scientific reports

Check for updates

OPEN

Using fuzzy decision support to create a positive mental health environment for preschoolers

Xinyue Li

The preschool period is a crucial time for behavioural and social-emotional development and the cultivation of mental well-being. Preschoolers may be affected by various traumatic problems. During this process, preschoolers may develop hazardous behaviours such as defiance, aggression, speech delays, difficulty socializing, and emotional dysregulation. To assess their mental health before starting school, preschoolers need early detection, intervention, and assessment. However, data shortages, heterogeneity, privacy issues, model interpretability, and generalization restrictions hamper the review process. This study sought to improve toddlers' behaviour by creating an effective decision-making mechanism. This study uses a fuzzy decision support (FDS) system using fuzzy rules and a degree of membership function to overcome the obstacles. Fuzzified data from the Preschool Pediatric Symptom Checklist (PPSC) was utilized to study preschoolers' behavior. Follow guidelines to decrease uncertainty to get a fuzzy set value. Afterwards, de-fuzzification was done according to the membership level needed to make effective mental health decisions. The FDS process identifies the relationship between a child's behaviour and attention level with maximum accuracy (97.98%), specificity (96.79%), sensitivity (97.08%), and minimum error (0.28). Behavioural prediction helps improve preschoolers' mental health and activities effectively. The system's excellence was analyzed using different metrics, ensuring 96.79% specificity and 97.98% accuracy. The dataset used in this study may lack sufficient diversity, limiting the generalizability of the findings across different socio-economic, cultural, and demographic groups. Future work should explore integrating real-time data collection methods like wearable devices or mobile applications to gather more comprehensive and dynamic behavioural data.

Keywords Preschooler, Mental health, Data scarcity, Fuzzy decision support, Preschool pediatric symptom checklist (PPSC), Fuzzy rule, Degree of membership

A mentally healthy childhood enables individuals to acquire social skills and reach emotional milestones[1,2]that ensure the ability to respond well to certain problems. Mentally healthy children live positively and respond well in school, home, and communities. If children have any mental issues[3–5], they may face serious problems in learning, handling their emotions, and in their behaviour. Once children are affected by mental illness, their thinking ability and patterns change, which impacts their functioning in various places. Most children experience worries, fear, and disruptive behaviours at home, during play, and at school because of mental disorders[6]. Children with mental health issues are difficult to distinguish from those with normal childhood development because symptoms may emerge at different ages. Children are affected by numerous mental illnesses such as anxiety, attention-deficit disorder (ADD), autism spectrum disorder (ASD), eating disorders, depression, and mood disorders[7]. Children affected with anxiety have worries and fears that interrupt their participation in social situations[8]. Children with ADD have difficulties with impulsivity, attention, and hyperactivity[9]. These conditions in children are difficult to predict; they exhibit a few signs, such as persistent sadness, avoiding social interactions, hurting themselves, outbursts, drastic mood changes, changes in eating habits, difficulty sleeping, weight loss, difficulty focusing, avoidance of school, and changes in academic performance. Once mental health conditions infect children, they should be diagnosed and treated depending on their signs and what happens in daily life[10]. As such, children must be evaluated by psychologists and psychiatrists in terms of their medical history, medical examinations, emotional trauma, mental health, family history, symptom review, timeline, academic history, interviews, conversations with them, and standardized assessments[11]. Most researchers utilize all this information to identify mental health problems in preschoolers[12]. Researchers have suggested that mental

Graduate School, Philippine Women'S University, 1004 Manila, Philippines. email: lixinyue188@outlook.com

health issues have various negative consequences for poor cognitive development, functional impairment, and poor academic performance.

Several researchers have used machine learning (ML) and data mining techniques to predict mental health outcomes among school children[13]. Various ML algorithms—such as convolution neural networks (CNNs), support vector machines (SVMs), naïve Bayes (NB), and random forests (RFs) have been used to determine risk factors for depression and anxiety[14]. Researchers have also used social media platforms such as Reddit to identify suicide-related risk factors. In addition, ML models such as the XGBoost technique have been applied to students' mental information to identify anxiety during the COVID- 19 pandemic[15]. ML and data mining techniques, such as NB and RFs, recognize depression and anxiety in 73% and 71% of patients, respectively. This study was conducted on Bangladeshi university students in which the RF method revealed student stress, anxiety, and depression levels of up to 89.7%, and the logistic regression approach reached 74.5%[16]. Furthermore, a study was carried out with up to 20- to 70-year-old adults in which ML algorithms were used to predict anxiety and other mental disorders with maximum recognition accuracy. However, predicting mental health problems in preschoolers is challenging. Recently, various ML techniques have been widely applied to determine children's mental health. Nevertheless, these learning concepts have limitations such as data scarcity, heterogeneity, privacy, model interpretability, and generalizability[17]. The mental health observation system requires a large volume and high data quality, which can be applied in training. Hence, data from numerous resources such as social media, wearable devices, and electronic records have been collected. However, the system needs to deal with the issue of data heterogeneity because the single model makes it difficult to integrate diverse resources. The main research factor is data privacy because preschoolers' mental health information is more sensitive and requires complete protection for personal information, which is difficult to maintain. Finally, the generalized model cannot be applied to other populations because they vary in environment, culture, and demographics.

