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Article

Does machine learning risk reinforcing societal prejudice in education?

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Abstract: Machine learning is increasingly being applied in sectors ranging from healthcare to finance; however, in education, it is typically only used for predicting students' grades. On the other hand, deeply rooted societal prejudice is more challenging to measure, so could machine learning contribute to the current discourse? As a result of a gap in existing literature in the use of machine learning in education, this study uses this novel approach to investigate the potential links between the levels of prejudice of college students and their parents' levels of education. An Implicit Association Task (IAT) was used to collect the information from the participants. Before applying three different machine learning models: Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbour (KNN). It was found that KNN marginally outperformed not only the DT model but also SVM, with the results being validated by using the Statistical Package for Social Scientists (SPSS). This demonstrated a clear correlation between the parents' education and their children's prejudice levels. The paper adds to the limited research that is available on the use of machine learning in education and proposes that a larger study be conducted to provide a more nuanced understanding of prejudice in education.

Keywords: machine learning; prejudice; education; parents; children; implicit association task (IAT)

1. Introduction

Machine learning was first developed in the 1950s to help solve decision-based problems [1]. For example, in 1952, Arthur Samuel developed machine learning algorithms which determined the outcome of a player's move and therefore contributed to winning the board game Draughts [1]. The same idea was also highlighted when IBM's Deep Blue supercomputer beat the international chess grandmaster Garry Kasparov in 1997 [2]. This was not Deep Blue's first attempt having lost to Garry in 1996; however, after having its intelligence upgraded by programmers, the process went some way in proving that computers were better at dealing with complex tasks than humans [2].

Machine learning applications are predicated on input and computed outputs relating to a specific subject. For example, historical and future financial market performance; and typical with atypical cell pathology, more commonly referred to as computational pathology [3]. At the same time, machine learning algorithms have had a significant development generally and are used substantially in healthcare, where they help detect abnormal cells in patients, enabling earlier detection and treatment of diseases [3]. Apart from that, they are also applied in business to model financial data based on historical changes in stock markets [4]. Fast forward to now, they are being used to make risk-based decisions on individuals' mortgage applications [4].

Saying that, machine learning is not without its flaws, as biased outcomes can be obtained if the data on which it is being trained is not of high quality. It could be argued that this brings an obvious question to the forefront of one's mind regarding the possibility of such biases being minimized. Yet machine learning is not typically used in educational environments other than occasionally to predict students' performance in terminal examinations based on historical performance. Therefore, this research aims to explore the application of machine learning models to education. In order to achieve this, the prejudice levels of students studying in a sixth-form college (tertiary education) will form the basis of this research. As existing literature does not explore the use of machine learning in this way, this paper presents a novel contribution to advancing the discourse around its application in education.

Research questions

Finally, the answers will be sought to the following inductive research questions:

RQ1. How does academic literature conceptualize prejudice within cohorts of people with differing access to education and intellectual opportunities?

RQ2. Which machine learning model is best to determine if there are links between parental levels of education and their children's levels of prejudice?

RQ3. In the context of this study, does machine learning have a meaningful role within education?

To achieve the aforementioned aims of this paper, a critical evaluation of the literature surrounding the topic of prejudice will be conducted, highlighting why it is believed to be an important topic worthy of exploring through this study. Following that, details of the approach taken for this research will be presented, before the findings and subsequent discussion, offering some insight into the extent to which the hypothesis has been achieved and the research questions answered. Lastly, the paper will offer some suggestions for ways in which the research could be taken forward.

2. Literature review

This section of the research critiques existing literature on prejudice from an educational perspective. Coupled with that, a brief overview of machine learning, which follows, represents the theoretical basis for this study.

2.1. Prejudice

Education affects people in different ways; therefore, it is an emotive topic for most [5]. Hughes [5] states that education and prejudice are closely linked, and as such, they both impact individuals' lives. While good education should equip a person with a robust level of moral and intellectual code, it could be argued that education has failed a person if they merely make assumptions about others, harboring dislikes before they even get to know them [6]. Carvacho et al. [6] argued that levels of income and education are interrelated and that individuals with higher levels of prejudice are often working class. Going back to 1959, this view was already posed in Lipset's [7] seminal work, suggesting that adverse experiences in life often impact individuals negatively as they could plant deep-seated prejudices towards, for example, political authoritarianism. Lipset's theory [7] posits that individuals can be hindered from comprehending diverse groups and ideas if they do not have sufficient access to educational and intellectual resources. Opposing that view, critics argued that there needs to be more nuance in defining the working classes [8, 9]. Houtman [8], for example, focuses his claims on the correlation between the levels of education and social class, while Kraus et al. [9], on the other hand, argue for a combination of income, education, and occupational status indicators.

One of the key issues surrounding studies of prejudice is that there is not a single universally accepted definition of what it might be. However, Kite et al. [10] suggested that prejudice is not dissimilar to the classic tale of the five blind men where they had to describe the elephant by touch. The tale states that each man correctly described the part they could feel, but their description of the tail, for example, has little, if any, resemblance to the way an elephant actually looks [10]. Kite et al. [10] go on to argue that, while a lot of theories regarding prejudice explain one piece of the puzzle, there is yet to be an all-encompassing concept pulling all the pieces together.

Various theoretical frameworks can be used to explain the notion of prejudice and most focus on certain aspects of the phenomena, including:

- Ethnocentrism. Brewer [11] described ethnocentrism as:

  > … a view of things in which one's own group is the centre of everything, and all others are scaled and rated with reference to it. … Each group nourishes its own pride and vanity, boasts itself superior, exalts its own divinities, and looks with contempt on outsider [11] (p. 12).

- Social distance. Defined by Duckitt [12] as representing the extent to which members of one group would be prepared to accept some other group. For example, "close kinship by marriage", "to my street as neighbours", "to employment in my occupation", and "to citizenship in my country" [12] (p. 11).
- Stereotype. Ashmore and Del Boca state that stereotypes are "a set of beliefs about the personal attributes of a group of people" [13] (p. 16). The aforementioned Duckitt [12] argues, however, that the way stereotypes are conceptualized has shifted. For example, stereotypes are not only focused on personality trait descriptions such as "Germans are conscientious and hardworking" [12] (p. 11), but now include a broader range of personal and physical characteristics of the group: "Germans are blond and tall" [12] (p. 11).

The way people respond to situations and other individuals they encounter is shaped by the above beliefs and values, irrelevant of how they conceptualize prejudices. However, such prejudices are systemic throughout society, with varying degrees of harm attached to them. For example, an individual complimenting a boy on how big and strong he is growing up to be, or a girl on how pretty she is. Other examples include making assumptions that all disadvantaged children should have free access to after-school clubs or that the transgender athletes should have restrictions imposed on which sports they can compete [14].

Yet, these prejudices are not new. Indeed, Duckitt [12] attempted to explore an American-centric view of how historical trends shaped our understanding of prejudice (**Figure 1**).

TIME PERIOD	SOCIAL AND HISTORICAL CONTEXT	SOCIAL SCIENCE QUESTION	VIEW OF PREJUDICE	PREDOMINANT THEORIES
Prior to 1920s	White domination and colonial rule	Identifying deficiencies of "backward peoples"	A natural response to "inferior peoples"	Scientific racism
1920s–1930s	White domination is challenged	Explaining why minority groups are stigmatized; measurement of attitudes and stereotype content	Irrational and unjustified attitudes	Psychodynamic
1930s–1940s	Universality of White racism in the United States	Identifying universal processes underlying racism	An unconscious defense	Psychodynamic
1950s	Legacy of Nazi ideology and the Holocaust	Identifying the prejudice-prone personality	An expression of pathological needs	Psychodynamic
1960s	Black civil rights movement	How social factors influence prejudice	A social norm	Sociocultural
1970s	Persistence of racism in the United States	How prejudice is rooted in social structures	An expression of group interests and intergroup relations	Intergroup relations
1980s to now	Inevitability of prejudice and intergroup conflict	Identifying universal processes underlying intergroup conflict and prejudice	An inevitable outcome of normal thought processes or evolution	Cognitive and evolutionary

Figure 1. Historical studies of prejudice, Duckitt [12].

