A Combination of Forward Chaining and Certainty Factor Methods in a Child Mental Health Expert System with Accuracy Comparison Using the Strengths and Difficulties Questionnaire

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Abstract : The increasing complexity of child mental health issues requires accurate detection and intelligent decision-support systems for early identification and intervention. This study analyses emotional and behavioural difficulties among 500 children aged 11–17 years using the Strengths and Difficulties Questionnaire (SDQ) dataset and develops an expert system integrating Forward Chaining and Certainty Factor methods. Results indicate that most respondents had relatively low difficulty levels across SDQ dimensions, although substantial proportions showed high Emotional Symptoms and Conduct Problems scores, suggesting potential psychological concerns. The proposed expert system achieved 90% accuracy, demonstrating good performance in distinguishing Normal and Abnormal categories, although classification of the Borderline category remained challenging. Higher scores in Emotional Symptoms, Conduct Problems, Hyperactivity, and Peer Problems, alongside lower Prosocial Behaviour scores, were associated with greater likelihood of Borderline or Abnormal classification. These findings demonstrate that integrating Forward Chaining and Certainty Factor can effectively support early screening and decision-making in child mental health assessment.

Keywords : Expert System, Child Mental Health, Strengths and Difficulties Questionnaire (SDQ), Forward Chaining, Certainty Factor, Classification.

***Abstrak** : Meningkatnya kompleksitas masalah kesehatan mental anak memerlukan deteksi yang akurat dan sistem pendukung keputusan cerdas untuk identifikasi serta intervensi sejak dini. Penelitian ini menganalisis kesulitan emosional dan perilaku pada 500 anak berusia 11–17 tahun menggunakan dataset Strengths and Difficulties Questionnaire (SDQ) serta mengembangkan sistem pakar yang mengintegrasikan metode Forward Chaining dan Certainty Factor. Hasil penelitian menunjukkan bahwa sebagian besar responden memiliki tingkat kesulitan yang relatif rendah pada berbagai dimensi SDQ, meskipun sebagian cukup besar menunjukkan skor tinggi pada Gejala Emosional dan Masalah Perilaku, yang mengindikasikan potensi permasalahan psikologis. Sistem pakar yang dikembangkan mencapai akurasi 90%, menunjukkan kinerja yang baik dalam membedakan kategori Normal dan Abnormal, meskipun klasifikasi kategori Borderline masih menghadapi kendala. Skor yang lebih tinggi pada Gejala Emosional, Masalah Perilaku, Hiperaktivitas, dan Masalah Teman Sebaya, disertai skor Perilaku Prosocial yang lebih rendah,* *berkaitan dengan kemungkinan lebih besar terhadap klasifikasi Borderline atau Abnormal. Temuan ini menunjukkan bahwa integrasi Forward Chaining dan Certainty Factor dapat secara efektif mendukung skrining dini dan pengambilan keputusan dalam asesmen kesehatan mental anak.*

Kata Kunci: *Sistem Pakar, Kesehatan Mental Anak, Strengths and Difficulties Questionnaire (SDQ), Forward Chaining, Certainty Factor, Klasifikasi*

INTRODUCTION

Child mental health represents a fundamental component of children's overall well-being, as it plays an important role in shaping their physical growth, emotional stability, and social development. Mental health difficulties experienced during childhood may lead to various negative consequences in the future, such as decreased academic achievement, behavioral challenges, difficulties in maintaining social relationships, and a higher probability of developing long-term psychological disorders during adulthood. Therefore, early identification and appropriate intervention are essential strategies to minimize the potential impact of mental health problems among children (Ribeiro et al., 2023; Viswanathan et al., 2022).

Accurate detection of child mental health conditions requires reliable and systematic assessment approaches. One of the most commonly utilized screening instruments in psychological and clinical settings is the Strengths and Difficulties Questionnaire (SDQ). The SDQ is a standardized screening tool developed to assess behavioral and emotional conditions among children and adolescents. This instrument evaluates five major aspects, including emotional symptoms, peer relationship difficulties, hyperactivity/inattention, conduct problems, and prosocial behavior. The results obtained from SDQ scoring provide an initial overview of a child's psychological condition and indicate the possibility of experiencing mental health-related difficulties (Aadland et al., 2022; Danielson et al., 2023; Toseeb et al., 2022).

