

Personalizing Student Major Selection through Artificial Neural Network Prediction Models

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Article Info

Article history:

Received 28 May 2025

Received in revised form 19

June 2025

Accepted 11 July 2025

Keywords:

Artificial Neural Network

Student Majoring

Major Prediction

Classification

Abstract

This research focuses on a well-known problem in secondary education that a student may have a hard time in choosing their study major to fit their interest, gifts, and long-term goals. Concentrating on the SAINTEK (science and technology) and SOSHUM (social sciences and humanities) streams of Indonesian high schools, the study will incorporate an Artificial neural network (ANN) to provide an insight into the student preferences based on multidimensional data through modeling and predicting purposes. A 44-item questionnaire was distributed to 205 students of SMA Negeri 1 Karanganyam to gather the inputs that involved personal interests, parental influence, career perspective, and psychosocial characteristics. It was trained and validated with Stratified K-Fold Cross Validation that delivered good performance scores of average accuracy at 87% and precision value at 89- 91 recall and an F1-score of 90. In addition to the algorithmic validation, qualitative interviews of some of the students indicated that the prediction of the model corresponds to what these students perceive about their academic leanings. The obtained results argue that ANN systems can be used, not only as an error-free classifier but also as an educational decision-support system that can be used to augment student guidance with personally-tailored, data-driven advice. The proposed study locates ANN in the larger pedagogical mission of responsiveness and student-centered planning as such, the study also advances the new discourse of ethical and effective uses of artificial intelligence in education.

Introduction

In its deepest sense, education is not a simple and direct transfer of phenomena, as one can accept it as a process of transformation, which brings to the horizon, a holism in the learners, in a changed manner. It aims at developing mental development, emotional understanding, professional focus, and moral direction-enabling people to both realize personal capacity and make up something to society. Integrative philosophy prevails in the Indonesian educational environment, with the national education goals suggesting the promotion of the spiritual, intellectual, and social growth simultaneously (Sujana, 2019; Rahman et al., 2022). However, a standing gap can be noticed in terms of the assistance that is offered to students when they make one of the most decisive crossings of their scholarly lives - when they choose the undergraduate major. The choice is usually rendered during the last years of senior high school, it is far beyond the administration level of formality, and once made has permanent repercussion over the academic advancement, labour-market preparedness, psychological status, and identity development. One of the realities around which this is particularly salient relates to Indonesia where students are required to not only choose between science and technology (SAINTEK) and social sciences and humanities (SOSHUM) but where the binary choice is likely to affect a student in terms of the university as well as vocational orientation.

Nevertheless, empirical evidence has continuously indicated that secondary students get to experience minimal systematic counsel when it comes to the major-selection procedure which makes them vulnerable to extrinsic determinants. The choice is often inspired by peer pressure, parental ways of thinking, or social stereotypes, instead of introspective, evidence-based thinking (Nur Hidayat, 2016; Yuma & Rizaldi, 2018). According to Irene Guntur quoted by Nurdin et al. (2016), a significant portion of Indonesian learners cannot correlate their educational preferences with their passions and skills. These are not issues only faced in Indonesia, international literature has been supportive in the fact that there is disalignment between student aptitude and academic major that leads to increased academic disaffection, changing of major quite often, increasing chances of dropping out, and dissatisfaction at both academic and career paths (Estafetta, 2018; Howard & Navarro, 2016; Fouad, 2007). The tendency among students to stall on their choices is never accepted as the major cause of an issue but as a reflection of the unreasonable constraints in the delivery of recessive, pre-existing, and efficient counseling. In the sphere of educational establishments under the care of the civil school, there are problems with the ratio of counselors to pupils, as the index is often above the recommended level and the school counseling facilities are under-staffed and under-funded. These limits compel the need to have complementary aid systems that can enlighten the students to make consequential decisions.