Duckitt [12] found that many existing studies of prejudice were indeed prejudiced, often misinterpreting research to portray a negative result. For example, scientific racism underpinned research at the start of the 20th century to "prove" the superiority of whites (Caucasians), who, it was believed at the time, were superior people in terms of physiology, morality, and mental abilities that sought to justify racist social policies[12]. If it is to be believed that minority groups were not inferior and prejudice was a social problem, then why is it so ubiquitous? The answers started to come through the work of Miller and Bugelski [15] and psychodynamic theory, specifically that prejudice was a psychological defense mechanism where people became frustrated and acted with hostility and aggression towards specific groups. For example, using minority groups as scapegoats resulting from economic and social hardships due to the lack of employment. More recently, interest in prejudice has focused on cognitive theory. Hergenhahn and Henley [16] argue that stereotyping is a way in which individuals can process large amounts of data. For instance, they argue that it is easier to consider members of a group as homogeneous than as unique and complex individuals [16]. Therefore, the argument is that stereotyping and prejudice are not always believed to be "bad", but rather a framework for cognitive processing [16].

Not only do prejudices, however conceptualized, impact an individual's social mobility and the opportunities afforded to them, but they also have the potential to negatively impact their levels of self-efficacy [17-20]. Bandura [19] defines self-efficacy as how an individual exudes confidence in their ability to exert control over their own behavior, motivation, and social environment, which is a necessary component in achieving social mobility.

Children are not born with these prejudices; instead, they learn from those around them. However, rather than accepting responsibility, emerging prejudices in children are often brushed off or attributed to biology—'it's just boys being boys'.

Pirchio et al. [21] argue that parents play a critical role in shaping a child's attitude towards other groups of individuals. In their study, they found that children as young as three were able to show forms of social discrimination, such as a preference for those of the same skin color as their own and those speaking the same language [21]. Extending on that, and by the age of seven, Kinzler et al. [22] claim that these biases were both explicit (conscious and intentional attitudes) and implicit (unconscious attitudes towards others). Increasing the age to ten and over, the level of explicit (conscious) prejudice starts to reduce, but implicit remains the same [22]. This results in individuals saying that they are not prejudiced towards others, but through their actions and behaviors, they demonstrate that, in fact, they are [22].

Going back to Pirchio et al. [21], they concluded that a child's explicit prejudice is largely unrelated to their parent's either overt or subtle prejudices. However, a child's implicit prejudice is positively influenced by parents' level of subtle prejudice. These findings reinforce those of Castelli et al. [23], who also demonstrated that parents' prejudices are linked to those of their children.

The question remains whether levels of prejudice can be identified by utilizing machine learning approaches. The remainder of this literature review explores machine learning and the extent to which it can be used to identify levels of prejudices before they become apparent or potentially harmful. What can be concluded so far, is that by the time children enter formal education, prejudices are already well-developed. So, can machine learning algorithms contribute to what is already known about them?

2.2. Machine learning

As previously mentioned, machine learning has become a key tool in solving complex problems [24,25]. Most machine-learning algorithms are classified as either supervised or unsupervised; however, the use of machine learning in education is not as widespread as one might expect when compared to sectors such as science and healthcare [25]. In education, machine learning is typically used to predict students' performance. The use of machine learning algorithms to complete this task is not new, as predictions of students' performance have been calculated for many years using students' attainment at age 11, their GCSE grades at age 16, plus their attainment in A-levels at age 18. What machine learning offers is the ability to calculate predicted grades using multiple variables more quickly than previously. Kharb and Singh [26] use various machine learning algorithms (Linear Regression, Support Vector Regression, and Decision Tree Regression) to explore what factors influence students' performance in mathematics and Portuguese language in two different schools in Portugal. They found that with some reliability, they were able to predict student outcomes based on various factors, such as demographic data and, interestingly, the prior attainment of parents in these subjects [26]. In a similar study, Pallathadka et al. [27] demonstrated the accuracy of different algorithms when applied to student performance data. As it can be seen in **Figure 2**, the Support Vector Machine (SVM) algorithm outperforms the other 3 in terms of accuracy.

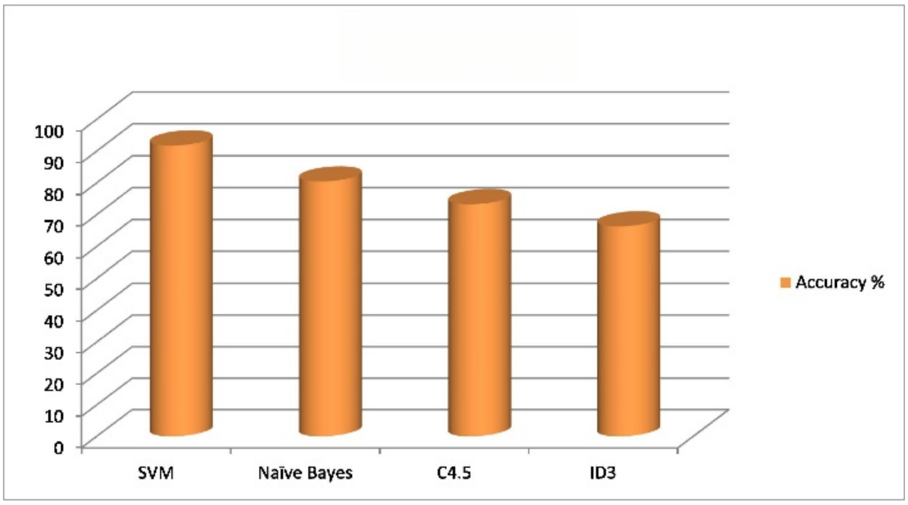

Figure 2. Accuracy results from Pallathadka et al. [27].

To some extent, it could be concluded that this is unsurprising, as SVM works well with both classification and regression models across text, image, bioinformatics, and geographical datasets [28].

It is this idea of predictive analytics that is still relatively new in education, compared to the fields of manufacturing, banking, retail, and marketing, where these approaches are more established [29]. The notion of finding relationships between an output value and a range of variables is ideally suited to supervised machine learning algorithms [29]. This compares favorably to unsupervised machine learning, which seeks to summarize data and build descriptive models. It assumes that all the data is of equal weight, while in supervised learning, certain variables will be more important to the model than others [29]. Moreover, Halde [29] argued that neural networks proved particularly effective for numerical relationships as they can capture the non-linear relationships between dependent and independent covariates [30]. Furthermore, Halde [29] goes on to critique the Bayesian algorithm in predicting the same student performance but including as a variable students' preferred learning style. By doing that, it was found that the output from the Bayesian algorithm was less accurate; however, that could have been linked to the view of learning styles being discredited as opposed to the accuracy of the algorithm itself [31].

It appears that from the literature examined in this chapter, machine learning does have a role to play in education, even though it has limited scope due to the complexity of the variables involved. The objective nature of making a predictive outcome based on input data in manufacturing, for example, cannot compare to the complexity of how humans interact with their surroundings.

The next section of this paper explores the methodology and methods that underpin this study, the data sample and collection techniques, and the choice of machine learning algorithms used to analyze the data.

3. Methodology

This section of the paper outlines the research design, including the methodology. It will begin by discussing research paradigms, then move on to the methods used in the study, and finally, it will examine data analysis and practical implementation.

3.1. Research design

According to Mackenzie and Knipe [32], the first step in research is considering the study's theoretical framework. Academic authors frequently differ on their definitions and naming conventions regarding paradigms [32–36]; however, the three most common paradigms are positivism, interpretivism, and pragmatism [32,37].

Scientists posit that reality is absolute and objective and, therefore, can be measured [35]. This position is akin to the positivist paradigm, where researchers seek to establish universal truths and generalizable laws through observations and measurements of any given hypotheses [33, 36]. On the other hand, scholars who adopt an interpretivist approach recognize that reality is subjective and shaped by an individual's beliefs and values [34]. Usually related to the social sciences, interpretive research claims are only valid at the time the research was undertaken [35]. Finally, pragmatism, according to Bergman [38], adopts the stance of selecting the best elements of existing paradigms and combining them, although he advises that adopting a pragmatic approach does not mean 'anything goes' [38] (p. 12).

This research adopted a pragmatic approach due to using a combination of paradigms but also a combination of methods as well. The hypothesis that machine learning can be used to determine whether levels of prejudice of sixth-form college students and their parents' educational attainment can be a proxy to model future levels of prejudice is framed in a positivist way, which was tested through a measurable response to a questionnaire. At the same time, a series of interpretive research questions were also answered, an approach that highlighted Bergman's [38] vision of taking the best of existing paradigms. Equally, having the flexibility to adopt two competing paradigms in a single study, pragmatism appeared to be the most sensible way forward.