The analysis of mental health, especially in the setting of preschoolers, is greatly influenced by demographic diversity and familial risk factors. Parental education levels, cultural origins, socioeconomic position, and geographic location are some of the demographic characteristics that may greatly impact children's mental health outcomes. The prevalence of mental health problems may be higher, for example, among children from poorer socioeconomic families because these children may be more likely to experience environmental stresses, including financial instability and inadequate healthcare access. Also, cultural norms around mental health may have an impact on how kids from diverse backgrounds feel about getting care and how they grow emotionally and psychologically. In addition to genetics, parental education level is a factor in mental health because parents with more education may be better able to see the warning symptoms of mental illness in their children and get them help sooner. Compounding the likelihood of developing mental health difficulties in children are familial risk factors, such as mental health illnesses in parents, living in single-parent homes, or having a history of mental illness in the family.

Therefore, this manuscript utilized the FDS system to resolve privacy, scarcity, and model generalization problems. The fuzzy system employs rules and a fuzzy membership function based on expert knowledge, which helps make effective decisions. The fuzzy system needs only input that is mapped to qualitative categories such as "low," "medium," and "high." As such, the fuzzy system does not provide sensitive personal data; hence, the FDS maintains data privacy for sensitive information. The defined qualitative categorization is generalized to unseen data for various domains. Thus, FDS addresses the above issues while predicting preschoolers' mental health and creating a positive environment for children. FDS uses linguistic rules and fuzzy logic to determine whether an environment is complex or ambiguous. The fuzzy set and membership function provide the mapping process that changes the crisp input to the degree of the membership function (0 to 1). The mapping process is performed according to if-then rules, reducing vague information's computational complexity. The decision support system uses fuzzy qualitative criteria to handle uncertainty in preschool mental health decisions. The proposed study focuses on the Fuzzy Decision Support (FDS) System, which combines mental health treatment with early childhood education. With this research, the importance of equipping preschoolers with mental health-friendly surroundings is growing. The FDS system, which uses fuzzy logic, helps educators and caregivers diagnose, monitor, and treat mental health issues. Standard systems use static metrics, whereas the FDS system uses qualitative data to provide customized insights and suggestions. By establishing a connection between data-driven decisions and children's overall health, this study opens the door to preventative measures and lays the groundwork for resilient mental health throughout life.

Given the above context, this study aims to:

- Analyze the environment of preschoolers by utilizing their qualitative behaviour to create a positive impact.
- Utilize the FDS to categorize low, medium, and high output in classification, which increases the precision of mental health predictions.
- Develop the FDS system for exploring changes in children's emotions, such as ADD, anxiety, and anti-social tendencies, by conducting comprehensive research and behavioural analysis.

In sum, this study aimed to develop an FDS for analyzing preschoolers' behaviour to improve their learning experience.

Related works

Hassan and Mokhtar[18] introduced an ontology-driven decision support system for identifying ASD. This study used 676 classes and 124 properties to analyze ASD using the protégé ontological framework. Physicians used a decision support system to perform the text annotation process during the analysis. The retrieved characteristics helped create a framework to improve autism identification and treatment rates.

Andermo et al.[19] examined preschool children's mental health rooted in their school-based physical activities. This study intended to explore the mental health status of children who engage in sedentary behaviour during school activities. The research used population information from January 2009 to October 2019, in which 4- to 19-year-old children and adolescents' details were utilized to explore children's mental health. The collected data were processed with the help of random effect meta-analysis, employed to study children's mental health. The analysis effectively identified depression, anxiety, mental health problems, negative effects, poor self-worth, and poor self-esteem among children.

According to Dehghandar et al.[20], the fuzzy expert system (FES) was created to detect and forecast MetS in children and adolescents. With a fuzzy system, they wanted to study MetS in children and adults. A non-communicable disease prevention and monitoring program provided 800 participants for the MetS trial. The fuzzy system uses systolic blood pressure, age, diastolic blood pressure, waist circumference, nutritional status, waist-height ratio, and obesity information as inputs. The information provided 240 test data points and 560 training data points. The data was analyzed using a fuzzy method that accurately diagnosed sickness and MetS.

Gui and Suh[21] applied fuzzy clustering analysis (FCA) to examine young children's perception of graphic education. This research used preschool children's multichannel characteristics to develop and design a graphic education system for children. The clustering method analyzed every child's characteristics, and similar children were grouped to improve the overall performance of the educational system. The system identified the children's behaviour with minimum segmentation time (171.48 s) compared to other techniques.

Li[22] investigated children's health according to their behavioural characteristics. The system intended to develop a smart kindergarten by assessing student health. This study used the analytic hierarchy process (AHP) and a back propagation neural network (BPNN) to analyze students' mental health status. The AHP system explores the relationship between strong applicability and the critical level when making decisions. In addition, a judgment matrix was constructed to identify the relationship between student learning and mental health according to the weight gain analysis of the BPNN.

Liu et al.[23] recommended using a fuzzy differential equation (FDE) to analyze children's mental disorders according to audio-visual family restoration. Initially, user experience was analyzed according to preschool children's characteristics because mobile devices influence them. The collected information was scrutinized using the fuzzy approach, which helped to improve treatment. In addition, audio-visual functional therapy was applied to reduce mental disorders and improve overall treatment.

