*Research Article*

# Research on Ethical Issues and Coping Strategies of Artificial Intelligence Algorithms Recommending News with the Support of Wireless Sensing Technology

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This study shows how well the wireless sensing technology may be used to forecast how people would react to AI- (artificial intelligence-) driven customization in digital news sites. We randomly picked participants to enroll in an online questionnaire. This study determines the ethical issues and coping strategies of AI-based news using sensor technology. The study proposed an improved naïve Bayes classification algorithm to forecast the acceptance of AI-driven news sites. Additionally, the technology acceptance framework characteristics continue to be crucial in determining adoption decisions. The findings demonstrate that the observed contingency has a large direct influence and an indirect effect that is moderated by improved user interaction and positivity in forecasting the acceptance of AI-driven news sites.

## 1. Introduction

Computer scientists, statisticians, and clinical entrepreneurs all agree that AI, and particularly machine learning, will play a crucial role in bringing about this change in healthcare. The phrase "artificial intelligence" (AI) is commonly used in the tech industry to refer to a computer's ability to reason, learn, and complete other tasks typically associated with human intelligence [1]. Adaptation, sensory comprehension, and communication are also part of this category of processes. Simply described, traditional computational algorithms are programs that, like an electrical calculator, have a single, well-defined output for a given set of inputs: "if this is the input, then this is the result." AI can learn the rules (function) by being exposed to extracting useful information from the massive amounts of digital data generated by healthcare delivery [2]. Artificial intelligence often takes the form of a hybrid system combining software and hardware components. In the realm of computer science, artificial intelligence focuses mostly on algorithms. Artificial neural networks (ANNs) are a theoretical backbone upon which to build AI programs. It is a representation of the human brain as a network of neurons linked together through weighted communication channels. Artificial intelligence employs a wide variety of methods to discover intricate nonlinear connections inside enormous data sets (analytics) [3]. Through training, machines learn to refine their algorithms and improve the reliability of their predictions (confidence).

The introduction of new technology brings with it the worry that it could become a fresh entry point for errors and security lapses. This is especially important to keep in mind because patients often interact with clinicians at extremely vulnerable points in their lives [4]. Cooperation between AI and clinicians, in which the former provides evidence-based management and the latter serves as a medical decision guide, has the potential to be highly beneficial if properly utilized (AI-health). It has the potential to improve healthcare delivery in areas such as diagnosis, medication discovery, epidemiology, individualized treatment, and organizational effectiveness. Researchers emphasize the need for a robust governance structure to safeguard human lives from all potential threats posed by AI solutions, including those arising from immoral behavior [5]. Unless the underlying

database and information technology system can limit, it may be challenging to use this type of data [6]. Nonetheless, AI in EHRs can be utilized to advance research, enhance treatment quality, and reduce waste. If properly developed and taught with sufficient data, in addition, AI can help create innovative models of healthcare delivery by studying clinical practice trends gleaned from electronic health data [7]. The function of AI in a content generation is not acknowledged. Even when an AI algorithm was utilized, the byline in news stories, for instance, seldom ever credits the algorithm. Without this notice, readers cannot infer from the text alone if an AI was utilized [8]. It might be challenging to offer acceptable and relevant news items to readers. The rationale is that the news domain has particular difficulties that set it apart from other application domains for recommender systems [9].

Future pharmaceutical research and development could benefit from the use of artificial intelligence (AI). Drug research might become less time-consuming and more cost- and data-efficient with the use of AI, which could use robots and models of genetic targets, pharmaceuticals, organs, diseases, disease progression, side effects, and therapeutic potency and safety [10]. Accelerating and improving the drug development process efficiency can be possible with the help of artificial intelligence (AI). There have been prior attempts to use AI to find treatments for the Ebola virus; however, like with any pharmacological trial, finding a promising lead molecule is no assurance of a safe and effective therapeutic [11]. The application of patient care could be greatly enhanced by implementing AI into clinical practice, but first, substantial ethical concerns must be addressed. Four primary ethical hurdles must be overcome before the medical applications of AI can reach their full potential [12]. Data privacy, security, algorithmic fairness, biases, and the ability to obtain users' informed consent before using their information are all crucial. It is not just a question of law but also of politics, whether or not AI systems can be regarded legitimate. It has been suggested that the ability to assign responsibility to a particular person or organization could be threatened by machines that operate following a set of undefined rules and learn new patterns of behavior. Concerns have been raised because of this ever-widening issue. Unfortunately, there may be no human to blame if something goes wrong when using AI. The potential for harm is unclear, and the increased reliance on robots will make it much harder to hold anyone accountable for their actions [13].