3.2. Data collection

Data collected is often categorized as either qualitative or quantitative [32, 39] although research literature often incorrectly associates them with different paradigms [39]. However, it could be said that maintaining a rigid view of data and its association with a particular paradigm can limit researchers.

This study used an Implicit Association Task (IAT), a common assessment applied in social psychology to assist in understanding an individual's unconscious bias. Originally published in 1998 by Greenwald et al. [40], it had several iterations in refining the scoring system where participants were asked to associate words and names in differing categories and then repeat the process once the categories had been reversed [41–43]. The implicit association test (IAT) is an assessment intended to detect subconscious associations between mental representations of objects (concepts) in one's memory. Its best-known application is the assessment of implicit stereotypes held by participants. The test has been applied to a variety of belief associations, such as those involving racial groups, gender, sexuality, age, and religion.

In this study, the IAT study examined people's level of perceived prejudice. The study's premise is that those with lower levels of prejudice would respond at about the same speed, regardless of whether the categories were switched or not. On the other hand, those with higher levels of prejudice would take longer to respond after the switch due to the association of a specific word with a particular side of the screen [40]. Other scales, such as the Prejudice Perception Assessment Scale (PPAS) [44] and the Self-Perception of Prejudice and Discrimination Scale (SPPD) [45], were also available. Still, they mainly focus on an individual's experience of prejudice as a recipient.

Additionally, the IAT assessment was deployed online so that the target number of participants could complete the test. Demographic data was also collected including gender, age and importantly, the highest level of education from one or both parents (depending on the family situation). The categories used are:

- Doctoral degree.
- Postgraduate degree.
- Undergraduate degree.
- level or equivalent.
- GCSE.

The above groups mirrored the ones used by the British Social Attitudes survey [46], which allowed for several additional inferences to be concluded.

As already alluded to, the IAT procedure involves a series of repeated tasks with slight variations between them. Participants were shown a word on a computer screen, which they had to categorize. For example, on the left of the screen might have been the category "Pleasant" while on the right of the screen "Unpleasant". The word could have been "Gloom" in the center of the screen. For each word that appeared in the middle of the screen, the participant had to select which category the word belonged to using the corresponding key on the keyboard (see **Figure 3**). In subsequent iterations, the position of the categories changed position, so "Pleasant" would appear on the right and "Unpleasant" on the left side.

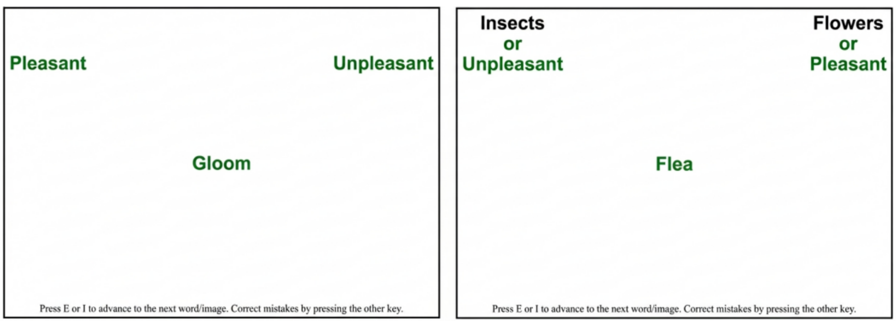

Figure 3. Screenshot of the IAT tool.

Before deploying the survey, a small pilot study was conducted with a couple of students to check that they could access the PsyToolkit [47, 48] platform which was later used in order to deploy the test. That application was selected because it allowed for easy coding and deployment of psychological studies. On completing the IAT test, the system provided detailed responses for each participant's test and an overall score. It is the overall score, plus the demographic data which was subsequently used in the machine learning models.

3.3. Participants and data collection

The sampling frame for this study was sixth-form college students at an institution in South-East England. A convenience sample was used, and participants were self-selecting. After confirmation was obtained from the college's vice-principal, an email was sent to heads of subjects asking if they could forward details of the study to students in their respective departments. The email contained the necessary participant information, outlining the background and purpose of the study and what their participation would involve. In addition, there was a link to the survey website along with details of their right to withdraw at any point before the completion of the survey, confidentiality guarantees, and assurances of anonymity. It had to be noted that the right to withdraw after the survey was completed was not possible, as the data was completely anonymous. The flowchart below (**Figure 4**) illustrates the process that was undertaken.

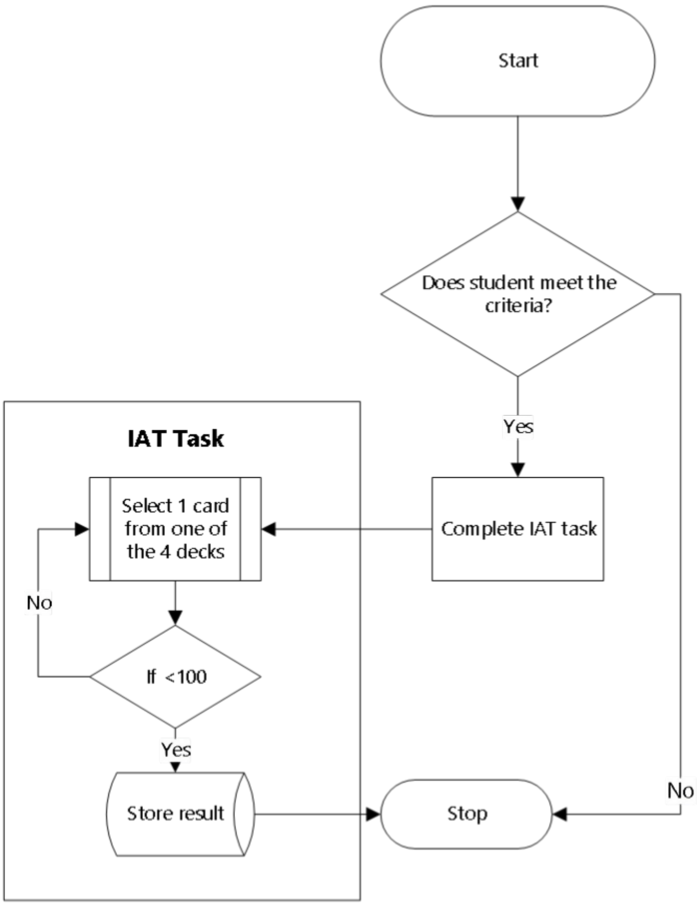

Figure 4. Flowchart of the process undertaken.

To analyze the data obtained from the IAT, the data was modeled in MatLab.

Before this could be done, the machine learning and statistical add-in for MatLab was installed. MatLab then modeled the data using a range of algorithms to determine the best model for the data inputted. The details of each of the machine learning algorithms are discussed in the following section.

4. Findings and discussion

This section provides an insight into the analysis of the data collected before moving on to a discussion on what these mean. In total, there were 624 visitors to the welcome screen of the IAT study. There were 188 completed surveys, and 148 incomplete surveys, totalling 336 surveys. Only the 188 (*n* = 188) completed surveys were used in the dataset for processing.

4.1. Demographics

Table 1 details the gender of participants, while **Table 2** provides the gender and **Table 3** outlines the highest levels of educational attainment of the participant's parents.

Table 1. Participants age ranges.

Age	Number (percentage)
16	24 (13%)
17	96 (51%)
18	60 (32%)
19	4 (2%)
20	4 (2%)

Table 2. Gender of participants.

Gender	Number (percentage)
Male	165 (88%)
Female	23 (12%)

Table 3. Participants' parent's educational attainment.

Educational level	Number (percentage)
GCSE (or equivalent)	43(23%)
A-level (or equivalent)	53 (28%)
Undergraduate degree	32 (17%)
Postgraduate degree	56 (30%)
Doctoral degree	4 (2%)

The IAT data collected via PsyToolkit (referred to as the IAT Effect) provided details of whether the respondent showed a tendency to be prejudiced (denoted by a positive value) or not (a negative value). In total, 148 participants demonstrated a positive prejudicial tendency with 40 demonstrating a negative predisposition towards being prejudiced. This data (educational level, IAT effect, gender, age) was used by MatLab machine learning algorithms. A sample of data can be seen below (**Figure 5**).

Age	Gender	Education level	IAT Effect
17	2	6	-26
17	2	7	-14
18	1	3	-6
18	2	2	-6
17	2	8	-6
17	2	2	-6
18	2	2	-4
18	2	3	-2
18	1	3	-2
16	2	2	-2
16	2	7	0
18	2	2	0
16	2	3	0

Figure 5. Sample of data extracted from PsyToolkit.