Qasrawi et al.[24] examined schoolchildren's risk factors for depression and anxiety using various ML techniques. This study employed information on 3,984 students collected from the West Bank Refugee School. The information was collected depending on their behaviour and academic performance and explored using neural networks, RF approaches, SVMs, decision trees, and naïve classifiers. ML techniques can predict mental health risk factors with maximum accuracy. The classified results indicate that students are involved in violence at school and home and that they have academic performance-related anxiety as well as depression.

Al-Shami[25] introduced the (2,1) fuzzy set approach to make effective applications using multi-criteria decision-making methods. This study compared the (2,1) fuzzy set using fundamental operations with the information fuzzy system. In addition, accuracy and score values were analyzed to predict the fuzzy set (2,1) rank. Then, an aggregation operator was applied to address the decision-making problem, which ensured usability and effectiveness.

Al-Shami et al.[26] introduced (a, b) a new generation of fuzzy sets to address decision-making problems. This study analyzed the non-membership and membership degrees to solve decision-making issues. Here, arithmetic operations were utilized along with an aggregator operator to reduce the complexity of the multi-criteria decision-making process.

Ibrahim et al.[27] utilized k_m^n rung picture fuzzy information to solve multi-criteria decision-making issues. The system used the rung picture fuzzy set, the weighted average, and geometric operations to create an effective fuzzy set. In addition, the VIKOR and TOPSIS techniques were included to improve the overall fuzzy process. Using rung picture information in fuzzy sets ensures system effectiveness and feasibility.

Amir Hossein Khabbaz et al.[28] suggested Reinforcement Learning and Fuzzy Logic for Serious Games for Children with Autism. An AI agent is used to fine-tune the difficulties in this research via gameplay. To assess the children's communication abilities in real-time, the game's tasks might increase in difficulty as the youngsters master them via play. After a while, the author uses fuzzy logic to make an educated guess about the player's capability. Fifteen autistic youngsters took part in the tests that assessed the proposed serious game. According to the findings of the experiments, the suggested approach helps autistic youngsters improve their communication skills.

Davar Giveki[29] proposed the optical flow-gated recurrent neural network for human action recognition. A new deep neural network that uses the suggested GRU is introduced to identify human activities. The success of the suggested GRU in action recognition using an end-to-end learning model is shown by evaluations on well-known datasets such as YouTube2011, UCF50, UCF101, and HMDB51. These evaluations highlight the method's generalizability. An engine block assembly dataset was gathered and used to test the performance of the suggested technique, further demonstrating the model's functionality and usefulness in addressing real-world challenges. At last, the author checked how well the suggested technique handled different types of noise. The collected findings prove that the suggested approach is quite effective and resistant to noise.

Marjan Ghobadi Fard et al.[30] recommended the Fuzzy Logic-based Method for Modeling and Recognizing Yoga Pose. The current ambiguity makes it possible to differentiate between human postures using fuzzy logic concepts. The author proposes a model for action recognition based on fuzzy logic in this work. Feature extraction considers fuzzy membership functions that emphasize the discriminative stance associated with each action. It also uses a multilayer perceptron classifier to detect human activities. Yoga postures may be more accurately classified by discussing different ways of assessing poses and identifying important elements in depth. Tests conducted on the reference datasets show how well the suggested approach works.

Impact of fuzzy decision support on the mental health of preschoolers

This study examined and created the FDS to help educators and caregivers identify the signs and risk factors of mental health problems in preschoolers. The FDS uses fuzzy logic to identify emotional changes like ADHD, anxiety, and antisocial tendencies in preschoolers' qualitative behavioural changes. This study used the Preschool Pediatric Symptom Checklist (PPSC)[31] to explore preschoolers' mental health. The PPSC consists of 18 items, including a behavioural and emotional screening instrument created as an important concept for young children's well-being surveys. These resources are intended to predict preschoolers' and infants' behaviour and emotional problems in earlier stages. This study used 18- to 60-month-old children to observe their mental health. The children were screened with 21 items to identify behavioural and emotional problems. The screening process was completed with the help of childcare providers who helped to predict disorders of defiance and problems related to attention deficit hyperactivity disorder (ADHD). The screening process was conducted on three groups of samples: pediatric primary care practice (292 families), referral clinics (354 families), and replication samples (171 families). The parents in the first two groups had 73 drafts of PPSC questionnaires that consisted of items about demographic information, questions about family risk factors, (yes/no) questions about behavioural changes, and questions about anxiety, depression, and problematic behaviour. According to the assessment, PPSC scores are assigned to children to predict their mental health status. During the assessment, if the children are assigned 0, they did not respond at all, 1 means they somewhat responded, and 2 means they very much responded. Suppose the child achieves a total score of 9 or a high score that shows that the child requires further evaluation. The gathered behavioural information about the child is examined using the FDS system to identify mental health decisions. Fuzzy logic offers a conceptual framework that emulates human thinking, making it suitable for accommodating learners' varied and evolving requirements, behaviours, and interactions. The hybrid approach incorporates machine learning to use data-driven insights, improving decision-making processes' flexibility and scalability. Due to this synergy, the system can give context-aware recommendations and improve accuracy by analyzing trends in varied datasets. This strategy works well in e-learning because targeted and immediate interventions improve student engagement and performance. Figure 1 outlines the structure of the FDS-based mental health analysis.