The use of modern computing techniques can obscure the reasoning behind an AIS's output, making meaningful scrutiny impossible [14]. To put it another way, the process by which an AIS produces its results is not transparent at all. Although the underlying computer science behind an AIS may be sophisticated, the implementation may be designed to be opaque to a clinical user who lacks the necessary technical training, while being intuitive to a trained expert in the subject. Emerging ML-HCAs cover a wide range of goals, potential implementations, and applications. ML-HCAs can be anything from entirely on their nonautonomous mortality projections, manual coverage and resource alloca-

tion, and artificial intelligence. Scientists should detail how these findings, together with their projections, might inform future research [15]. This information is essential for establishing the study's viability and for guiding future research. AI in healthcare must be flexible enough to deal with a constantly changing environment full of disruptions without compromising its ethical underpinnings, so that it may best serve the needs of its patients. However, a simple, crucial part of establishing the safety of any healthcare software is the capability to check the software and determine how the software might fail. In many respects, the process used to develop software is comparable to the addition of ingredients to a pharmaceutical or the incorporation of physiological mechanisms into a mechanical device [16]. Black box issues can arise with ML-HCAs since their inner workings are not always evident to evaluators, clinicians, or patients. It is incumbent upon researchers to detail how these findings, together with their projections, might inform future directions of the investigation [17]. The information is used to determine the final cost of the study and to guide similar efforts in the future.

Because of the intangibility of the digital economy and the upheaval that comes with quickly advancing technology, psychiatry is facing new ethical challenges as a result of its increasing reliance on computers. Classifying people based on large amounts of data may have far-reaching, unintended consequences outside of medicine [18]. Applications or medical websites with low-quality information all carry the risk of adverse health outcomes, including the postponement of necessary medical attention. Public and private data, as well as medical and nonmedical data, no longer have the clear distinctions they previously did in our society. Doctors may harm patients with mental illness by suggesting they employ technology without first addressing the additional ethical considerations that arise from doing so [19]. Several questions will be posed to facilitate the discussion of these ethical concerns. There is a wide gap between patients in terms of their exposure to and proficiency with digital tools, technical proficiency, Internet safety, and familiarity with the digital economy. The "digital divide" refers to the gap in Internet access that exists between people with different levels of income, education, and age, as well as the telecommunications infrastructure. Internet and smartphone use among the elderly and people having both mental and physical impairments is much lower than the general population, although access has substantially grown over the previous decade around the world [20]. Sometimes, the impoverished only have spotty, unstable access to the Internet. Differences in technological competence, online literacy, and usage patterns are now reflected in the digital divide. It is commonly considered that millennials and Gen Zers alike are fluent in all things digital. But even among people who have never known a world without computers and smartphones, there is a wide range of proficiency online. The broad adoption of digital technology like cell phones and video games can be attributed to their simplicity of use for those with no technical training. From learning the ins and outs of technology to mastering its use to accomplishing one's goals and resolving one's problems, the definition of "digital competency"

has expanded [21]. Self-assessments of technical proficiency tend to be inaccurate, and even someone who is comfortable with technology and knows how to use it effectively may be unfamiliar with the concepts behind today's interconnected digital economy.