Despite its widespread application and effectiveness as a child mental health assessment instrument, the interpretation of SDQ results requires appropriate expertise, clinical understanding, and consideration of individual characteristics. In this regard, expert systems offer significant potential as supportive tools for improving the process of early mental health detection. An expert system is a computer-based application designed to replicate the reasoning processes and decision-making abilities of human experts in a specific field. Through embedded knowledge and predefined rules, such systems can assist in analyzing SDQ results, generating assessments, and providing recommendations based on expert knowledge. Recent research indicates that artificial intelligence and intelligent computational approaches have increasingly been explored for mental health assessment, diagnosis, monitoring, and decision support among children and adolescents (Andrew et al., 2023; Choo et al., 2024).

The integration of Forward Chaining and Certainty Factor (CF) methods in expert system development has become an emerging approach for improving the accuracy of child mental health detection. Forward Chaining is a rule-based inference technique that begins by processing available facts and gradually derives new conclusions through a sequence of logical reasoning steps. In this study, the Forward Chaining method is applied to analyze SDQ assessment results by matching collected information with predefined clinical rules to identify potential mental health conditions. Meanwhile, the Certainty Factor method is utilized to measure the level of confidence associated with the system's conclusions. This approach enables the system to represent uncertainty by quantifying expert confidence in the assessment outcomes generated from SDQ data.

Several previous studies have investigated the implementation of expert systems and artificial intelligence-based approaches for identifying child and adolescent mental health problems; however, opportunities remain to improve system accuracy, reliability, and effectiveness. Recent reviews indicate that AI applications in adolescent mental health are increasingly directed toward diagnosis, monitoring, and prediction, although issues related to model validity, transparency, and clinical implementation remain important considerations (Andrew et al., 2023; Sharma et al., 2025). Therefore, this study aims to develop an expert system entitled "A Combination of Forward Chaining and Certainty Factor Methods in a Child Mental Health Expert System with Accuracy Comparison Using the Strengths and Difficulties Questionnaire (SDQ)". The proposed system is expected to support early detection, provide appropriate recommendations, and assist evidence-based decision-making in child mental health assessment.

With continuous advancements in information technology, intelligent expert systems have considerable potential to become valuable supporting tools in psychological assessment and clinical practice. Digital and AI-based approaches have demonstrated increasing potential for supporting early identification and assessment of mental health difficulties among children and adolescents (Choo et al., 2024; Nishimura et al., 2024). This research integrates SDQ-based evaluation with psychological knowledge derived from established approaches to child mental health assessment. The developed system is expected to contribute to improving children's mental health management by enabling earlier identification of psychological difficulties and supporting the implementation of more effective intervention strategies.

RESEARCH METHOD

This study employed a quantitative approach with an experimental research design aimed at developing, implementing, and evaluating an expert system to assist in identifying children's mental health conditions based on the Strengths and Difficulties Questionnaire (SDQ). The quantitative approach was selected because the data obtained consisted of numerical scores representing emotional and behavioural symptoms that could be processed statistically to generate classifications of mental health conditions, while the experimental design was used to develop and test the system through data processing, classification model construction, inference mechanism implementation, and performance evaluation. The SDQ was employed as the primary instrument because it is a widely used screening instrument for identifying emotional and behavioural difficulties among children and adolescents and has demonstrated validity and discriminative capacity across different population contexts (Aadland et al., 2022; Danielson et al., 2023; Toseeb et al., 2022). The study population comprised children aged 4–17 years, while the research data were obtained from randomly selected Year 5 and Year 6 pupils at Immanuel Elementary School. The SDQ consists of 25 items covering five dimensions, namely emotional symptoms, conduct problems, hyperactivity/inattention, peer relationship problems, and prosocial behaviour, with each item rated on a three-point scale: 0 (*Not True*), 1 (*Somewhat True*), and 2 (*Certainly True*). The completed SDQ responses were stored in a file named *dataset.xlsx* and used as the primary dataset for system development and testing. The use of SDQ scores as the basis for classification is also supported by research demonstrating its utility as an initial screening instrument for mental health problems among children and adolescents, including in the Indonesian context (Aadland et al., 2022; *Screening for Emotional Problems*, 2022).