New achievements in technology, especially the area of artificial intelligence (AI), offer an encouraging trend in dealing with the shortcomings. ANNs are capable of processing data with a multidimensionality and pinpointing relationships that are beyond human analysts and they are designed to imitate patterns found in the human brain in their structure. Their ability to engage in non-linear classification makes them particularly appropriate to decision making situations which involve many, interacting variables. The empirical studies indicate that they are effective to forecast student graduation rates (Pratama et al., 2024), academic performance (Nguyen et al., 2020), and loyalty in a higher-education environment (Singh, 2021). The more advanced one, which include ANNs along with optimization algorithms (e.g., Particle Swarm Optimization (Rudianto et al., 2022), Long Short-Term Memory (LSTM) networks (Choi & Kim, 2021) used to conduct time-based predictions, exemplify the maturity of this technology. As these systems have been hypothetically postulated, they are currently available tools that have provided a specific utility to various industries such as healthcare, transportation, marketing and education among them.

Although the potential efficacy of artificial neural networks (ANN) in various fields of prediction has been proved, the application of artificial neural networks to secondary-school counseling, in general, and to the prediction of academic major interests in students, in particular, has so far been marked by the scarcity of empirical research and the lack of development of the corresponding theory. Just about every existing application focuses on technical parameters, like precise or accuracy, without incorporating such outcomes into existing educational theories or student development models. As a result, there is a risk that a highly individual and development-related choice of academic or vocational path will be reduced to the paradigm of an algorithm result. The current paper challenges such reductionist stance and promotes the opinion that ANN can be used as a pedagogical support instead of a computational classifier. Based on the existing theoretical approaches, such as the vocational personality theory by Holland (1997), the career construction model by Savickas (2013) and the person-environment fit theory by Lent et al. (1994), the study envisions ANN being placed in a wider context of educational vision: that would encourage the students to form their identities, develop their agency, and provide them with guidance and discipline in acquiring their own future visions of studies. When applied in a reasonable fashion, educational data

mining does not oust common sense, but it adds a reflective layer to the practice of counseling to the students and counselors relying on empirical patterns (Papamitsiou & Economides, 2014; Whiston, 2002).

In order to answer these questions, the study was conducted in SMA Negeri 1 Karanganom, Klaten, where researchers designed and tested ANN-based system, which had the capacity of predicting whether the student is inclined towards SAINTEK or SOSHUM streams. The information was based on 205 respondents who took part in a questionnaire composed of 44 questions that covered determinants of major selection i.e. internal dispositions (e.g., self-confidence, interest), external influences (e.g., family, peers), as well as general socio-economic considerations. The findings show that ANN model achieved accuracy of 75.5 percent and precision of 99.5 percent which implies a good predictive power (Rufaidah, 2015). In order to ensure the rigor of methodology, the given research used the Stratified K-Fold Cross Validation to assessment the working of the ANN model rather thoroughly and, afterwards, conducted the direct interviews with the students of high-schools to ensure that there were no discrepancies between privately administered orientations and the model forecasts. The triangulated design that combines the precision of quantitative approach and corroboration of qualitative ones increase the contextual and psychological reliability that are often missing in purely computational studies.

The general aim of the research is two-fold. On the one hand, it aims at proving the idea that ANN can offer accurate, contextually-sensitive predictions to help explain the academic orientations of high-school students. As to the other, the work aims to demonstrate that such predictive models used with ethical and reflexive intention are transitional tools that can be used in educational ecosystems. All these systems have the ability to not only enhance the precision of the guidance, but also youth to reconstruct the very model through which academic choices are discussed by students when shaping their lives. Through this, the research contributes to the goal within educational circles to embrace intelligent systems not only in the capacity of automation but in the betterment of a fairer and more equal, and personalized experience in schools (Williamson & Piattoeva, 2020; Eynon, 2015). With educational organizations moving towards evidence-based learning customization and digital enhancement, the current paper provides a well-theorized and tested model of the responsible and meaningful role of AI in the futures of students.