Self-diagnosis on the Internet is becoming increasingly common, and it may have particular appeal for those who feel they have a mental illness due to stigma, a need for privacy, and a need to save money. More than 50 million people use the iTriage app each year to check their symptoms and find a doctor, and one-third of all American adults use the Internet to make their diagnoses. Online symptom checkers for mental health conditions are plentiful [22]. Online ads for direct-to-consumer (DTC) genetic and another laboratory testing may also be tailored to individual patients. In certain online mental health groups, diagnosis is a common topic of conversation. Self-diagnosis is a common practice among certain patients, and this can lead them to attempt self-treatment. Nowadays, it is possible to get just about any prescription medication from an Internet drugstore. Among the most commonly supplied types of pharmaceuticals by unregulated online pharmacies, those used to treat mental health issues are among the most problematic. Many fake pharmacy websites look exactly like those of actual pharmacies because they are professionally developed and include fake quality seals [23]. Approximately one-third of people with mental illness use some kind of dietary supplement, many of which are self-selected, acquired online, and linked to exaggeration. Few of these apps were evaluated, and those that did only saw limited brief pilot programs. Certain health-related websites engage in deceptive practices or advocate for potentially harmful actions. To give just one example, the company Lumosity was penalized for making false promises about how playing video games and using mobile apps may improve users' brainpower [24]. Some Alzheimer's disease self-tests available online lack validity and reliability and violate professional ethics guidelines. Abuse-producing substances like opioids, stimulants, and hallucinogens can all be purchased online. Some online resources openly advocate harmful activities including self-harm and eating disorders. Some people even attempt to treat themselves by constructing potentially lethal transcranial direct current stimulation devices according to online tutorials [25].

With the rise of IoT devices, emotion recognition software is commonly considered the next logical step in the development of computing technology. In this future, we will not need computers or gadgets since we will have access to AI-powered cognitive assistants that can communicate with us in our native tongues, interpret our facial expressions, voice, and written emotions and provide us with constant support will form the basis of emotion recognition in the future [26]. Users will need fewer technical abilities. There is a desire for personalized medical aides for both doctors and patients. Recently received or applied for patents allow for the inference of mood and emotion from data collected from online and mobile platforms. Algorithms based on the massive amounts of data generated by people's everyday online activities are increasingly being used by businesses and governments to profile citizens, gauge their emotional states, and anticipate their future actions. Publicly available social media data sets are being used by researchers in fields as diverse as computer science, linguistics, and psychology to make predictions about things like depression, suicide risk, psychopathy, psychological illnesses, and the severity of illness of the mind [27]. The medical profession is investigating the use of pilot studies for bipolar illness, schizophrenia, and depression that have been conducted using passive data collecting in people. Information gathered from a smartphone's sensor, including where and when the device was used, how the user moved around, how they spoke, and what they said, as well as the contents of the smartphone can all be used to inform the development of parameters which are all used in academic and medical research. The commercial profiling of consumers and the medical monitoring of patients may appear similar at first glance. However, commercial enterprises' motivation for utilizing algorithms to describe emotional or mental conditions is profit rather than patient care. In the United States, most algorithms utilized by business entities are considered trade secrets and hence cannot be independently validated. Publicly available data did not permit replication of the published results, as demonstrated by Google Flu Trends (a flu-tracking tool). However, some businesses may indicate that they employ improved versions of published algorithms, but these businesses do not have the necessary training or credentials to offer medical diagnoses or recommendations. A "propensity to seek for depression," as determined by an algorithm from a for-profit company, should not be taken as a medical fact or used against a person in the context of employment, promotion, or credit. Companies are pouring a lot of money into this field, so in the future algorithms we will be able to better understand human emotions and mental states. The market for emotion recognition and detection was predicted to grow to $22.65 billion worldwide by 2020. The paper [28] developed a multimodal content retrieval framework that uses customization and relevance feedback approaches to improve the Quality of Experience (QoE) for end users by obtaining and presenting multimedia information that is specific to their demographics and other preferences. From the article [29], efficient relevance feedback (RF) methods, in addition to personalization strategies, may improve the user experience by delivering results that are more in line with the user's preferences. The paper [30] suggested vector-space models, to which this system is similar and to which it is applicable failed to handle queries with scalar values—for example, they cannot bring up movie scenes with fewer than two actors—a problem solved in our integrated framework through the use of exact match queries and a modified relevance feedback mechanism. The paper [31] proposed an interest-driven, multimedia retrieval framework to compute the semantic and content-level similarity between media items and query descriptor vectors. The paper [32] uses quality of service (QoS) evaluation indicators such as packet loss rate, latency, jitter, and throughput. These qualities of service measurements reveal the effect on the network's

quality but do not represent the user's experience. As a result, these QoS criteria cannot account for the intangibles that contribute to the quality of life for individuals.

