good sentiment and topic classification," in Proc. 50th Annu. Meet. Assoc. Comput. Linguist., 2012, pp. 90–94.

27. C. Cortes and V. Vapnik, "Support-vector networks," Mach. Learn., vol. 20, pp. 273–297, 1995.
28. A. Field, Discovering statistics using IBM SPSS statistics, 4th ed. London, UK: Sage, 2013.
29. R. Wilcox, Understanding and applying basic statistical methods using R. Hoboken, NJ, USA: Wiley, 2016.
30. K. S. Taber, "The use of Cronbach's alpha when developing and reporting research instruments in science education," Res. Sci. Educ., vol. 48, no. 6, pp. 1273–1296, 2018.
31. H. S. Abdullah, "A comparison of several intrusion detection methods using the NSL-KDD dataset," Wasit Journal of Computer and Mathematics Science, vol. 3, no. 2, pp. 32-41, 2024. doi: 10.31185/wjcms.251.