Methods

The research was conducted using the quantitative approach based on the computational experimental technique which aimed at determining the predictivity of the ANN algorithm used to classifying the academic interests of the high-school students into two major strands; SAINTEK (Science and Technology) and SOSHUM (Social Sciences and Humanities). All data was collected and analyzed at the SMA Negeri 1 Karanganom, Klaten and all the modeling and validation processes were carried out at Universitas Sebelas Maret Surakarta between 2024 and 2025. The current study used a cloud-based Python platform of Google Colab to realize the ANN implementation. This infrastructure supports the interactive execution of scripts, as well as easy extensibility with third-party libraries and frameworks, like TensorFlow and Scikit-learn, and so is helpful both in efficiency and in scaling up the progress in the development of the models.

The study group used was comprised of eleventh-grade academic children who attend school SMA Negeri 1 Karanganom. Using a simple random-sampling process, the study authors identified 205 respondents in order that each participant would have a uniform or equal chance to be included in the study hence improving the representativeness and external validity of the

sample. The data were collected by use of questionnaire with 44 items which sought to establish the range of the factors affecting students in their choice of their academic major. These forces were intrinsic factors like personal interests, personal talents as well as extrinsic factors which include parental acceptance, future career opportunities, economic status, peer pressure, residential area as well as access to information through the use of social media. The psychological aspects of persuasion, namely confidence level and self-awareness, were also measured in the survey to develop a detailed image of the decision-making system (Rufaidah, 2015). The multidimensional framework guaranteed that the instrument yielded a whole picture of forces that influenced the academic decision of students.

In order to maintain the accuracy and reliability of the data, there were intensive validity and reliability processes established. The validity of the content and construct were determined with the help of the experts in the fields of education and psychology who estimated how well each item corresponded to the properties that were being studied (Ida & Musyarofah, 2021). The quantitative measure of reliability was Cronbach Alpha coefficient of internal consistency. The outcome degree of item consistency revealed a high level of consistency in the instrument as evidence of dependability (Amanda et al., 2019). The feasibility of the questionnaire was also tested by a panel of domain experts, as they reviewed each item in terms of its relevance, clarity and contextual appropriateness, and their findings confirmed that the instrument was appropriate to high-school participants prior to its deployment. After the finalization of the instrument, a preprocessing step followed: the data were cleaned, the categorical variables were encoded, the variables were normalized according to the needs of the models. The findings of such preprocessing were pooled into one dataset, which was further divided randomly into training and testing ones.

The ANN model took the form of multilayer perceptrons and its weight was adjusted through back propagation algorithm to reduce the error of prediction. In order to reduce overfitting and promote the generalization to the external validation set, the current study included the Stratified K-Fold Cross Validation approach when the chosen dataset was divided into a series of folds representing the original distribution of classes. A priori four folds were chosen since the ratio between the two classes was relatively balanced. Four confusion matrix based measures of model performance were accuracy, precision, recall, and F1-score. Accuracy represented the share of correct predictions to all predictions, precision represented the ratio of true positives to all the predicted positive results, recall represented the ratio of true positives and all positives and the F1-score was the non-homocidal average of precision and recall, thus giving a balanced measure, to the extent of the majority when class imbalance had existed.

The research design was sequentially systematic in its nature and included four different phases, which included planning, collection of data, analysis, and reporting. In the first part of the planning process, the instrument was designed, the sampling method was obtained, and ANN modeling environment was created. The subsequent data-collection stage consisted of the distribution of survey tool and additional semi-structured interviews with a portion of the students in order to cross-validate the model predictions with the preferences that the participants claim to have regarding academics. The interviews were done in a neutral, confidential location, free of any teacher and school-personnel to compensate with the social-desirability bias and produce truthful answers. After data collection, the investigators undertook the analysis phase during which the ANN model was trained and validated and the findings analysed and compared with those of the students.