## 2. Materials and Method

The results show that better user engagement and positivity reduce the impact of observed contingency on predicting acceptance of AI-driven news sites and that the direct influence of observed contingency is considerable. Here, we present an enhanced version of the naïve Bayes classifier for gauging interest in AI-powered media outlets.

### 2.1. Data Analysis

*2.1.1. Preprocessing Using Min-Max Normalization.* To normalize a property, the values are transformed such that they all fall within a predetermined interval. About classification frameworks, normalization is a crucial step when using computational models or proximity measures. The training phase of classification using a neural network back propagation approach may go more rapidly if the input values for each measured attribute in the training set are normalized. The purpose of min-max normalization is to make the original data linear. Assume that the lowest and maximum values for attribute $X$ are min $X$ and $maxX$. B value of B, $a_x$, is mapped to $a_x$ in the range [new- min $x$, new- max $X$] by using the following formula:

$$\ddot{B}_y = (B_y - \min x)/(\max x - \min x) \\ * (new_{\max x} - new_{\min x}) + new_{\min x} \tag{1}$$

A data set's original values retain their correlation after min-max normalization. If a later normalization input scenario takes $X$ outside of the starting date range, the risk of an "out-of-bounds" error rises.

*2.1.2. Feature Extraction Using Principle Component Analysis (PCA).* To reduce the number of variables while preserving as much information as feasible, principal component analysis (PCA) applies a series of orthogonal linear transformations to the original variables. Let $M$ be an $n \times s$ data matrix, where $n$ and $s$ represent the number of factors and observations, accordingly. For simplicity, we will assume that the means of the whole $Y$ column are 0. $U_1 = \sum_{y}^{t} = \alpha_1$ y $M_y$, where $\alpha_1 = (\alpha_{11}, \cdots, \alpha_1{}^s)$ and $s$ is the definition of the first principal component. $s$ is selected to maximize $V_1$'r variance, i.e.,

$$\propto_1 = \arg \max_{\propto} \propto^s \widehat{\sum} \propto \text{ subject to } \|\propto_1\| = 1, \tag{2}$$

with $\Sigma = (M^P M)/n$. All of the remaining key ingredients are defined below, in order:

$$\propto_{k+1} = \arg \max_{\propto} \propto^s \widehat{\sum} \propto \tag{3}$$

depending on

$$\|\propto\| = 1 \text{ and} \propto^s \propto_h = 0, \forall 1 \le g \le h \tag{4}$$

According to this definition, the first $h$ k eigenvectors are the first k loading vectors.

Since SDB is formulated in terms of eigen decompositions to determine AI-driven news using sensor techniques, it is related to $N$'s singular value decomposition. Let us pretend $N$ stands for TRUE.

$$N = UOG^s, \tag{5}$$

where $U$ and $G$ are orthonormal matrices of $m \times p$ and $p \times p$ rows and columns, respectively, and $E$ is a diagonal matrix with diagonal components $p_1$, ..., $pw$ in descending order. $K$ is the loading matrix of the main components because the columns of $K$ are the eigenvectors. We can see that $V_g = u_g E_g$ since $NG = UO$, $U_K$ is the $K^{th}$ column of $U$. Recognize that the $RUO$ is a good low-rank estimate of the data matrix.