4.2. Machine learning

Before the data could be inputted into Matlab, a series of machine learning pre-processing steps needed to be taken. There are several pre-processing approaches that can be used, with most following the same or similar steps, typically including 3, 4 or 7 stages [49–51]. The main distinction between each model is the level of detail into which activities are segmented. When deciding on the appropriate model to utilize, it is crucial to take into account the types of data present in the dataset. The data from the IAT could be simplified to binary, 1 for prejudice or 0 for not. However, it could also be ordinal, where the data could be ranked, for example, by levels of prejudice. Unfortunately, there is no agreed delineation of levels of prejudice.

The raw data was checked in order to ensure that there were neither any missing values nor noise, such as NaN (not-a-number) entries where the expected input was a number. Therefore, data interpolation or imputation [52] was not needed. This was done at a very early stage by removing the 148 incomplete data from the 336 surveys in the total dataset. This left the 188 surveys that were used.

The data was both free of missing values and noise; however, without careful planning, one could introduce potential responses such as N/A (not applicable), which would have brought into question the validity of the dataset. In planning the survey, opportunities were built in to minimize possible noise within the dataset. This was primarily done by ensuring that individuals could not select options such as "N/A" or "Other", resulting in every entry having a valid response.

The accuracy of the data was determined by implementing Five-fold cross-validation. This was a preferred method when compared to Hold-Out validation because the dataset was relatively small (188 entries). The data was divided into five groups, each of them used for training and testing, until all sets were fully utilized (**Table 4**).

Table 4. 5-fold testing of the data.

Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Training	Training	Training	Training	Testing
Training	Training	Training	Testing	Training
Training	Training	Testing	Training	Training
Training	Testing	Training	Training	Training
Testing	Training	Training	Training	Training

Having completed the necessary preliminary stages, a series of algorithms were built and trained using the data.

4.3. Model 1—Decision tree

The first model applied was a classification-based decision tree. This was selected as it is one of the simplest supervised learning models available [50] and can handle both numerical and categorical data. This method makes systematic choices relating to the optimum route based on weighted conditions [50], similar to a flowchart (see **Figure 4**).

Figure 6 below is a scatter plot of IAT Effect versus Educational Level. The plot details the educational levels from level 2 (GCSE) through to level 8 (Doctoral level). The plots show there were no responses for levels 4 and 5; this is due to these options not being available in the IAT survey.

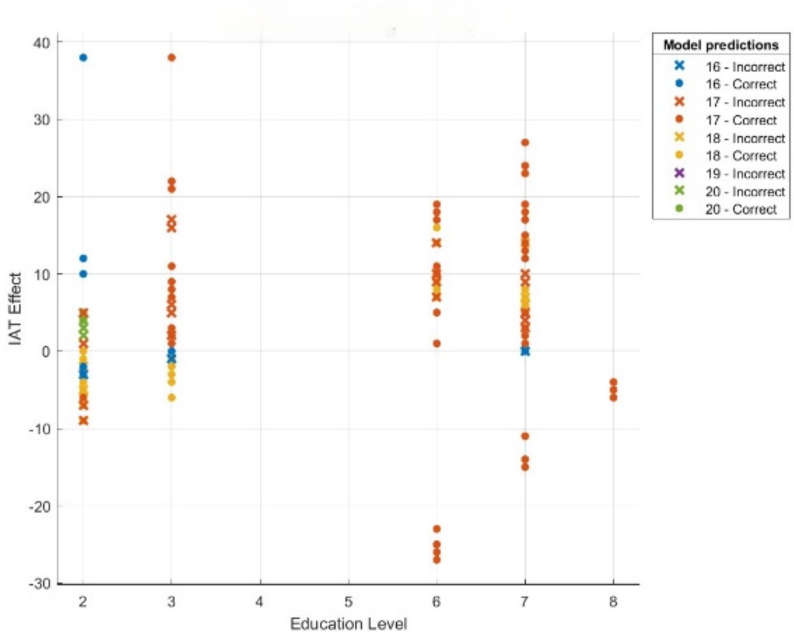

Figure 6. Scatter plot from the Decision-tree model.

The model demonstrates a 73.4% accuracy (**Figure 7**) and was quick to train at only 5.65 s. Unsurprisingly, the confusion matrix (**Figure 8**) shows the greatest accuracy with 17-year-olds, possibly due to having the highest frequency in the population group, $n = 96$.

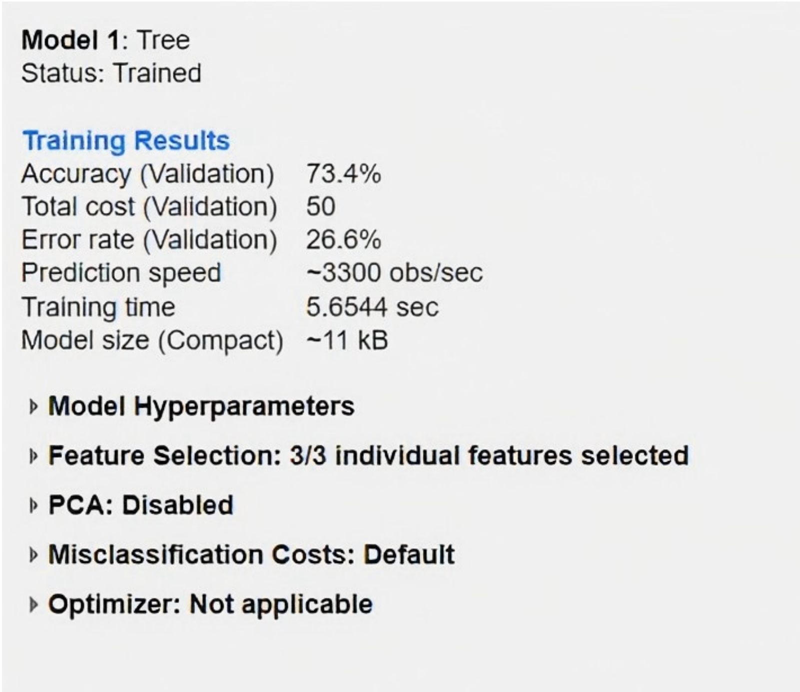

Figure 7. Summary of the Decision-tree model.

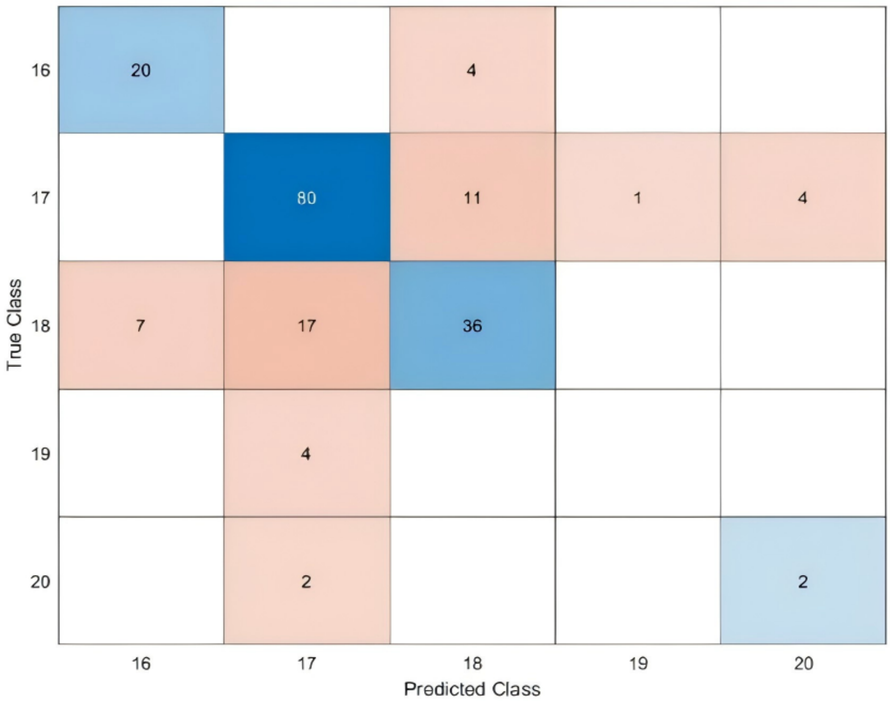

Figure 8. Decision-tree confusion matrix.