The last stage focused on reporting the results analytically and scholastically. Ethics was upheld and the study was voluntary and anonymous, informed consent was obtained in both

data-collection activities and all the practices were done according to the existing ethical guidelines. The rigorous methodological process that was illuminated in this research was aimed at creating a detailed, objective and evidence-based recommendation tool that can assist student counseling services in matching academic program to individual aptitudes and interests.

Results and Discussion

This study involved 205 eleventh-grade students at SMA Negeri 1 Karanganom who completed an online questionnaire comprising 44 items related to interests, social support, job prospects, and other factors. The data were then analyzed using an Artificial Neural Network (ANN) algorithm to predict students' interests in the SAINTEK or SOSHUM subject clusters. The validity and reliability of the instrument had been tested previously, with results supporting the suitability of the measurement tool used. The ANN model was implemented and tested using the Stratified K-Fold Cross Validation technique with $k = 4$, as the data proportions between classes were fairly balanced (Srinivasan et al., 2019; Ünalán et al., 2024). The prediction results showed high accuracy, supported by evaluation metric values: accuracy 0.90, precision 0.88, recall 1.00, and F1-score 0.93. These values indicate that the ANN model has excellent classification capabilities in recognizing patterns from student data (Muhaimin et al., 2024).

Table 1. Evaluation of ANN Model

Matrix	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	Fold 10
Accuracy	0.76	0.9	0.81	0.9	0.76	0.8	0.85	0.75	0.85	0.9
Precision	0.8	0.93	0.86	0.88	0.91	0.92	0.87	0.76	0.87	0.87
Recall	0.86	0.93	0.86	1	0.71	0.79	0.93	0.93	0.93	1
F1 Score	0.83	0.93	0.86	0.93	0.8	0.85	0.9	0.84	0.9	0.93

To strengthen the prediction results of interest classification directed by the ANN model, researchers conducted semi-structured interviews with 42 students included in the test data. These interviews aimed to determine whether the classification outcomes generated by the system aligned with the students' actual interests and intended academic directions. The interviews were conducted directly in the school environment; however, they were carried out without the presence of teachers or school staff to minimize external influence and ensure the authenticity of students' responses.

The results showed that all students confirmed that the classification produced by the ANN was consistent with their actual interests and major choices. No discrepancies were found between the classification results and the students' academic aspirations, reinforcing the belief that the ANN approach is not only statistically valid but also contextually and psychologically valid. Nevertheless, it is important to acknowledge the potential for confirmation bias, as students were aware of the ANN's predictions before giving their responses. Additionally, the complete absence of disagreement among respondents could suggest the influence of social desirability bias, where students may feel inclined to agree with the system's results to meet perceived expectations. To enhance the trustworthiness of such qualitative validations in future studies, a blinded interview protocol where students provide reflections without prior exposure to prediction results should be considered. This would help to mitigate potential biases and more accurately capture authentic perspectives. Data distribution analysis using Principal Component Analysis (PCA) further supports the visual interpretation of the separation between the SAINTEK and SOSHUM classes, showing a fairly clear separation between the groups (Thai et al., 2021).