In the various geometrical understanding of SDB, straight manifolds are the best fit for information. This concept aligns with how SDB is built. Make $iy$ the $y^{th}$ row in $X$. Take the first $h$ main components together, which equals $h_k = [h_1|\cdots|h_k]$. $h_k$ is a $r \times g$ orthonormal matrix by definition. Each observation should be projected to the linear region covered by $\{h1, \cdots, hk\}$. The projected data are $w_g$ $N_y$, $1 \le y \le n$ and the projection operator is $W_k = h_g hs$. By reducing the overall $g_2$ approximation error, one may determine the optimal projection.

$$\min_{A_h} \sum_{y=1}^{n} \left\| j_y - A_g A_g^s j_j \right\|^2. \tag{6}$$

Parameters in applications may be specified in a variety of length scales and measurement systems. As a consequence of parameter standardization, the marginal variance of every variable is equal to 1. Principal component analysis using this approach will provide both the raw data's correlation coefficient and the unified data's covariance matrices. Keep in mind that the eigenvalues of the covariance matrix and the correlation matrix are not always the same.

*2.1.3. Prediction Using the Improved Naïve Bayes Classification Algorithm.* Under the concepts of consistency and unbiasedness of an estimate, a greater classification rate may be attained by expanding the learning field (sample) size within the same data set (population) using the sensor technique. Our INBC only updates the learning field to provide the best performance using the previously evaluated data. For instance, we have a basic training data set (the first phase of data) that consists of daily meteorological observations over the last 10 years. Likewise, the study predicts the technology of acceptance of digital media news using sensor techniques. To progressively improve the initial training data set, we then split the second phase of data (a few previously validated weather records) into some predetermined

Calculate $N(C_k V_{Ai,j'})$, $N(V_{Ai,j'})$ and $P(C_k)$ from the first phase of data.
Prompt for the *StepSize*, a fixed number of data records, for evaluating the performance of AI-driven news using sensors.
Initialize $start - pos = 0$ ; $end - pos = 0$ ; $index = 1$
Do
    Set $start - pos = 0$ ; $end - pos + 1$
    Set $end - pos = index \times StepSize$
    Prompt for the **NB** Approx. (**RF** from Eqn (2) or **IPD** from Eqn (3))
    **For** each $k = 1$ to $P$ **do**
    Begin
        Calculate $P(C_k|V_{A,,j''}) = P(C_k)\prod_{i=1}^{n}\prod_{j''=start-pos}^{end-pos}(NB\,Approx./P(C_k))$
        Find the highest conditional probability of $A_{i\in[1,n]}$
    End
    Update $N(C_k V_{Ai,j'})$, $N(V_{Ai,j'})$and $P(C_k)$ with the second phase of data
    Set $index = index + 1$
**While** $end - pos < m_2$
**For** the rest of each $start - pos \leq j'' \leq m_2$
    Calculate $P(C_k|V_{A,,j''}) = P(C_k)\prod_{i=1}^{n}\prod_{j''=start-pos}^{m_2}(NB\,Approx./P(C_k))$for all k
    Find the highest conditional probability of $A_{i\in[1,n]}$
Evaluate the classification rate of all $k$ and the overall performance.

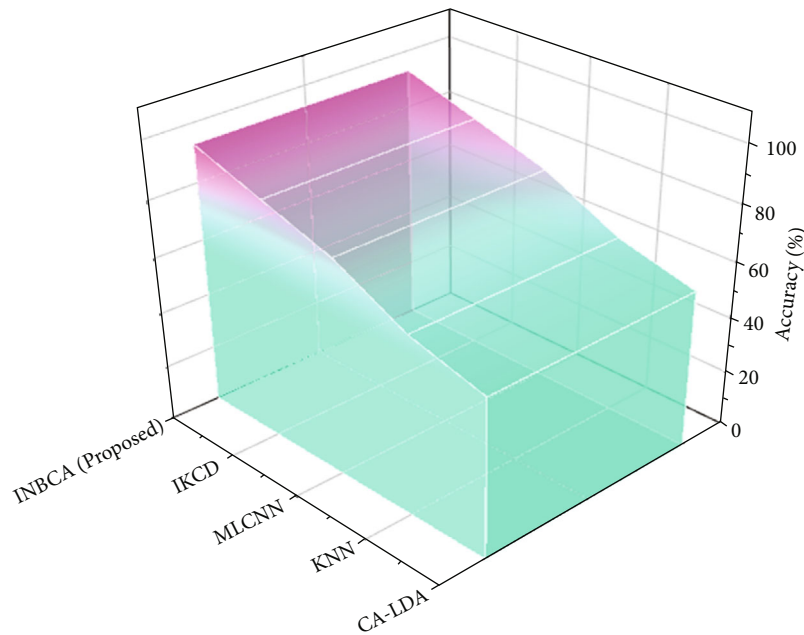ALGORITHM 1: The improved naïve Bayes classification algorithm.