The receiver operating characteristic (ROC) curve (see **Figure 9**) plots the true and false positives at different thresholds, based on respondents' age. Characteristically, the Area Under the Curve (AUC) values are between 0 and 1 (0% and 100%). The higher the value, the greater the accuracy of the predictions that are made. As it can be seen from **Figure 8**, the AUC is 0.8016, representing a reasonably accurate model. However, for 19-year-olds, the model was particularly inaccurate at 0.4124.

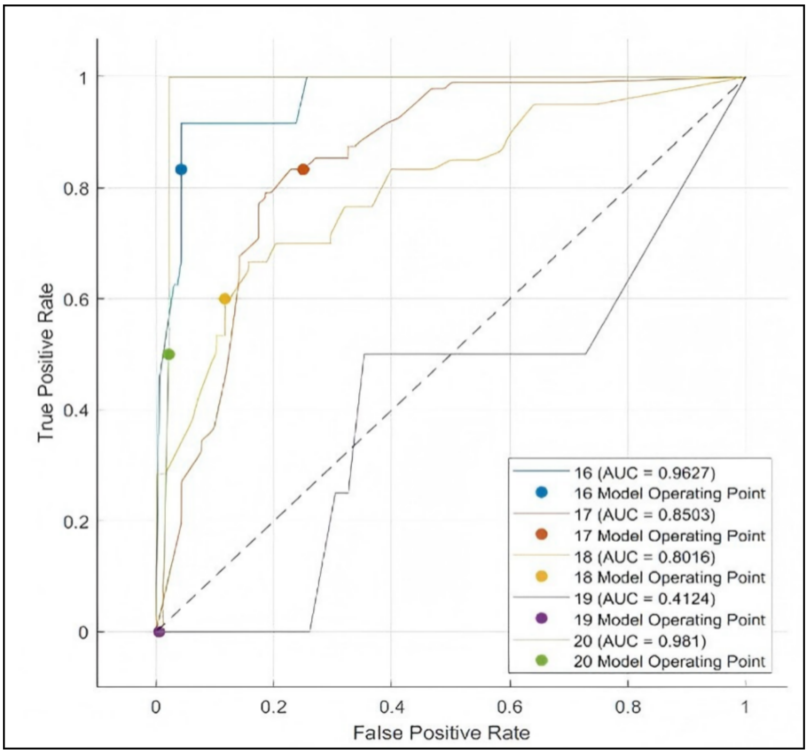

Figure 9. Decision-tree receiver operating characteristic (ROC) curve.

4.4. Model 2—Support vector machine (SVM)

The second model used was a support vector machine. Like the decision tree, SVM is a supervised machine learning algorithm that can be used for regression but more commonly for classification problems (as per this study) [53]. The primary objective of SVM is to identify points at which data can be segregated into different categories. In addition, SVM is particularly good for smaller datasets and plots each item as a point in n-dimensional space, where n equals the number of features, in this case 5 (one for each level of educational attainment). Once plotted, the algorithm tries to find the most appropriate hyperplane (a decision boundary) to classify the data [53]. In this study, the hyperplane was non-linear as the data is not linearly separable (**Figure 10**):

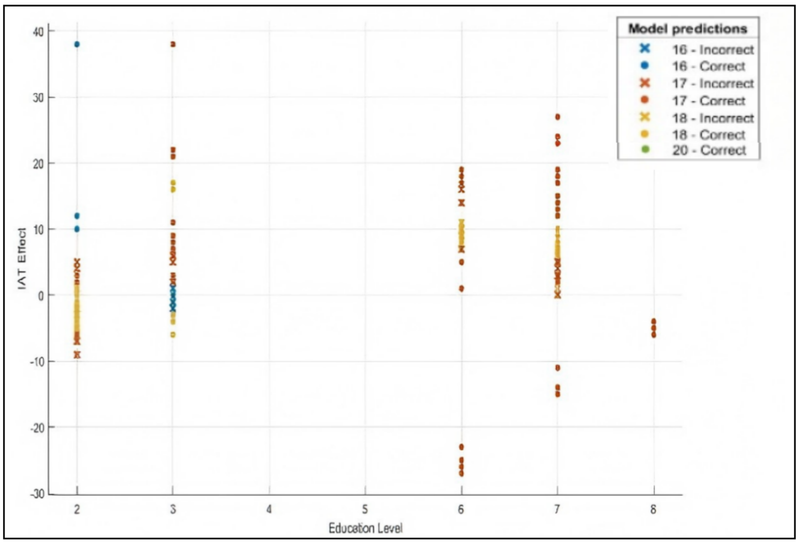

Figure 10. Scatter plot from the SVM.

The model demonstrates a 75% accuracy (**Figure 11**), 1.6% more accurate than the decision-tree model (**Figure 7**), but was significantly slower to train at 18.7 s. The confusion matrix (**Figure 12**) is slightly less accurate with 17-year-olds compared to the decision-tree model (**Figure 8**), but overall the spread of incorrect identifications was less.

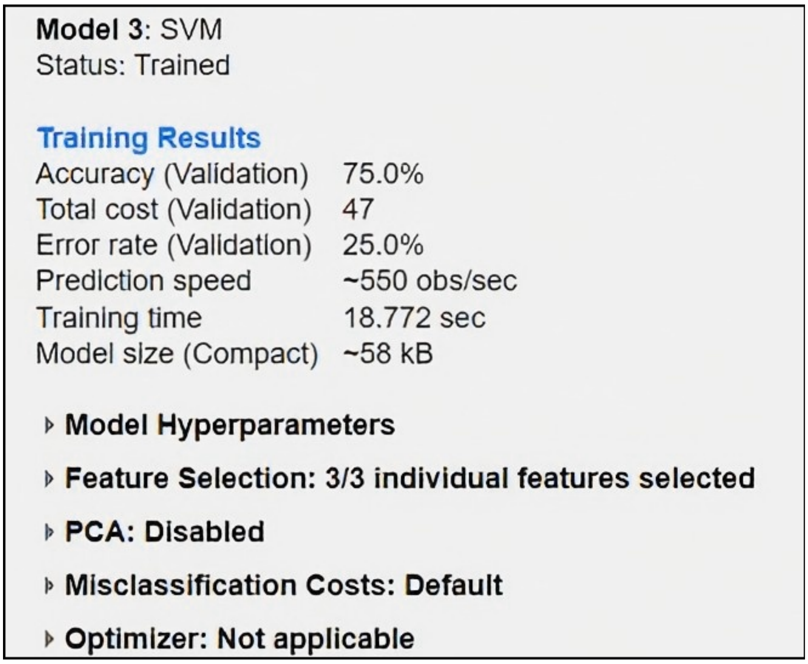

Figure 11. Summary of SVM model.

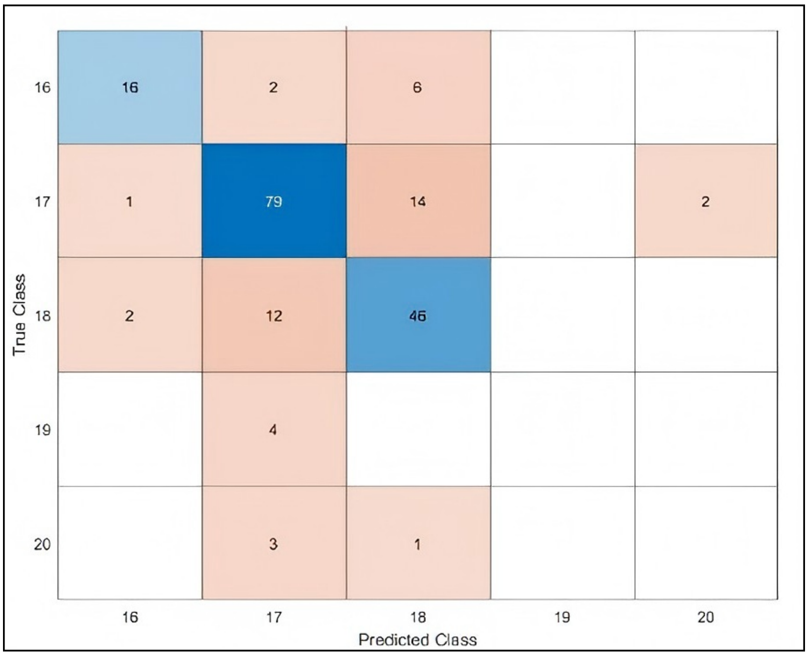

Figure 12. SVM confusion matrix.