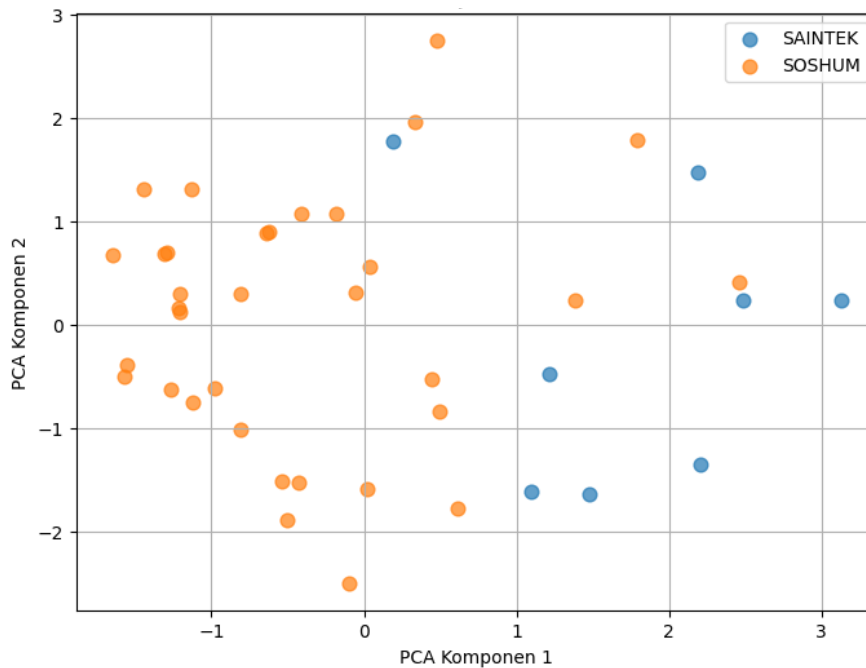


Figure 1. Data Distribution Test

The model's performance was also compared with previous studies. Pratama et al. (2024) reported an accuracy of 72.32% in predicting student graduation using ANN, while Rudianto et al. (2022) achieved 98.27% by combining ANN and Particle Swarm Optimization. These findings reinforce that ANN has high flexibility for various prediction contexts in education and other fields, such as customer loyalty (Singh, 2021) and airport capacity (Choi & Kim, 2021). The model's performance was also compared with several previous studies. Pratama et al. (2024) reported an accuracy of 72.32% in predicting student graduation using ANN, while Rudianto et al. (2022) achieved a 98.27% accuracy by integrating ANN with Particle Swarm Optimization. These results demonstrate the algorithm's adaptability and potential across different prediction contexts. ANN has also been employed successfully in domains beyond education, such as in predicting customer loyalty (Singh, 2021) and airport capacity (Choi & Kim, 2021).

However, while such comparisons provide insight into the algorithm's flexibility, it is important to emphasize that success in other domains does not guarantee comparable performance in educational settings. The underlying data structures, feature semantics, and behavioral dynamics vary significantly. For example, customer behavior modeling often involves transactional or behavioral logs, while educational decisions are shaped by psychosocial, emotional, and contextual factors. Therefore, domain-specific customization and validation are essential.

In this study, the ANN model achieved a high level of accuracy, precision, recall, and F1-score during Stratified K-Fold Cross Validation. Furthermore, the final test set evaluation—using previously unseen data—showed perfect classification performance, where all 8 SAINTEK and 34 SOSHUM students were correctly predicted. This produced 8 true positives (TP) and 34 true negatives (TN), with no false positives (FP) or false negatives (FN), indicating excellent generalization capability.

Despite this impressive result, such perfection on a small test set must be interpreted with caution. It may indicate potential overfitting, especially if not followed by extensive external validation across different cohorts or schools. Consequently, this study does not claim that

ANN is universally applicable but rather highlights its potential when applied carefully and contextually within student interest classification. While the ANN model has demonstrated accuracy, pedagogical relevance, and adaptability within the scope of this research, its deployment in broader educational decision-making systems should be accompanied by rigorous domain adaptation, ethical considerations, and sensitivity to context-specific constraints.