Participants were selected from urban and rural regions to ensure that environmental impacts on preschoolers' mental health were properly represented. Low-income to middle-income families may have had different mental health care accesses. Some parents had just a high school graduation, while others had more academically advanced degrees. Because of this variation, the research included a wide range of parental impacts on children's mental health. Family members of various racial and ethnic groups comprised the participants, demonstrating the community's diversity. This variety is needed to understand how cultural influences, including parenting techniques, mental health perspectives, and community resources, affect detecting and treating behavioural and emotional issues in early children. Single-parent homes, parental mental health issues, including anxiety or depression, and economic instability were shown to be important family risk factors. This study know these variables affect kids' mental health and behaviour. Mental health concerns in parents may cause inconsistent parenting and emotional inaccessibility, which can worsen child behaviour. Single parents may lack time and money to meet their children's requirements. Financial insecurity may cause stress and limit access to education and healthcare, which can harm young children. Including these risk variables to contextualize

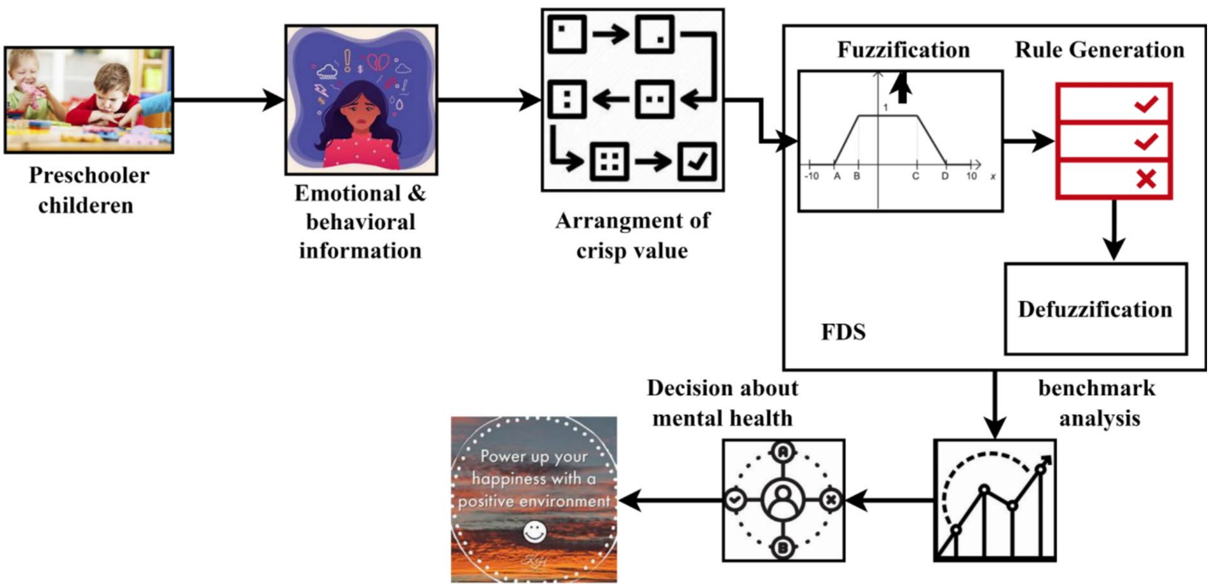


Fig. 1. Structure of the FDS-based mental health analysis of preschoolers.

children's behavioural and emotional struggles and appreciate systemic concerns that may affect their mental health. Because of its simplicity, dependability, and emphasis on diagnosing behavioural and emotional issues in young children, the PPSC scoring system was chosen. Using their replies, the method gives kids ratings of 0 to 1 or 2. This permits a more detailed evaluation of symptom intensity and makes the technique straightforward to apply in various contexts. The early diagnosis of at-risk youngsters requires a score of nine or above as a criterion for subsequent examination. This scoring method is especially beneficial when time and resources for comprehensive mental health evaluations may be constrained in pediatric and childcare settings. The research incorporates PPSC scores into the FDS system, using these standardized metrics to provide data-driven insights for mental health decision-making, hence improving the accuracy and effectiveness of the screening process.

This study complies with ethical standards and is approved by the Scientific Research Ethics Committee of the Graduate School in Philippine Women's University. All methods were performed following relevant guidelines and regulations. This study obtained the informed consent of all human participants. For children, permission was obtained from the guardian.

The FDS system

Generally, medical science and knowledge have several uncertainties when analyzing people's health. In particular, when examining preschoolers' mental health, there are various uncertainties, such as limited expressive abilities, developmental variability, external influences, and limited self-awareness. Limited expressive abilities lead to struggling while expressing one's emotions and feelings, which creates anxiety and depression. In addition, young children are easily influenced by cultural factors, family dynamics, and socioeconomic conditions. These factors affect children's mental health and are difficult to separate from those impacting typically developing children. As such, FDSs have been applied in medical science to address uncertainty issues. The fuzzy approach considers every feature in medical applications and provides recommendations effectively. The FDS is defined according to the membership function with a 0 to 1 interval. The defined membership value quantifies the input and visually represents the fuzzy set. For fuzzily, every member is represented by a membership rank used to classify the members into a particular class. The membership function is defined with a closed interval $[0,1]$, and the members are defined as the degree of membership in the set.