The ROC shown in **Figure 13** has a higher average value (0.93338) compared to the decision-tree model which was 0.8016 (**Figure 9**), representing a more accurate model. Most noticeable was the improvement in accuracy for 19-year-olds, the model which has increased from 0.4124 (**Figure 9**) to 0.9592 in the SVM algorithm.

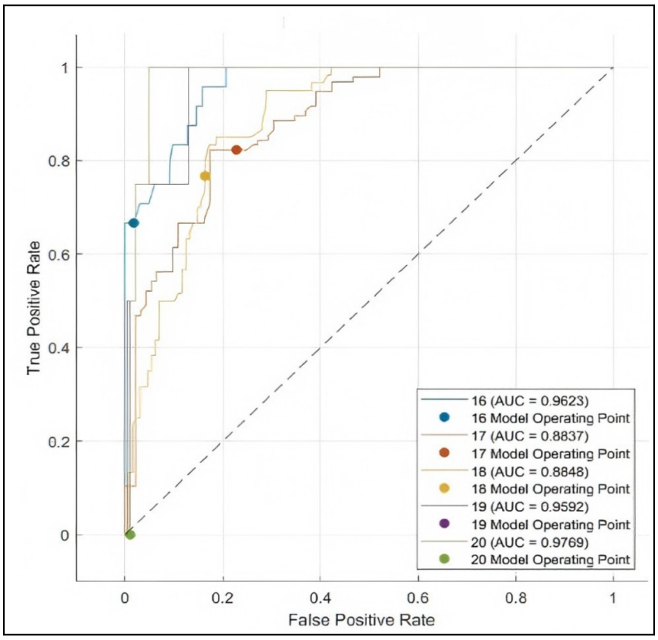

Figure 13. ROC for SVM.

4.5. Model 3—K-nearest neighbor (KNN)

The final model used was the k-nearest neighbor algorithm, which like the previous two are supervised machine learning classification model that uses proximity to make classifications or predictions [54]. The KNN is often considered to be easy to implement due to not making any assumptions about the distribution of the data and due to the limited number of parameters [54]; however, it does have some limitations. This includes being prone to overfitting, which is where the model tries to fit the data so accurately for the training data that it does not work effectively with new data [55]. In addition, the KNN algorithm can be subject to what is known as the curse of dimensionality [56], which is where the dataset has a high number of attributes (**Figure 14**). This is not an issue in this study, as there are only four attributes: age, gender, educational level and IAT effect. KNN is often used in pattern recognition, data mining, and intrusion detection.

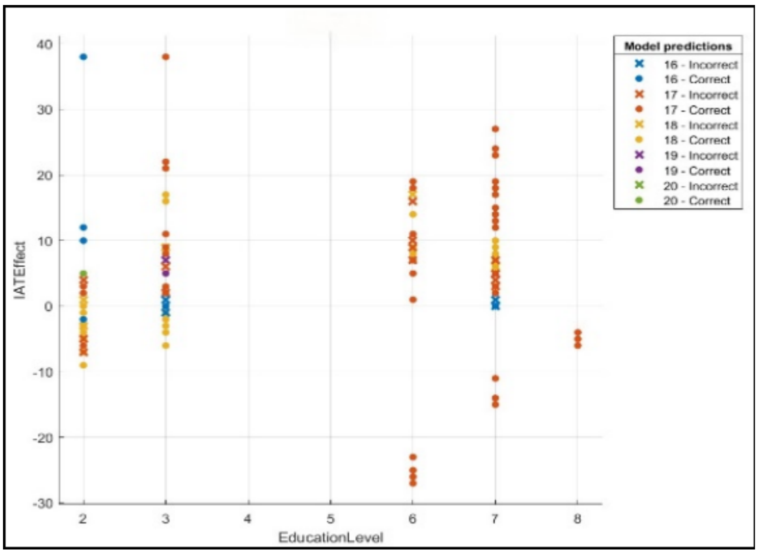

Figure 14. Scatter plot from the KNN.

The model demonstrates a 75.5% accuracy (**Figure 15**), which is more accurate than both the decision-tree model (**Figure 7**) and the SVM model (**Figure 11**). Training time was 4 s faster than the SVM model. The confusion matrix (**Figure 16**) is slightly less accurate with 17-year-olds, compared to the decision-tree model (**Figure 8**), but more accurate for 16-year-olds.

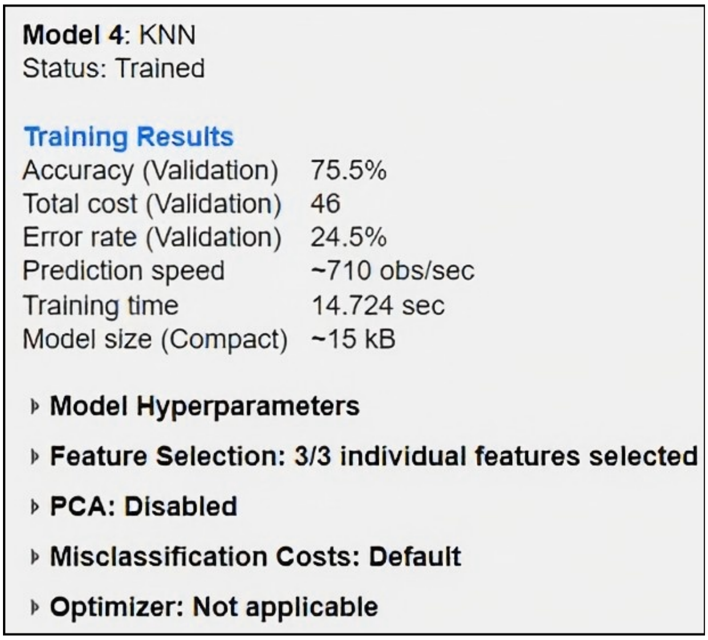

Figure 15. Summary of KNN model.

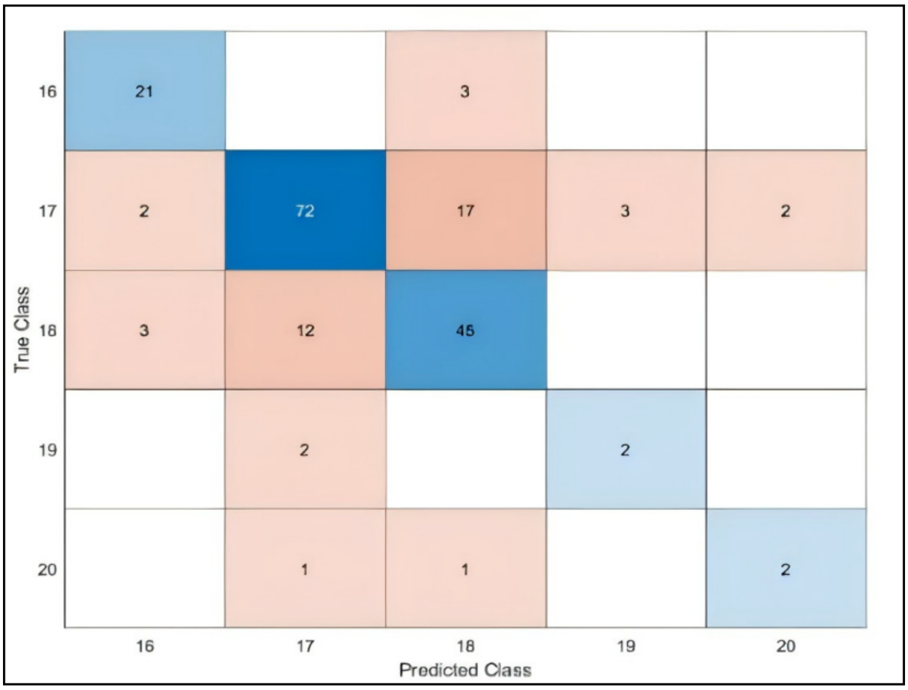

Figure 16. KNN confusion matrix.

Table 5 provides a summary of the accuracy of the 3 confusion matrices, with the highest accuracy scores for each model identified in bold.

Table 5. Summary of the confusion matrices.

Age	Decision tree	SVM	KNN
16	20	16	21
17	**80**	**79**	**72**
18	36	48	45
19	-	-	2
20	2	-	2

The ROC shown in **Figure 17** has a lower average value (0.79904) compared to the SVM model of 0.93338 (**Figure 13**) and the decision-tree model, which was 0.8016 (**Figure 9**), representing less accuracy at the individual age level.