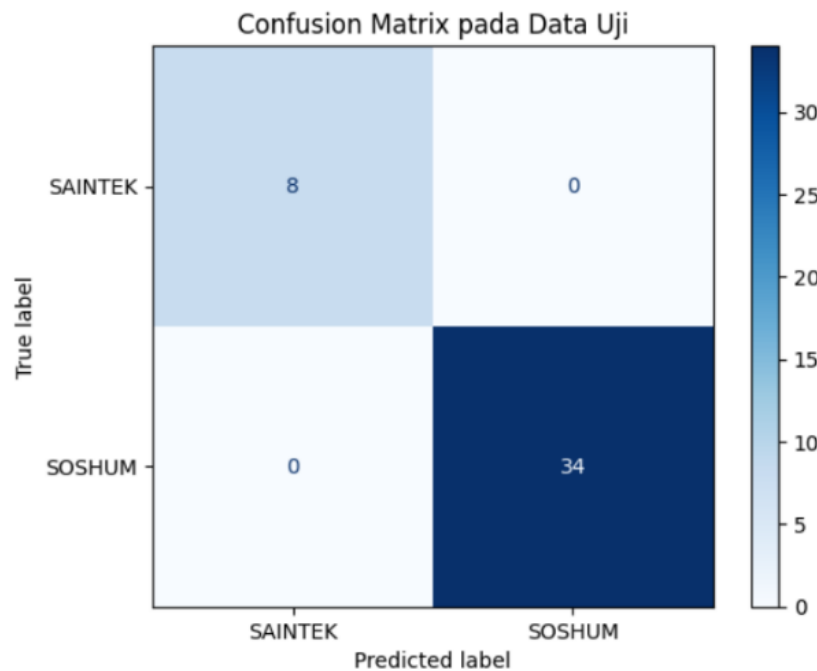


Figure 2. Confusion Matrix

Educational Implications of AI-Based Major Recommendation Systems

Even though the main aim of the study was the implementation of Artificial Neural Networks (ANNs) to predict academic-stream preferences of students, the most prominent contribution of the research can be relegated to the wider areas of educational change and creation of individual student support systems. This is further supported by a developing and increasing line of evidence within which the study finds that, when carefully applied, data-driven models are capable of revolutionising how institutions understand and respond to their students in their development. The current work argues that automated neural-network (ANN) programs are an intervention, (not simply computational operational tools), which can reorganise how students construct their identities and make important career choices in the face of both the cognitive expansion and the identity consolidation that occurs during the adolescent stage (Crocetti, 2017; Gati & Asher, 2001). Such empirical evidence raises a vital concern amongst educators, policymakers, and guidance professionals that need to reconsider the current state of prevailing practices with the emergence of new technology that has the potential to open academic counseling to anyone who values it.

The issues about the decision of academic majoring in education are quite documented but still remain largely unserved. Many studies demonstrate that students are regularly merely left to make their life-defining academic decisions based on intuition, peer pressure, and/or parental compulsion but not what they establish to be an evidence-based process in particular at the secondary level of schooling (Fouad, 2007; Lent et al., 1994). The following misalignments between their interests and academic disciplines result in high dropout rates,

personal distress, and low academic motivation, which overrepresent students of underserved communities (Whitcomb & Singh, 2021; Howard & Navarro, 2016). Facing up to ongoing gaps in the area of school-counseling, this work provides a strong argumentation about the widespread expansion using ANN-based decision-support tools. Those systems are not meant to eliminate human counselors instead, it empowers them with predictive intelligence, which will identify dormant trends in student data, and allow more and earlier interventions, which can then dramatically transform the courses being followed by students.

The above findings that reveal 90 percent of accuracy in predicting or categorizing stream preferences among students are more than an instrument accomplishment. They are an indicator of a paradigm shift toward a form of individual educational needs, which are compatible with previously conceived pedagogical viewpoints demanding adaptive environments leaning on instructions and demands of individual students (Means et al., 2010; Peng et al., 2019; Su et al., 2004). Current environments which imply intense counselor caseloads that could go well beyond several hundred students (McCarthy et al., 2010) strongly support the idea of scalable systems based on AI. Static aptitude tests only give a one-dimensional sketch as compared to multifaceted architecture, which interprets a wide range of variables spanning socio-emotional, environmental, and cognitive measures to come up with a counseling profile that shows similarities to the informed opinion of skilled professionals (Gamboa et al., 2023). In a natural extension of such support systems, disproportionate distribution of scarce counseling resources, particularly in an education climate where psychological and career counseling is limited in availability, is encouraged.