The collected data subsequently underwent preprocessing, including calculation of scores for each SDQ dimension, missing-data handling, normalisation, and feature engineering. Scores for each dimension were calculated by summing the item scores within the corresponding subscale, while missing values were handled using mean imputation based on the available item scores within the same subscale. Normalisation was then performed using Min–Max Scaling to transform the values to a range of 0–1, allowing each variable to be processed proportionally within the classification mechanism. Feature engineering was conducted by generating the Total Difficulties Score (TK) as an overall representation of the level of difficulties based on the relevant SDQ problem dimensions. The preprocessed dataset was subsequently used to construct a Decision Tree classification model using the Classification and Regression Trees (CART) algorithm, which was integrated with a Forward Chaining mechanism for rule-based inference and the Certainty Factor (CF) method to represent the degree of confidence associated with the classification results. The dataset was divided into training and testing sets at a ratio of 80:20, while class imbalance in the training data was addressed using the Synthetic Minority Over-sampling Technique (SMOTE). The developed model generated three categories of mental health conditions, namely *Normal*, *Borderline*, and *Abnormal*. The system-generated classifications were subsequently compared with the SDQ interpretation results as the reference standard to evaluate the accuracy and consistency of the system. The system was implemented using the Python programming language, supported by JupyterLab, PyCharm or an equivalent development environment, and relevant Python libraries for data preprocessing, modelling, and system implementation. The development of a computational expert system is consistent with the growing application of artificial intelligence in child and adolescent mental health, particularly as a supporting technology for screening, classification, and early decision-making; however, such systems should be regarded as decision-support tools rather than substitutes for professional diagnosis (Andrew et al., 2023; van Schalkwyk, 2023).

RESULTS AND DISCUSSION

Data Preparation

The initial stage in developing the expert system involved preparing and organizing the collected research data. This stage consisted of several procedures to ensure that the dataset was suitable for further analysis and model development.

Data Loading

The research dataset stored in the dataset.xlsx file was imported into the Python programming environment using the pandas library. The dataset contained SDQ questionnaire responses representing various dimensions of children's emotional and behavioral conditions. The data structure and examples of recorded observations within the dataset are presented in Figure 4.1.

```
df = pd.read_excel('dataset.xlsx', index_col=0)
df.drop(['Tanggal Lahir','Jenis Kelamin','Tanggal Hari ini'], axis=1,
inplace=True)
df
```


ID	PR1	H1	E1	PR2	C1	P1	C2	E2	PR3	H2	P2	C3	E3	P3	H3	E4	PR4	C4	P4	PR5
1	2	1	1	2	1	2	2	0	2	1	2	0	0	1	1	2	1	0	2	2
2	2	2	1	2	1	0	0	2	1	2	2	1	1	1	2	2	1	1	2	1
3	2	2	1	1	2	1	0	0	1	0	2	1	1	0	2	1	2	1	0	1
4	1	0	1	2	2	0	0	2	2	1	2	0	0	2	0	0	1	2	2	2
5	1	1	0	1	0	0	2	1	2	0	2	0	1	1	1	1	2	0	0	1
6	2	1	0	2	0	0	1	1	2	0	2	0	1	1	2	1	2	0	0	1
7	2	1	1	1	0	0	0	2	2	0	2	0	0	1	0	2	2	0	0	2
8	2	2	1	2	1	0	1	2	1	0	2	1	0	1	2	2	1	1	0	1
9	2	2	0	1	0	1	1	0	2	0	2	1	0	1	0	0	2	0	1	1
10	1	2	2	1	0	0	1	0	0	0	2	0	1	1	2	1	2	0	2	0
11	1	1	1	1	1	0	1	1	1	0	2	1	1	0	1	2	1	1	1	1
12	2	0	1	1	2	2	2	1	1	0	2	1	1	0	0	1	1	0	0	1
13	2	1	1	2	1	0	1	1	1	1	2	0	1	0	0	0	1	1	0	1
14	2	1	2	1	2	0	2	1	1	1	2	0	1	1	1	1	2	1	1	1
15	1	2	2	1	1	0	1	1	1	2	2	1	2	0	1	2	2	1	1	1
16	2	1	1	2	0	0	1	1	2	0	2	0	0	1	1	1	2	0	0	2
17	2	1	2	1	2	2	1	2	2	0	2	1	1	0	1	2	2	2	0	2
18	1	2	1	1	0	1	2	1	1	2	1	0	0	0	1	1	1	1	2	1
19	2	1	0	2	1	0	1	2	2	2	2	0	2	1	1	2	2	0	0	1
20	1	2	0	2	0	0	1	0	1	0	2	0	0	1	0	1	2	1	0	2
21	2	2	1	2	2	0	1	1	1	1	1	1	1	1	1	2	2	2	2	2
22	2	2	2	1	0	0	2	2	1	2	2	0	0	1	2	1	1	0	0	1
23	2	1	1	2	0	0	0	2	2	0	2	0	0	1	0	1	2	0	0	2
24	1	1	2	1	2	1	2	2	2	2	2	1	2	2	1	2	1	1	2	0
25	2	2	1	1	2	1	1	1	1	1	2	1	2	1	1	1	2	1	1	1