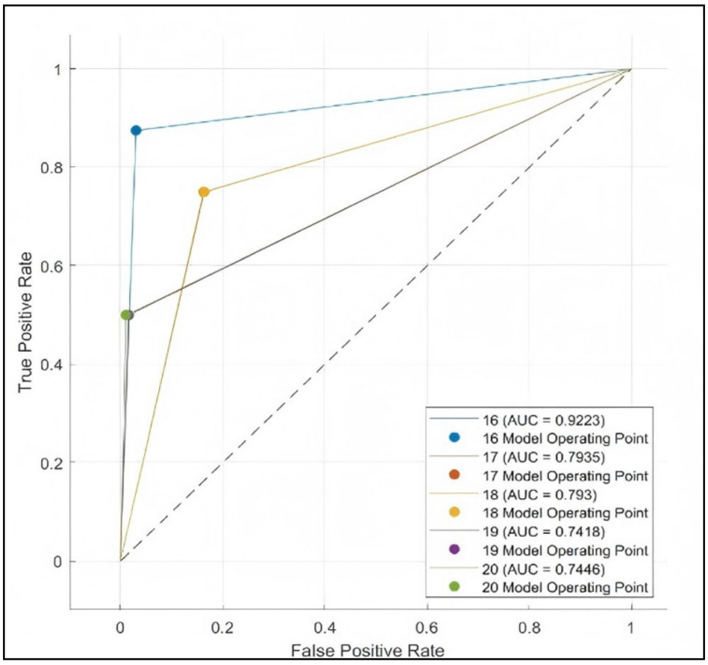

Figure 17. ROC for KNN.

4.6. Statistical testing

To determine how accurate the results are, additional statistical testing was completed using SPSS. A Pearson Correlation was calculated to measure the strength of the relationship between the IAT Effect and the Educational Level. A negative value between the two variables indicates a negative correlation between the variables, while a positive value indicates a positive correlation. The data in **Figure 18** shows that there is a negative correlation $r(4) = -0.095$, $p \leq 0.001$. This means that there is a slight negative correlation between the level of educational attainment and the level of prejudice. The higher the level of education, the less likely an individual is to be prejudiced. However, as the value is just marginally below 0, then this is not a strong correlation. Indeed, the *p*-value is a statistical measure of how significant the results are. Typically, values are either measured at 0.05 (95%) or 0.01 (99%) confidence in the findings. In this case, the *p*-value is less than 0.01, meaning that the results of the correlation are statistically significant. Therefore, one can be confident that there is a marginal relationship between IAT effect and the prior educational attainment of parents.

Correlations			
		Education level	IAT Effect
Education level	Pearson Correlation	1	-0.095
	Sig. (2-tailed)		0.197
	Sum of Squares and Cross-products	395.234	-10.553
	Covariance	2.114	-0.056
	N	188	188
IAT Effect	Pearson Correlation	-0.095	1
	Sig. (2-tailed)	0.197	
	Sum of Squares and Cross-products	-10.553	31.489
	Covariance	-0.056	0.168
	N	188	188

Figure 18. SPSS output showing correlation and IAT effect.

A Chi-square test was also undertaken to determine whether the two categories (IAT Effect and Educational Level) are related or independent. The data from **Figure 19** shows that $X^2(104, N = 188) = 358.7, p \leq 0.001$. Therefore, one can reject the statistical null hypothesis (not to be confused with the research hypothesis) that there is no relationship between IAT Effect and Educational Level and assume the alternative hypothesis, that there is a relationship between the two factors.

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	358.756[a]	104	<0.001
Likelihood Ratio	344.319	104	<0.001
N of Valid Cases	188		

Figure 19. SPSS output showing Chi-Squared output between educational level and IAT effect.

Note: a. 132 cells (97.8%) have expected count less than 5. The minimum expected count is 0.09.

As this data was tested with a correlation test and a separate chi-square, it could be said with some confidence that there is a relationship between the IAT Effect and the Educational Level of participants' parents, albeit a small one.

The next part of this paper discusses in more detail what these results mean, referring back to the literature previously discussed in Section 2.

4.7. Discussion

In line with the aforementioned, this section discusses the study's results on whether machine learning could be used to determine if parental educational achievement is a determinant factor for levels of prejudice in their children, in other words, the surveyed sixth-form college students in this specific investigation. It is important to note that a search of existing literature does not offer any studies from which comparisons can be made. However, appropriate comparisons and references will be made to the literature allied to this study. As it could be seen, three machine learning models, namely decision tree, SVM, and KNN, were applied to the same classification datasets in order to explore which model (if any) provided the most accurate results.

One of the very first observations is that the difference in model accuracy is 2.1%, with the decision-tree model being the least accurate, KNN the most accurate, and SVM closely behind by 0.5%. It is also fair to point out that the only significant variation between the models was in the time taken to train them (see **Figures 7**, **11**, and **15**). The quickest algorithm turned out to be the decision-tree model at 5.65 s, which is due to the simplicity of the Boolean logic used to determine which data is the most important [57]. Interestingly, the slowest model was the SVM at 18.7 s, some 13.05 s slower, and while existing literature suggests that SVM outperforms other machine learning models [58–60], this was not the case in this instance, where KNN clearly outperformed SVM. This is because the training dataset (n = 188) was larger than the number of variables used for training, hence KNN being more efficient than SVM [61].

The confusion matrix of the three machine learning models (**Figures 8**, **12** and **16**) provides details of true and false positives and negatives thus offering a more nuanced overview of the data rather than simply looking at the overall accuracy. This is particularly important if, as in this study, the number of respondents by age differs [62]. The data demonstrated that the SVM model correctly predicted the levels of prejudice in 67% of 16-year-olds, compared to 88% for KNN. However, the decision-tree model was more accurate when it came to 17-year-olds which was possibly due to having almost four times the number of respondents who were age 17 in the group (see **Table 1**). Remarkably, KNN struggled with predicting both 17- and 18-year-olds (75% for both); compared to SVM which performed better for 17-year-olds and marginally better for 18-year-olds. Saying that both KNN and SVM performed better in the combined category of 17- and 18-year-olds when compared to the decision-tree model while, overall, KNN performed best by predicting the prejudice of participants more accurately. Highlighting the difference in performance margins of the models in this study, it is important to point out that KNN beat SVM by one respondent and 4 respondents respectively against the decision-tree model.

In terms of the ROC curve (**Figures 9**, **13**, and **17**), the plots from all three models are above the classifier line (diagonal dashed line), illustrating greater confidence in the level of classification, and this was true for all age groups across all models. However, there were some variations with KNN predicting more true positives, which was also reflected by the confusion matrix. Overall, those respondents who were aged 19 or 20 were more likely to have a true positive rate, probably due to the small sample size of these age groups. The data from the ROC curve reinforces what is already known from the confusion matrix, although it would offer greater insight if the data obtained from participants had been categorized, indicating how prejudiced someone is, similar to the Likert Scale [63].

Figure 20 represents the overall number of respondents who demonstrated prejudiced tendencies based on their parents' educational attainment. More participants scored a negative value on the IAT assessment where their parents had GCSE or equivalent qualifications compared to those with degree-level qualifications.

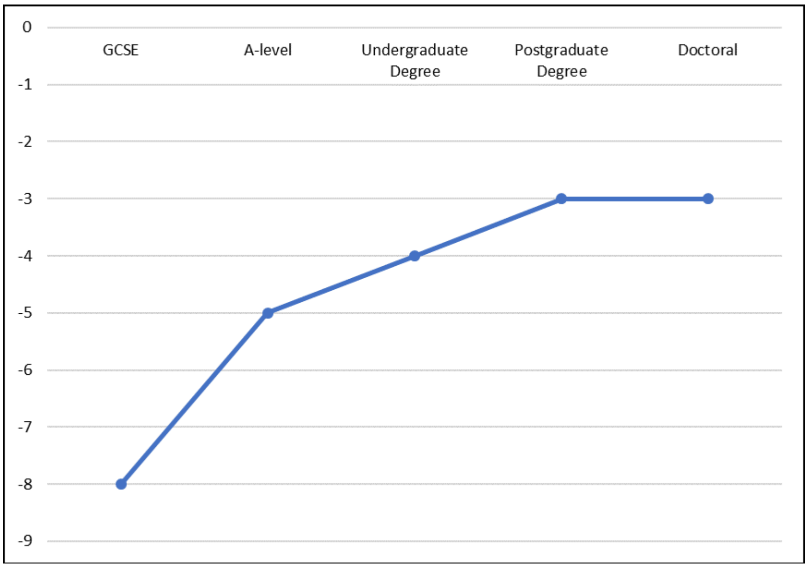

Figure 20. Number of participant responses less than zero by parents' prior educational attainment.