FIGURE 1: Accuracy.

TABLE 1: Accuracy.

| Models | Accuracy (%) |
| --- | --- |
| CA-LDA | 57 |
| KNN | 64 |
| MLCNN | 77 |
| IKCD | 85 |
| INBCA (proposed) | 93 |

data sets (step size). Such a new training model can calculate the classification rate of the third phase of data (some updated and tested). The combined effects of the second and third waves of data will be determined, and they participate in the discussion on ethical AI management. They highlight both theoretical and practical issues with AI ethical management and provide a tentative research agenda for the future. Naïve Bayes is one of the quickest and easiest machine learning techniques for forecasting a collection of data sets. It applies to classes with two categories or more. When compared to other algorithms, it is superior at
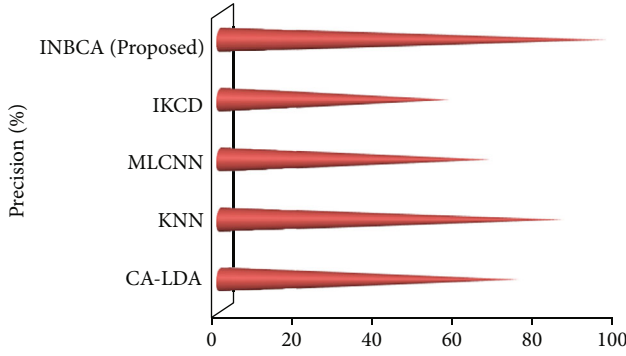
Figure 2: Precision.

Table 2: Precision.

| Models | Precision (%) |
| --- | --- |
| CA-LDA | 74 |
| KNN | 85 |
| MLCNN | 67 |
| IKCD | 57 |
| INBCA (proposed) | 96 |

making predictions across several classes [33]. Algorithm 1 demonstrates how our INBC approach using the sensor approach will enhance classification precision and speed.

## 3. Results and Discussion

The results show that better user engagement and positivity reduce the impact of observed contingency on predicting acceptance of AI-driven news sites and that the direct influence of observed contingency is considerable. With the help of sensor techniques, the influence of predicting acceptance will be derived. Here, we present an enhanced version of the naïve Bayes classifier for gauging interest in AI-powered media outlets.

A model's ability to correctly classify data may be evaluated using many different performance criteria. The article used a wide variety of measures, not only accuracy, precision, recall, and F1 score. For argument, let us say that the values of the class variables in a binary classification job may be thought of as either positive (P) or negative (N). Cases that the model correctly classified as positive (P) are called true positives (TP), whereas those classified incorrectly as negative (N) are called false negatives (FN). True negative (TN) cases are those that the model properly identifies as negative (N) cases, whereas false positive (FP) cases are those that a model incorrectly identifies as positive (P) cases.

Results for various performance metrics, including accuracy, precision, recall, and F1 score, may be given in equations (7)–(10).

$$\text{Accuracy} = \frac{(B + A)}{(B + A + D + C)}, \tag{7}$$

$$\text{Precision} = \frac{A}{A + C}, \tag{8}$$

$$\text{Recall} = \frac{A}{A + D}, \tag{9}$$

$$\text{F1 score} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}, \tag{10}$$

where A is true positive, B is true negative, C is false positive, and D is false negative.