Assuming that the reference set is $\mathcal{H}$, the fuzzy set $\mathcal{F}$ is defined on $\mathcal{H}$, and the membership function is represented as $\mu_A(x)$. $\mu_A(x)$ is defined from $\mathcal{H}$ to $[0,1]$. Then, the membership of A elements of $\mathcal{H}$ in set $\mathcal{F}$ is defined using Eq. (1).

$$\mathcal{F} = \{(x, \mu_A(x)) : \mu_A(x) : \mathcal{H} \to [0,1]\} \tag{1}$$

Trapezoidal and triangular membership functions are utilized during the analysis process of mental health decisions, as defined in Eq. (2).

$$\mu_A(x) = \begin{cases} \frac{x-\alpha}{m-\alpha} & \alpha < x \leq m \\ \frac{b-x}{b-m} & m < x \leq b \end{cases} \tag{2}$$

Equation (2) is the triangular membership function applied to the fuzzy set when the membership function appears at only one point. Here, x is the input, and (α, m, b) is the parameter in the triangular function. Then, the trapezoidal function is computed using Eq. (3), employed in the set when the maximum membership appears in one interval.

$$\mu_A(x) = \begin{cases} \frac{x-\alpha}{m-\alpha} & \alpha < x \leq m \\ 1 & m < x \leq n \\ \frac{b-x}{b-m} & m < x \leq b \end{cases} \tag{3}$$

In addition, the triangular and trapezoidal membership and non-membership functions must be computed while exploring every input of preschoolers. The non-membership function is estimated using Eq. (4).

$$\nu_A(x) = \begin{cases} 1 \quad if\ x < a \\ \frac{s-x}{s-\alpha} \quad if\ \alpha \leq x \leq s \\ \frac{0 \quad if\ x=s}{\frac{\frac{x-s}{b-s} \quad if\ s \leq x \leq b}{1 \quad if\ b<x}} \end{cases} \tag{4}$$

The computed $\nu_A(x)$ ensures the degree of non-membership value of $\mathcal{H}$ to A, and it must satisfy two conditions: $\{(\mu_A(x), \nu_A(x)) \in [0,1]\}$ and $\{(\mu_A(x) + \nu_A(x)) \leq 1\}$. In the FDS, the fuzzy numbers of the degrees $\mu_A(x)$ are 0 and 1; the degree of the $\nu_A(x)$ value is the complement of the $\mu_A(x)$ value. The combination of $\mu_A(x)$ and $\nu_A(x)$ creates complexity while handling decision-making. Thus, fuzzy set components such as fuzzy rule databases, fuzzifiers, inference engines, and de-fuzzifiers are utilized to improve decision-making. The overall components of the FDS are illustrated in Fig. 2.

Figure 2 illustrates the components of the FDS system, which include fuzzification, fuzzy rule base generation, an inference engine, and de-fuzzification. These components reduce decision-making complexity while analyzing preschoolers' mental health. The fuzzification receives input X from the data sources that have to be converted into fuzzy set $\mathcal{F}$ and the degree of membership $\mu_A(x)$. Then, fuzzy rules are generated according to the expert's knowledge and used to map the input to the membership value. The mapping process P is performed in

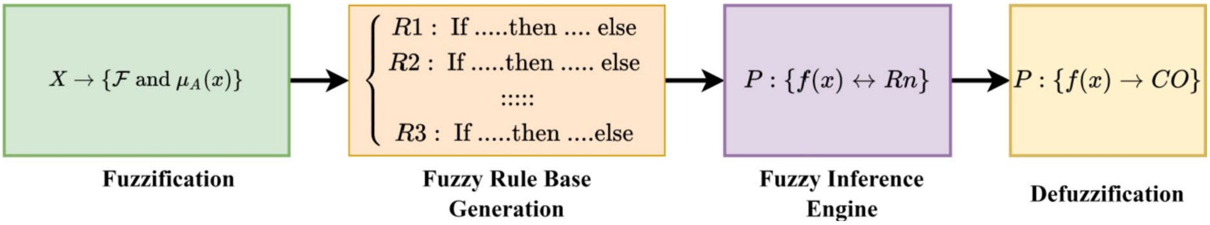


Fig. 2. Fuzzification and De-fuzzification Process.

the inference engine. Finally, de-fuzzification is performed to convert the fuzzy output into a crisp output (CO), which helps to provide recommendations, classifications, and decisions for specific applications.

First, fuzzy sets are created using clean, real-world input data (such as behavioural ratings from the Preschool Pediatric Symptom Checklist) inside the framework of the Fuzzy Decision Support (FDS) system. This is accomplished by using membership functions that specify the extent to which each input falls into a certain fuzzy category (e.g., low, medium, or high) according to established thresholds. For example, according to the membership function, a behavioural score of 8 may be categorized as moderate,' with a membership degree of 0.7 falling into that category and 0.3 into the 'high,' respectively. The system can interpret the fuzzy inputs better because they reflect the inherent ambiguity and imprecision in the real-world data. The defuzzification technique is then used to make decisions based on a clear value rather than a fuzzy one. Common techniques for this include the centroid and the mean of maxima approach. A fuzzy set depicting the severity level or the required intervention is produced by combining the fuzzy results from the inference system using fuzzy rules. This process may be used for many behavioural disorders, such as anxiety or aggressiveness. The defuzzification process produces a single, usable result by calculating the weighted average of the values in the fuzzy set. For instance, to ascertain the necessary degree of intervention, a fuzzy output suggesting the need for a gentle intervention may be transformed into a specific suggestion, such as a score of 7 out of 10.