The technological breakthrough also aligns with the basic theories of career development, especially such ones as the theory of vocational personalities by Holland (1997) and the person-environment fit model. Both of them assume that career satisfaction and success are based on the ways interests of a person correlates with the features of the selected environment. ANN actually simulates that alignment process with the help of combining indicators in the ANN used in this study (such as personal interest, parental influence, and psychological self-evaluation) to perform computational modeling. Other empirical studies by Raju & Schumacker (2015) and Nguyen et al. (2020) show that machine learning classifications and predictions based on educational data are better than traditional psychometric measures. Therefore, the current research would remodel ANN-based models not simply as a secondary method of administrative triage, but rather as an operational continuation of currently existing frameworks of educational psychology.

Moreover, the evidence-based approach to school counseling and the concept of ANN actually creates its philosophical validity. Evidence-based practice in this field also implies the combination of generally proven intervention with measuring of the variables considering the client. Such integration enables counselors to tailor the interventions to his or her clients hence improving the efficacy of the counseling. Working out empirically based psychosocial classification schemes and capitalizing on operationalization of multifactorial assessment, the ANN framework represents the employment of current technology resources to enhance evidence-based conception of counseling practice. To be empirically justified and to have a systematic evaluation of its impacts, Whiston (2002) believes that interventions in the field of educational guidance need to be empirically justified and systematically tested in terms of an impact. The current research is a direct answer to this mandate since it is combined with the validation of the prediction by the post-prediction interviews with the students. The quantitative prediction and the qualitative corroboration of the model is given by the fact that all of the interviewed students confirmed that the classification was accurate, which would

leave a distinct triangulation of the research findings and constitute the statistical backbone of the research as well as the contextual validity.

In their work, White et al. (2015) as well as Ghaye et al. (2008) also confirm the view that intelligent systems are most efficient when designed to support iterative feedback and implemented in reflective practice circles.

One more very important observation, which can be made based on this study, is the area of student perception and systems trust as a theme rather ignored in the literature on AI implementation. The fact that the model is corroborated by student themselves not only points out to the predictive strength of the model, but it also suggests to the psychological and pedagogical appeal of the same. The more the learners see a system being fair, insightful, and sensitive about what the learners are going through, the more they will tend to have some relevance relating to what they come in contact with in respect to what the system produces (Dolata et al., 2022). This is especially when it is used in educational application the use of technology can hinge more on the nature of relationships than it can on technical effectiveness. Ensuring that students do not play the role of harmless receivers of AI suggestions, but instead active discoverers, educators can create a dialogic link between a student and a system, which is inherent to constructivist methodology in context of career education (Wu et al., 2025; Savickas, 2013).

The use of AI in educational decision-making, however, does not arise free of moral conflict. Academics have brought forward pressing concerns concerning facets of algorithmic transparency and fairness and how predictive models might be programmed with systemic prejudice (Williamson & Piattoeva, 2020; Eynon, 2015). The results of the current investigation, as potentially useful as they may be have to be put into the larger contexts of educational integrity and element of critical oversight. They should promote the exchange of ideas as opposed to closing down the conversation by students, parents, and educators more broadly, interpreting the recommendations shared and not blindly taking suggestions. According to Mac Fadden et al. (2024) and Dinker (2024), the lack of human interpretive layer entails that, without one, AI-driven tools may oversimplify the actualities in the educational context and unintentionally reinforce the inequalities already present in society. This is why ANN application in guidance terms requires in-depth teacher training, strict data control options, and child-friendly design procedures that ensure that the use of AI in the education sector is devoid of ethical compromises.