By using the above equations, we can determine the accuracy and precision of the existing methodologies with the proposed model. Accuracy is used to evaluate a classifier based on how well its predictions match the target label. You may also express this idea by looking at the percentage of correct answers across all examinations. Equation (7) displays the accuracy. Figure 1 shows a comparison between the accuracy of the conventional and suggested approaches. When compared to the standard method, the one proposed yields better results. Accuracy for CA-LDA [34] is at 57%, KNN [35] at 64%, MLCNN [36] at 77%, IKCD [37] at 85%, and the proposed INBCA at 93%.

Accuracy is measured in many ways, but one of the most crucial is precision. As stated in equation (10), it is calculated as the proportion of properly classified instances to the total number of occurrences of predictively positive data. Table 1 represents a numerical representation of accuracy.

Figure 2 displays the results of a comparison between the precision of the conventional and the suggested approaches. Compared to the proposed technique, the precision of previous approaches like CA-LDA, KNN, MLCNN, and IKCD ranged from 74% to 85%. We obtain a 96% degree of precision in the proposed INBCA. Table 2 denotes the numerical representation of precision.

A classifier's "recall," or the percentage of instances accurately labeled "positive," is a useful metric to have. A recall is used as an indicator of performance to choose the best model. Figure 3 shows a contrast between the recall of currently used and suggested methods. The suggested technique offers more accuracy than the standard approach. CA-LDA has 53%, KNN has 85%, MLCNN has 74%, IKCD has 88%, and the proposed INBCA has 97%. Table 3 denotes the numerical representation of recall.

By averaging the accuracy and recall ratings, we get the F1 score. This calculation will help find out how many false positives and negatives there are. Figure 4 displays the F1 score difference between the conventional and proposed methods. The proposed method outperforms the state-of-the-art strategies on the F1 score. The F1 score for the traditional approaches was 55 percent for CA-LDA, 84 percent for KNN, 64 percent for MLCNN, and 73 percent for IKCD. The F1 score for the recommended INBCA is 96% as defined in Table 4.

Computational complexity is a metric for how much time and memory (resources) a certain algorithm uses when it is executed. The computational complexity difference between the proposed and standard approaches is shown in Figure 5. The suggested approach performs better in terms of computational complexity than state-of-the-art
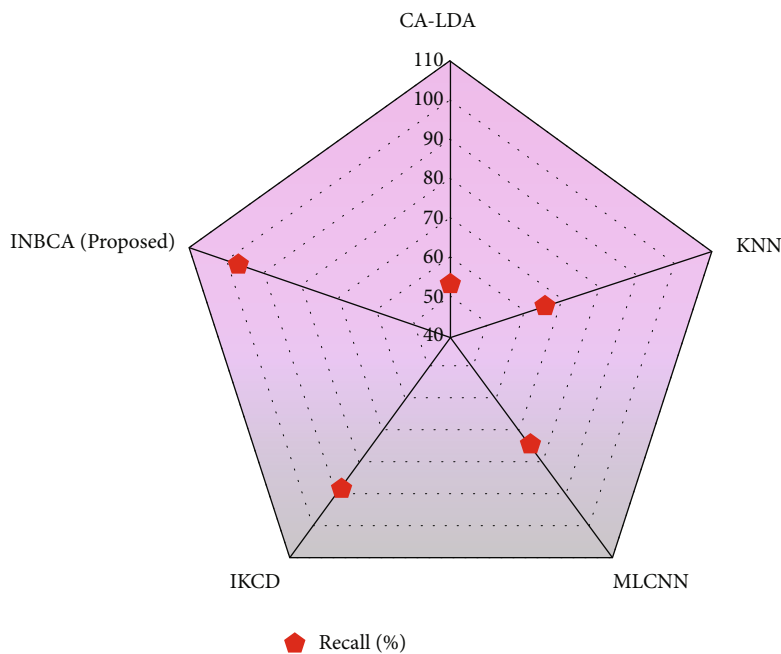
FIGURE 3: Recall.

TABLE 3: Recall.

| Models | Recall (%) |
|---|---|
| CA-LDA | 53 |
| KNN | 65 |
| MLCNN | 74 |
| IKCD | 88 |
| INBCA (proposed) | 97 |

TABLE 4: F1 score.