Fuzzification

Fuzzification is an important step in the FDS system in which the crisp input is converted into a fuzzy set, and the degree of membership is determined. The membership value is [0, 1]; if 0, the input does not fall under the fuzzy set; otherwise, it belongs to the fuzzy set. Here, the mapping process is defined as $x^* \in U \subset R^n$ to the fuzzy set $\mathcal{F}$in U. During this process, the triangular fuzzy generator reduces complex computations and perturbations.

$$\mu_{\mathcal{F}}(x) = \left\{ \left(1 - \frac{\left|x_1 - x_1^*\right|}{b_1}\right) \widehat{\mathcal{H}} \ldots \ldots \widehat{\mathcal{H}} \left(1 - \frac{\left|x_n - x_n^*\right|}{b_n}\right) \right. \left|x_1 - x_1^*\right| \le b_i \tag{5}$$

In Eq. (5), the positive parameter is denoted as b_i, and t-soft is represented as $\widehat{\mathcal{H}}$, which is chosen here as a minimum. According to the fuzzification process, the input is converted with the help of the membership function saved in the fuzzy knowledge base. The fuzzification process is applied to preschoolers' mental health analysis. The fuzzification process defines the fuzzy set and membership function. According to the analysis, the input is a social engagement fuzzy set (SEF) $\{SEF : low,\ moderate\ and\ high\}$. For the low category fuzzy set, the triangular membership function takes the parameters (0, 0, 30); the moderate fuzzy set has the parameters (10, 50, 70); and the high fuzzy set takes the parameters (80, 100, 100). The membership value of the SEF is defined in Fig. 3.

Figures 3(a) and (b) represent the fuzzification process based on a fuzzy set of low and moderate social engagement levels. Every fuzzy set is linked with the membership function (triangular), which denotes the children's response-related degree of the membership function concerning social engagement. Figure 3(a) shows that the membership value is minimal in the low fuzzy set when the SEF value is 0 and progressively increases until it reaches 20. For each entry with a low SEF, the $\mu_A(x)$ value is estimated by checking the conditions $\alpha < x \le m$ and $m < x \le b$ defined in Eq. (2). If input value x i satisfies $\alpha < x \le m$, then the $\mu_A(x)$ value is computed using $\left(\frac{x-\alpha}{m-\alpha}\right)$; otherwise, $\left(\frac{b-x}{b-m}\right)$ is utilized for $\mu_A(x)$. Figure 3(b) depicts the representation of the moderate SEF value-related degree of membership. The graphical representation shows that the membership value peaks at 50 and starts declining when it reaches 90. Similarly, the high SEF value is analyzed, and the fuzzification-related degree of membership analysis is illustrated in Fig. 3(c).

Figure 3(c) indicates that a high fuzzy set value is related to membership function analysis, in which the degree of membership is minimized to 80 and increases gradually when it reaches 100. The computed $\mu_A(x)$ value is denoted as the preschoolers' fuzzification process of social engagement. According to the analysis, social engagement is not always accurate to low, high, and moderate, which can be between because of various uncertainties and factors. Table 1 portrays the computations of low, moderate, and high-value-related $\mu_A(x)$ -generalization estimates.

The degree of membership quantifies the level to which each input value is an element of the given fuzzy set. The mathematical Equation is derived from triangle membership functions and their associated parameters. Fuzzification enables the expression of vague data and enhances the decision-making process when uncertainties