Moreover, ANN systems, such as the one offered at hand, should be considered as dynamic learning environment and not a fixed intervention per se. They would aim not only at predicting choice but also pursuing critical consciousness and life planning, which career counseling theorists have long wanted to promote (Diemer & Blustein, 2006; Cadenas & McWhirter, 2022). Working as a mirror, ANN predictions may serve as a catalyst to discussions of identity, purpose, and aspiration. These systems with the help of caring educators can help the student to make narrative coherence in their form of education a process which has always been associated with a higher level of motivation and perseverance among the students (Oxford & Bolaños-Sánchez, 2016; Oyserman & Destin, 2010).

The study exemplifies an interesting balance between technical and education in every aspect in comparative context. Other studies based on logistic regression (Alhassan, 2020) or hybrid machine learning (Lam et al., 2024) show satisfactory classification accuracy, although often do not involve multiple levels of validation with student opinions, or delve into educational theory as in the current study does. Comparatively, the study at hand goes beyond the evaluative capacity of being descriptive or predictive; rather, it manifests as an active

construct, which places the lived expertise of learners at the center of the academic process and puts their agency to the fore. Southeast Asian literature (Chen et al., 1999) has been over and over again about the necessity to match educational technology with cultural sensitivity and contextual certification, which is in place in this experiment, as the ANN system was administered to a true school set up and responses of real students were sought as part of system evaluation.

Moreover, the international feasibility of the systems of this kind is difficult to underestimate. The Redecker et al. (2010) argues that education in the future has to provide an instrument that can be used to make learners ready to participate in the fast-changing labour markets and, at the same time, considering the personal progression of the learner. AI models are a potentially huge addition to career-readiness programs, which can fundamentally change what we understand about students and how we help them become successful professionals when used responsibly. As a result, the current study goes beyond the assessment of the ANN effectiveness and becomes an appeal to the pedagogical revolution that prompts the educator to evolve out of the category of traditional limitations towards intelligent, ethical, and student-centered inventions.

Conclusion

In conclusion, it is seen that Artificial Neural Networks (ANN) can respond well to the prediction of the student preference of academic streams- SAINTEK versus SOSHUM- using the multidimensional variables of the individual (i. e. student) to familial and social and psychological attributes. Strong Stratified K-Fold Cross Validation training and validation of the ANN model led to high values of accuracy, precision, recall, and F1-score, which was confirmed by qualitative findings of the interviews conducted with students. Such results support the validity and competence of the predictive nature of the model and its aptness to apply to the specific context and be used as a classification machine in educational settings.

Still, the intellectual value of the work goes well beyond the performance in how algorithms work. The research makes a blueprint of what kind of pedagogical change should be embraced: it motivates teachers to be intelligent, ethical, student-centered innovators as well as to demonstrate that these models will work in real teaching and learning contexts. This discussion looks at the artificial neural networks (ANNs) in a way that it is not merely a technological innovation but also a pedagogical intervention aimed at reducing some of the inherent deficiencies in academic guidance especially in schools where counselors are not readily available. The ANN model provides educational stakeholders such as counselors, students, and school leaders the means of approaching their academic and career pathway decisions more reflectively, personally, and evidence-based by providing a scalable and data-informed support system. The fact that it complements the current psychological models like the person-environment fit and the career construction theory makes the system a legitimate addition to existing practices of human-led counseling and not a trademark. Its model reflects a balance between acknowledging the multifold educational decisions and open a dialogic process where the AI-based recommendations raise questions but do not direct it. As a result, the approach to its use should be positioned within ethical, transparent, and culturally responsive practices in order to make sure that it does not undermine but complements the student agency and development of identity.

Taking this finding at hand, it might be suggested that the research is likely to follow further integration of ANN-based recommendation systems into a more extended infrastructure of school guidance, preferably as part of a web- or mobile-based platform, which students, educators, and parents can access. Transferring this system to different schools and across

nominal representativeness in terms of demographics will be vital in experimenting on the generalizability and fairness of prediction results. Besides, the inclusion of other aspects--academic record, extra-curricular activities, and character tests, perhaps, can also increase depth of prediction and precision with long term goals of a student.

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