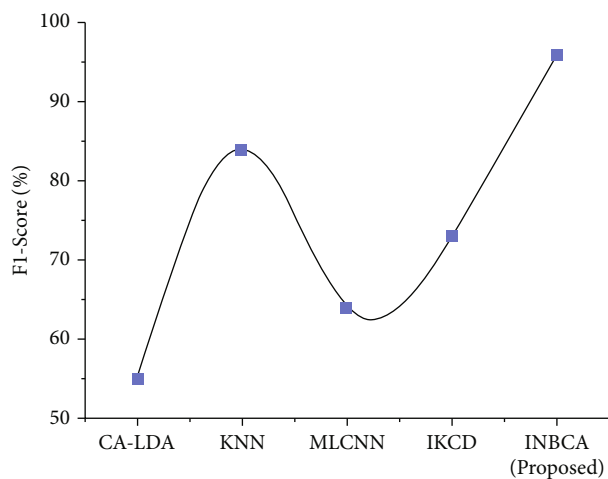| Models | F1 score (%) |
|---|---|
| CA-LDA | 55 |
| KNN | 84 |
| MLCNN | 64 |
| IKCD | 73 |
| INBCA (proposed) | 96 |



FIGURE 4: F1 score.
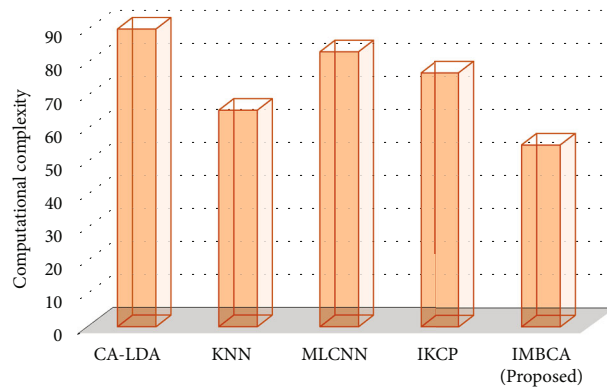


FIGURE 5: Computational complexity.

TABLE 5: Computational complexity.

| Models | Computational complexity |
|---|---|
| CA-LDA | 90 |
| KNN | 66 |
| MLCNN | 83 |
| IKCP | 77 |
| INBCA (proposed) | 55 |

methods. The standard techniques of computational complexity were CA-LDA for 90 percent, KNN for 66 percent, MLCNN for 83 percent, and IKCD for 77 percent. The suggested INBCA's computational complexity is 55%, as shown in Table 5.

From this study, it is observed that the proposed model has provided high accuracy and precision in evaluating the

acceptance behavior of individuals using sensor techniques. Effective interaction and optimism minimize the influence of observed contingency on the adoption of AI-driven news sites. This method also helps in determining the ethical challenges and coping strategies in the adoption of technology. Naïve Bayes is a simple but crucial probabilistic model. Smart machines, which are not artificial intelligence, operate only on algorithms and do not need training data. This note will utilize it as a running example. Specifically, we first address Maximum-Likelihood (ML) estimate in the situation of completely seen data, and then we analyze the Expectation Maximization (EM) technique in the case of partially observed data, where the labels for instances are absent [38].

## 4. Conclusion

This research demonstrates the potential utility of wireless sensing technologies for estimating readers' reactions to AI- (artificial intelligence-) driven personalization on digital news sites. We used a random selection procedure to recruit people to take part in an online survey. Using sensor technology, this research explores the ethical challenges and coping strategies presented by AI-based news and potential solutions to those challenges. This research suggested an improved version of the naïve Bayes classification approach (INBCA) to anticipate how people will react to AI-driven news websites. The results show that better user interaction and optimism reduce the effect of observed contingency on foretelling the acceptance of AI-driven news sites.

## Notations

E: Diagonal matrix
N: Singular value decomposition
G: Orthonormal matrices
K: Loading vectors
$g_2$: Approximation error.

## Data Availability

Data are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflict of interest.

## Acknowledgments

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