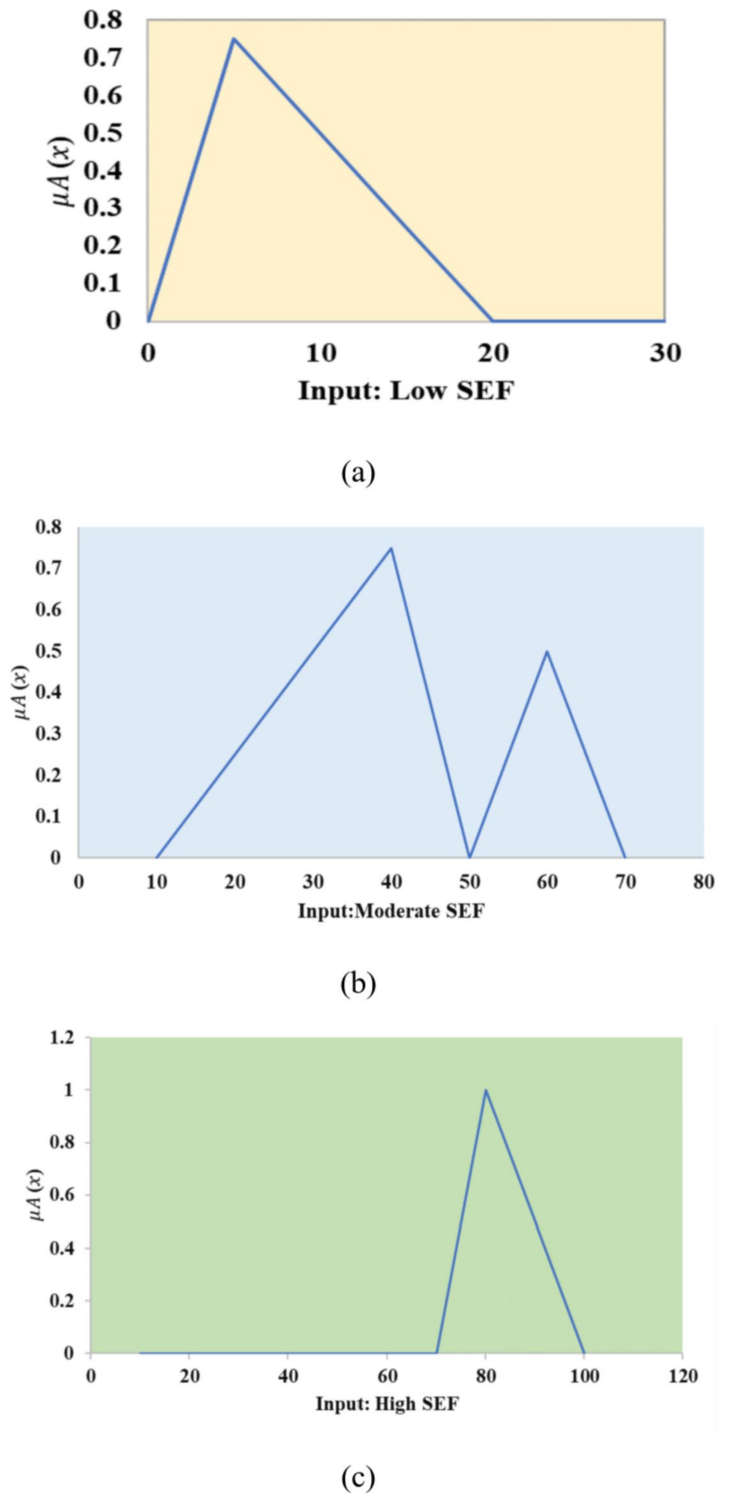


Fig. 3. Membership values. (**a**) low-SEF, (**b**) moderate-SEF, (**c**) high SEF.

are present. The fuzzy sets obtained and their corresponding degrees of membership can be subsequently employed in fuzzy inference systems to facilitate decision-making. Hence, the fuzzification process assesses how children's health information changes into a fuzzy processing format input. Likewise, children's mental health is assessed by various factors, such as activity level, eating pattern, sleep duration, the ability to focus, and sociability. The fuzzy system uses intelligible language rules that exploit imprecise, qualitative characteristics to yield indications regarding a child's cognitive and emotional development that necessitate support. The process of graduate fuzzification enables the integration of imprecise, real-world notions about human health and behaviour. Figure 4 outlines the fuzzification process of various factors and their respective outcomes.

	Low fuzzy set	Moderate fuzzy set	High fuzzy set
Membership parameter	(0, 0, 30)	(10, 50, 70)	(80, 100, 100)
Formula for $\boldsymbol{\mu}_{\boldsymbol{A}}\,(\boldsymbol{x})$	$\begin{cases} 0 & if\ x \le 0 \\ 0 & if x > 30 \\ \frac{x-0}{0-0} & if\ 0 < x \le 0 \\ \frac{30-x}{30-0} & if\ 0 < x \le 30 \end{cases}$	$\begin{array}{cc} 0 & if\ x \le 10 \\ 0 & if x > 90 \\ \frac{x-10}{50-10} & if\ 10 < x \le 50 \\ \frac{90-x}{90-50} & if 50 < x \le 90 \end{array}$	$\begin{array}{cc} 0 & if\ x \le 80 \\ 0 & if x > 100 \\ \frac{x-80}{100-80} & if\ 80 < x \le 100 \\ \frac{100-x}{100-80} & if\ 100 < x \le 100 \end{array}$

Table 1. $\boldsymbol{\mu}_{\boldsymbol{A}}\,(\boldsymbol{x})$ Generalization estimates.