Figure 1. Data Preparation

Data Cleaning

The data preprocessing stage included a data cleaning procedure to improve dataset quality and ensure that only relevant variables were used in the analysis. During this process, several attributes, such as Date of Birth, Gender, and Current Date, were removed because these variables were not directly related to the evaluation of children's emotional and behavioral conditions based on the Strengths and Difficulties Questionnaire (SDQ). After the cleaning process, the dataset consisted only of relevant SDQ-related features that were subsequently utilized for model development, training, and expert system implementation.

Decision Tree Modeling

This section describes the development of the expert system classification model designed to determine children's mental health status into three categories: Normal, Borderline, and Abnormal. The classification process was based on symptom indicators obtained from the Strengths and

Difficulties Questionnaire (SDQ). The development stages of the Decision Tree-based predictive model are explained as follows:

Training and Testing Data Splitting

The dataset was divided into training and testing subsets to evaluate the model's capability to perform classification on previously unseen data. The dataset was separated using an 80:20 ratio, where 80% of the data was allocated for model training and 20% was reserved for testing and evaluating the model's predictive performance.

Handling Class Imbalance

To address possible imbalance among diagnostic categories, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training dataset. Class imbalance occurs when one category contains substantially more samples than other categories, for example, when the Normal class dominates compared with Borderline and Abnormal classes. Such imbalance may cause the classification model to become biased toward the majority class and reduce its ability to accurately identify minority categories. SMOTE was implemented by generating synthetic samples for minority classes, thereby creating a more balanced data distribution and improving the model's ability to learn representative patterns from all diagnostic categories.

Development of Decision Tree Model

The Decision Tree algorithm was applied to construct a classification model capable of identifying relationships between SDQ symptom indicators and children's mental health categories. The generated decision tree consists of internal nodes representing relevant SDQ features or questionnaire items (for example, emotional or behavioral indicators), branches describing possible response conditions, and leaf nodes representing the final classification outcomes: Normal, Borderline, or Abnormal. The Decision Tree approach was selected because of its ability to generate structured and interpretable decision rules. This characteristic makes the model suitable for expert system development, particularly in psychological assessment contexts where transparency and explainability are important considerations.

Rationale For Selecting The Decision Tree Algorithm

Interpretability

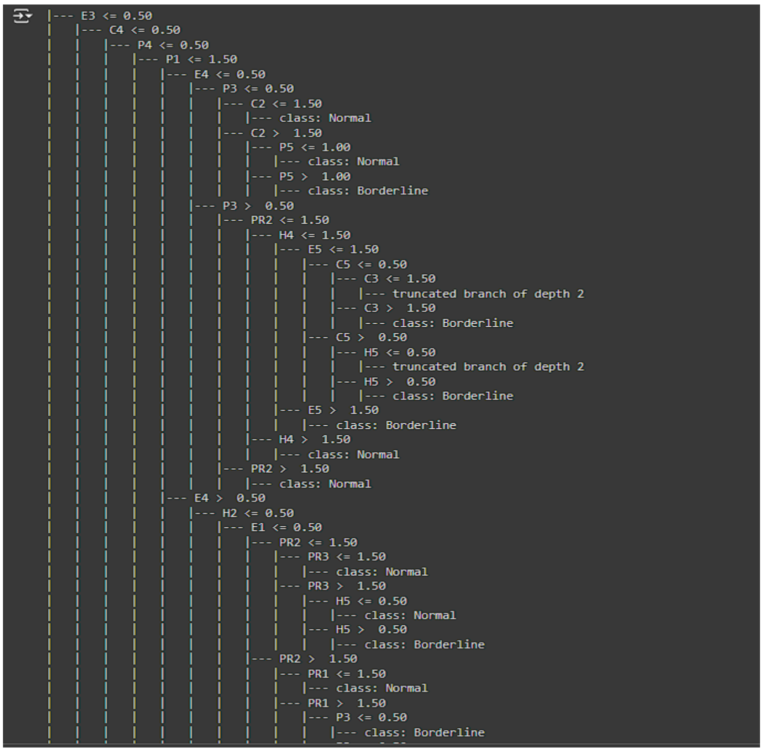
One of the main advantages of the Decision Tree algorithm is its ability to produce clear and understandable classification rules. The resulting decision structure can be easily interpreted by psychologists, educators, and parents, thereby increasing the transparency and usability of the developed expert system. In addition, because SDQ responses primarily consist of categorical variables, the Decision Tree algorithm is considered appropriate for analyzing and processing this type of assessment data.