Discussing the results further and going back to Carvacho et al. [6], who argued about the inverse connection between levels of prejudice and levels of education and income, this study, albeit not involving income levels, supports that view. This can also be seen in **Figure 20**, where the higher the educational level of parents, the fewer students demonstrated a prejudice through the IAT assessment, with the only caveat that the level 8 (doctoral) data is unreliable due to only 3 responses within this category. In addition, the scatter plots (**Figures 6**, **10**, and **14**) show no responses for levels 4 and 5, as the parental data collected was based on the final level of qualification, not an intermediary such as levels 4 or 5, which links with the prior decision to use the same metrics as the British Social Attitudes survey [46].

So, those students whose parents have a lower level of education, typically GCSE or equivalent, are more likely to find themselves (n = 19, 44%) scoring a negative value on the IAT assessment, indicating a disposition towards being prejudiced. Compared to those whose parents have A-levels or equivalents, where 16% identified as being prejudiced, those with parents having an undergraduate or postgraduate degree scored 13% and 7% respectively. Miller and Bugelski [15] state that this could be a result of psychodynamic theory, where individuals manifest the frustrations they experience in society, such as limitations on income, property ownership, and societal status, through being prejudiced against minority groups. A counterargument could be that individuals stereotype specific groups of society as a way of dealing with large amounts of complex data. Hergenhahn and Henley [16] would argue that those with similar characteristics are considered in the same way.

According to Hughes [5], a higher level of education should empower individuals with the ability to evaluate others with a certain level of intellectual and moral code. Delors [64] states that education is not just about acquiring knowledge and skills, but also the overarching ability for individuals to live together in society. Prejudice, therefore, lies at the intersection of learning to live together, and education as it draws on both for its reduction. If this was not the case, Hughes' [5] argument would not be valid and students in schools and colleges would not be taught about British Values (tolerance, democracy, respect, individual liberty, and the rule of law), enabling them to live together in a modern and diverse society [65]. The UK government is also committed to ensuring that more is done to address societal prejudices, recognising that there are still pockets within society and that education has a key role to play in further reducing them [66]. At the same time, reminding ourselves of Pirchino et al.'s work [21] who state that a child's unspoken prejudice is largely based on a parent's subtle prejudice, a view which is reiterated by Castelli et al. [23] stating that a child's prejudice is closely related to that of their parents. None of the literature examined in this study discussed whether there was any difference in levels of prejudice based on gender. From the data collected, only 24% of male students demonstrated any level of prejudice, compared to 48% of female students. However, the sample size of female students was 23 compared to 165 males (**Table 3**) therefore whether any meaningful observations can be drawn is inconclusive, but perhaps worthy of further exploration. From the data obtained for this investigation, 88% of participants did not score as prejudiced. This is above the value obtained from the British Social Attitudes survey which found in 2022, that 64% of those surveyed were not prejudiced, down from 82% in 2019 [46]; suggesting that the participants in this study were less prejudiced than the general population from which the British Social Attitudes were drawn.

Such a high level of non-prejudiced behavior that has been observed in this study is further validated by both the Pearson Correlation test (**Figure 18**) and Chi-square test (**Figure 19**), which show a small negative correlation between levels of educational attainment and prejudice. This means that the higher the level of parents' educational attainment, the less likely an individual is to be prejudiced, reinforcing what was previously stated by Hughes [5] about prejudice and learning being inextricably linked.

Another interesting observation arising from the data collected was that 44% of participants did not complete the survey in full. A brief analysis of the responses from those who did not complete the full IAT survey showed that they completed the required demographic information and data on their parents' educational level; however, they did not proceed to the actual IAT stage. This is despite having a large button and clear instructions asking them to move to the next stage of the survey. It is difficult to determine exactly why respondents did not move forward, but reflection offers a helpful insight. The possible reasons may include the attention span of participants, as it took on average 14 min and 34 s to complete the survey, plus it was done using a computer screen as opposed to on paper. This would be in line with Strom et al.'s [67] argument that the attention span, including deep reading, has deteriorated in colleges, with students just skimming the information on digital devices and performing better when tests are paper-based. Additionally, the survey and covering email were sent to subject leads within the college asking them to share the link with their respective students, so it is possible that there was inadequate explanation of the instructions. As the data is anonymous, it is not possible to ascertain the potential links between subject areas and levels of non-completion.

As a final thought, there is one particular issue that has not been addressed, and that is the extent to which students participating in the study have already had their views formed by familial inferences. Pirchino et al. [21] stated that attitudes start to form in children from as young as three years old, and according to Kinzler et al. [22], by the time a child reaches the age of ten, those attitudes are embedded within their consciousness. So, by the time they reach post-compulsory education, is it too late to unlearn those prejudices?

5. Conclusion

The study set out to explore the use of machine learning in education, which it has done through the hypothesis and research questions outlined at the start. What has been determined is that machine learning can be used to determine whether levels of prejudice of sixth-form college students and their parents' educational attainment can be a proxy to model future levels of prejudice. The study has demonstrated that there is a clear link between the educational attainment of parents and students' level of prejudice as determined by the IAT assessment. Students whose parents have GCSE or equivalent-level qualifications are more likely to demonstrate prejudiced tendencies than those with parents who have degrees. The exception to this, based on the small sample size were those with doctoral-level qualifications. This supports the claims Hughes [5] makes that education and prejudice are closely connected. Through the study, it was also found that female participants were more likely to demonstrate prejudiced tendencies than their male counterparts; however, existing literature does not explore the gender basis of prejudice. Machine learning provided some useful insight into the data that was collected. While it would have been possible to calculate some of the headline outcomes and provide statistical validation of the models through Excel or SPSS, what machine learning offered was a level of assurance that the outputs obtained were valid, particularly when interrogating the data related to age and gender. This was achieved by using the Five-fold cross-validation method (see **Table 5**) as part of the modeling. Moreover, the algorithms produced will be able to predict levels of prejudice of future students just based on their parents' prior levels of educational attainment. Saying that, having students complete the IAT assessment would provide continuous data to further refine the algorithms.

Of the three models tested, KNN overall provided the most accurate results and with a reasonable training time speed compared to the other two models. However, it is worth noting that each model has its own merits and that the difference between some of the factors considered when selecting the best model was marginal at best.

Furthermore, the findings demonstrate that machine learning does have a role in education. Machine learning as a tool can provide an insight into the student population that would not have been easily possible beforehand. By better understanding their cohorts of students, teachers could be considerate of potential prejudice as well as make more explicit reference to British Values and appropriate behaviors within class. Equally, college managers could use the information to determine the necessary level of college-wide interventions.

Overall, several points of reflection are highlighted by this study. To start with, prejudice is a complex and subjective topic, which makes it difficult to define. Furthermore, most studies on prejudice focus on an individual's experience of prejudice, while this research looks at the educational attainment of one group of individuals (parents) to ascertain levels of prejudice in another group (students). Despite an extensive literature search, no papers like this were found; therefore, it is believed that this paper contributes to new knowledge. At the same time, machine learning has allowed the data to be explored in a different way, and while SPSS was also used in this study, it was only to try and validate the findings from the machine learning algorithms. Ultimately, however, the analysis of the data is possibly more important and impactful than the processing itself, as it is the findings that are likely to change practice more than the data interrogation techniques.

There are however several limitations which are listed below:

- The gender of respondents was skewed towards male participants therefore any specific observations made about female participants would need to be caveated by the small sample size.
- Following on from this, the number of respondents whose parents had doctoral-level qualifications was very small, which like the point above needs to be caveated.
- What is not known is if there were any differences between the subjects that students were studying.

Based on these limitations, future work should focus on replicating this study with a larger dataset to provide greater insight into the extent to which parents' educational attainment impacts on their child/children's level of prejudice.

As a result of this study, practitioners should consider paying greater credence to the role of parents and their educational attainment related to the levels of prejudice of their children. In addition, they should consider the role that machine learning can have as a tool to enhance educational performance, focusing on the output from the algorithms rather than the process itself, thus promoting institutional policy changes where necessary.

The juxtaposition of this study has been the disciplines of computer science and education, and it is this approach that has yielded a benefit that could not have been obtained by focusing exclusively on one discipline. Rather than this being the exception in education, perhaps moving forward, the use of machine learning in education should become the norm.

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