Identification of Key Risk Indicators

The Decision Tree model can identify the SDQ variables that contribute most significantly to determining children's mental health classifications. This capability allows researchers and practitioners to recognize important symptom indicators associated with potential emotional and behavioral difficulties. Therefore, the model not only performs classification but also provides insights into the factors influencing diagnostic outcomes.

Integration with Forward Chaining and Certainty Factor Methods

The Decision Tree model was integrated with the Forward Chaining inference approach and the Certainty Factor (CF) method to improve the reliability and robustness of the expert system. Forward Chaining operates by processing user-provided SDQ responses and applying predefined decision rules to generate diagnostic conclusions. Meanwhile, the Certainty Factor method is used to quantify the confidence level of the resulting diagnosis by considering uncertainty derived from both user inputs and expert knowledge embedded within the system. This integration enables the developed expert system to provide not only classification results but also confidence-based assessments that better represent the uncertainty commonly encountered in mental health evaluation processes.



```
|--- E3 <= 0.50
|   |--- C4 <= 0.50
|   |   |--- P4 <= 0.50
|   |   |   |--- P1 <= 1.50
|   |   |   |   |--- E4 <= 0.50
|   |   |   |   |   |--- P3 <= 0.50
|   |   |   |   |   |   |--- C2 <= 1.50
|   |   |   |   |   |   |   |--- class: Normal
|   |   |   |   |   |   |--- C2 >  1.50
|   |   |   |   |   |   |   |--- P5 <= 1.00
|   |   |   |   |   |   |   |   |--- class: Normal
|   |   |   |   |   |   |   |--- P5 >  1.00
|   |   |   |   |   |   |   |   |--- class: Borderline
|   |   |   |   |   |--- P3 >  0.50
|   |   |   |   |   |   |--- PR2 <= 1.50
|   |   |   |   |   |   |   |--- H4 <= 1.50
|   |   |   |   |   |   |   |   |--- E5 <= 1.50
|   |   |   |   |   |   |   |   |   |--- C5 <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- C3 <= 1.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |   |   |   |--- C3 >  1.50
|   |   |   |   |   |   |   |   |   |   |   |--- class: Borderline
|   |   |   |   |   |   |   |   |   |--- C5 >  0.50
|   |   |   |   |   |   |   |   |   |   |--- H5 <= 0.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |   |   |   |--- H5 >  0.50
|   |   |   |   |   |   |   |   |   |   |   |--- class: Borderline
|   |   |   |   |   |   |   |   |--- E5 >  1.50
|   |   |   |   |   |   |   |   |   |--- class: Borderline
|   |   |   |   |   |   |   |--- H4 >  1.50
|   |   |   |   |   |   |   |   |--- class: Normal
|   |   |   |   |   |   |--- PR2 >  1.50
|   |   |   |   |   |   |   |--- class: Normal
|   |   |   |   |--- E4 >  0.50
|   |   |   |   |   |--- H2 <= 0.50
|   |   |   |   |   |   |--- E1 <= 0.50
|   |   |   |   |   |   |   |--- PR2 <= 1.50
|   |   |   |   |   |   |   |   |--- PR3 <= 1.50
|   |   |   |   |   |   |   |   |   |--- class: Normal
|   |   |   |   |   |   |   |   |--- PR3 >  1.50
|   |   |   |   |   |   |   |   |   |--- H5 <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- class: Normal
|   |   |   |   |   |   |   |   |   |--- H5 >  0.50
|   |   |   |   |   |   |   |   |   |   |--- class: Borderline
|   |   |   |   |   |   |   |--- PR2 >  1.50
|   |   |   |   |   |   |   |   |--- PR1 <= 1.50
|   |   |   |   |   |   |   |   |   |--- class: Normal
|   |   |   |   |   |   |   |   |--- PR1 >  1.50
|   |   |   |   |   |   |   |   |   |--- P3 <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- class: Borderline
```

Figure 2. Decision Tree

Discussion

The discussion section interprets the findings obtained from the developed expert system by examining how each SDQ symptom dimension contributes to the prediction of children's mental health classifications. The results demonstrate that the model successfully identified several psychological and behavioural indicators that distinguish among the three classification categories: Normal, Borderline, and Abnormal. The analysis focuses on the influence of the major SDQ domains, including Emotional Symptoms, Conduct Problems, Hyperactivity, Peer Problems, and Prosocial Behaviour, in determining children's mental health conditions. This finding is consistent with evidence indicating that the SDQ dimensions represent interconnected internalising, externalising, and prosocial domains rather than isolated aspects of child behaviour. The SDQ has also been demonstrated to be a valuable screening instrument for identifying emotional and behavioural difficulties among children with neuropsychiatric conditions, supporting its use as a multidimensional source of information for early identification (Grasso et al., 2022). In particular, emotional and behavioural difficulties may coexist with problems in peer relationships, while prosocial behaviour represents a distinct strength-related dimension that can provide complementary information about children's psychosocial functioning (Kern et al., 2022). Therefore, the classification patterns identified in this study support the view that child mental health should be interpreted through a combination of symptom domains rather than through a single behavioural indicator.

The classification patterns generated by the model indicate that children's psychological conditions are not determined by a single factor but rather by the interaction of multiple emotional, behavioural, and social dimensions. Emotional instability, behavioural difficulties, interpersonal challenges, and reduced prosocial tendencies collectively contribute to the identification of potential mental health concerns. This multidimensional pattern is important because child and adolescent mental health difficulties commonly involve overlapping symptom domains and cannot always be adequately represented by a single behavioural indicator. Dwyer and Koutsouleris (2022) emphasise that machine learning approaches may be particularly useful in child and adolescent psychiatry because they can identify predictive patterns across complex and heterogeneous datasets. Similarly, Rothenberg et al. (2023) demonstrated that machine learning can identify multiple risk factors that contribute to adolescent mental health outcomes across different cultural contexts. Consequently, incorporating multiple SDQ-based indicators into the expert system provides a more comprehensive framework for identifying early signs of emotional and behavioural difficulties. Previous research has similarly demonstrated that SDQ dimensions can capture distinct but related aspects of psychosocial difficulties among young people, supporting the use of multidimensional assessment rather than reliance on a single symptom category (Kern et al., 2022; Grasso et al., 2022).

Furthermore, the findings highlight the potential value of integrating artificial intelligence-based classification methods with established psychological assessment instruments such as the SDQ. The developed expert system assists in analysing complex symptom patterns and provides a systematic decision-support mechanism for preliminary mental health screening. By identifying the most influential predictive factors, the system can support parents, educators, and mental health practitioners in recognising potential risks and determining whether further professional assessment may be warranted. This interpretation is consistent with recent research on machine learning in child and adolescent psychiatry, which highlights the potential of computational models to support personalised assessment, prediction, and clinical decision-making while emphasising the importance of appropriate validation and clinical applicability (Dwyer & Koutsouleris, 2022). Paton and Tiffin (2022) similarly argue that machine learning has potential for personalised child and adolescent mental health care, although its clinical value depends on the appropriateness of the prediction task, the quality of available data, and the context in which the system is implemented. The use of AI in adolescent mental health has also expanded across diagnosis, monitoring, treatment, and prognosis, although concerns regarding methodological quality and risk of bias remain important considerations (Sharma et al., 2025).

The use of Decision Tree classification further strengthens the interpretability of the proposed expert system because the classification process can be represented through a sequence of understandable decision rules. This characteristic is particularly relevant in mental health applications, where users and professionals may require an explanation of how particular symptoms contribute to a classification rather than receiving only a predictive outcome. In contrast to highly complex models that may provide limited insight into their decision-making processes, tree-based approaches can provide a relatively transparent representation of how input characteristics contribute to classification. This is consistent with the broader development of explainable artificial intelligence (XAI), which emphasises the importance of making computational predictions understandable to users, particularly in sensitive healthcare settings (Jung et al., 2023). Allgaier et al. (2023) further demonstrated that explainability has become an increasingly important component of machine learning applications in healthcare because users need to understand how models arrive at their predictions. In mental health research specifically, Kerz et al. (2023) highlight the importance of explainable AI because prioritising predictive performance without adequate interpretability may reduce transparency and trust in automated mental health assessment.

The interpretability of the Decision Tree is also particularly important because the proposed system is intended as a decision-support mechanism rather than a replacement for professional judgement. Explainability can facilitate the examination of whether the classification logic is consistent with psychological knowledge and whether the identified predictors are clinically meaningful. Jung et al. (2023) note that effective explanations in healthcare should not merely expose model characteristics but should also support users' understanding, trust, and ability to evaluate the prediction. Similarly, Balla et al. (2023) identify explainability, transparency, ethical considerations, and clinical applicability as important issues in the development of artificial intelligence applications in paediatric healthcare. Thus, the use of an interpretable Decision Tree in the present expert system represents an important methodological advantage, particularly when the system is intended to be used by non-technical stakeholders such as educators or parents.

Overall, the results demonstrate that the proposed expert system has considerable potential as a supporting tool for the early identification of children's mental health conditions. The combination of Decision Tree classification, Forward Chaining reasoning, and Certainty Factor analysis provides a structured approach for transforming SDQ symptom information into interpretable classification results while also representing the level of confidence associated with those results. Such characteristics are particularly relevant to child mental health assessment because early recognition of psychological difficulties can facilitate timely referral and further professional evaluation. However, the system should be regarded as a preliminary decision-support instrument rather than an autonomous diagnostic tool. Recent evidence indicates that although AI and machine learning show substantial potential in mental health research, methodological limitations such as small samples, inadequate preprocessing, insufficient external validation, and limited transparency remain significant barriers to clinical implementation (Tornero-Costa et al., 2023). Similar concerns have been reported in child and adolescent mental health prediction research, where the quality of model development and validation varies considerably across studies (Dwyer & Koutsouleris, 2022). Therefore, future research should evaluate the proposed expert system using larger and more diverse datasets, external validation samples, longitudinal data, and comparisons with other classification algorithms. Such steps are necessary to establish the reliability, generalisability, and practical utility of the system before it can be considered for broader implementation in educational or clinical settings.

CONCLUSIONS

This study successfully developed and evaluated an expert system for the early identification of children's mental health conditions using the Strengths and Difficulties Questionnaire (SDQ) as the primary assessment instrument. Based on an SDQ dataset of 500 participants aged 11–17 years, the findings show that the proposed system was able to classify children's mental health conditions into Normal, Borderline, and Abnormal categories with an overall accuracy of 90%. Emotional Symptoms, Conduct Problems, Hyperactivity, and Peer Problems were associated with a greater likelihood of Borderline or Abnormal classifications, whereas stronger Prosocial Behaviour was associated with lower mental health risk. The integration of Decision Tree classification, Forward Chaining, and Certainty Factor provided an interpretable and structured approach for analysing SDQ symptom patterns and supporting preliminary mental health screening. Nevertheless, the lower performance in identifying Borderline cases indicates that this category remains a challenge and requires further model optimisation.

Future research should improve the classification performance of the system, particularly for Borderline cases, by exploring advanced machine learning, ensemble, feature selection, and hybrid modelling approaches. Future studies should also involve larger and more diverse datasets covering different age groups, educational backgrounds, social environments, and geographical contexts to improve model generalisability and reduce potential classification bias. For practitioners, including educators, counsellors, and mental health professionals, the proposed system may be used as a preliminary decision-support tool to facilitate early screening and identify children who may require further professional assessment, while diagnosis and intervention decisions should remain under the authority of qualified mental health practitioners. At the policy level, the implementation of technology-based mental health screening should be accompanied by appropriate validation, ethical safeguards, data protection, professional oversight, and continuous system evaluation. Such measures are important to ensure that the use of expert systems in schools and child mental health services remains accurate, responsible, and supportive of timely intervention.

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