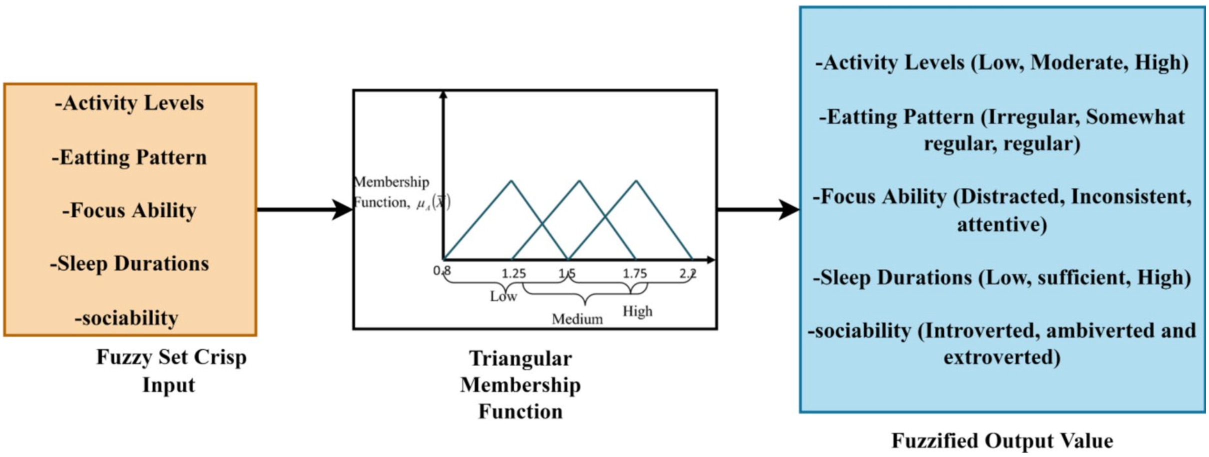


Fig. 4. Analysis of the fuzzified output of mental health-related factors.

According to Fig. 4, the crisp inputs are taken from different activity levels and fed into the triangular membership function, which is utilized to predict fuzzified output values such as low, moderate, and high. The inputs are mapped with the membership function to obtain the degree of membership. The obtained inputs are passed on to fuzzy rules to make effective decisions about a child's mental health.

Fuzzy rule generation

The next important step is fuzzy rule generation, framed using the "if-then" condition. The fuzzy set rule is the crucial FDS step framed according to the expert's knowledge. According to the PPSC's resources, the fuzzy rules are framed to identify the child's mental health. The generated rules are useful in creating a positive environment for children to improve their lives. Here, a few fuzzy rules are listed in Table 2.

According to fuzzy rules, the output fuzzy set is derived as a low-, moderate-, or high-risk list. The generated fuzzy set is utilized in clinical analysis to categorize preschoolers' mental health effectively. Then, the fuzzy inference engine employs the fuzzy set to identify the output, which helps to determine the child's mental health. The fuzzy set activity levels (low, moderate, and high), eating patterns (irregular, somewhat regular, and regular), ability to focus (distracted, inconsistent, and attentive), sleep duration (low, sufficient, and high), and sociability (introverted, ambivert, and extroverted) are the inputs to the fuzzy inference engine. The rules are framed by a combination of inputs that help to determine the child's mental behaviour output. Here, the output of the ability to focus is obtained by considering sleep duration and activity level. Likewise, anxiety and perfectionism are combined to frame the rules to obtain the output value. Here, the fuzzy set is $Activity\ Level\ :\{low,\ moderate,\ high\}$, $Eating\ pattern:\ \{irregular,\ somewhat\ regular,\ regular\}$, and $Ability\ to\ focus:\ \{distracted,\ inconsistent,\ attentive\}$. For the fuzzy set, the fuzzy rules are framed with the help of expert knowledge. The rule is *"If the activity level is moderate and the eating pattern is somewhat regular, then the ability to focus is inconsistent."*

According to the rules and criteria, the triangular membership function is applied to the parameters to obtain the output for the input. Let us assume that the activity level has a fuzzy set: low (0, 0, 30), moderate (20, 50, 80), and high (70, 100, 100). The eating pattern fuzzy set is irregular (0, 0, 30), somewhat regular (20, 50, 80), or regular (70, 100, 100). The ability to focus is set as distracted (0, 0, 30), inconsistent (20, 50, 80), or attentive (70, 100, 100). For the entire fuzzy set, the degree of membership is estimated for the above-defined fuzzy rule. Here, the activity level is 60, and the eating pattern is 60. The activity level of the membership function is moderate; it has a value of 0.33, according to Eq. (2). The degree of eating pattern of the membership function is somewhat regular at 0.33. Then, the fuzzy inference system is computed using the minimum value, which is defined in Eq. (6):

Rule No.	Fuzzy rules
1	If attention is very poor and aggression frequent, then the risk of ADHD is high.
2	If social withdrawal is a risk and motivation is very low, then depression is high.
3	If perfectionism is noticeable, anxiety is severe, and high anxiety is present.
4	If attachment issues are severe, speech development may be delayed, and there may be a high risk of ASD.
5	If a child has an insufficient eating pattern, the child is high in nutritional deficiency.
6	If a child is very withdrawn and his/her affect is flat, then the risk of depression is high.
7	If a child is somewhat inattentive and his/her impulse control is low, then the risk of ADHD is moderate.
8	If a child is very anxious and sleeps poorly, then the risk of anxiety disorder is high.
9	If a child is slightly aggressive and his/her empathy is low, then the risk of a behavioural disorder is moderate.
10	If social skills are very delayed and speech is delayed, then the risk of ASD is high.
11	If attachment to caregivers is insecure and affect regulation is poor, then the risk of attachment issues is high.
12	If the activity level is high and the eating pattern is irregular, then the child may be distracted.
13	If the child's activity level is moderate and the eating pattern is somewhat regular, then the child's ability to focus is inconsistent.
14	If the child's activity level is low and the eating pattern is regular, then the child may be attentive.
15	If a child's sleep duration is low and he/she is introverted, then the child may be distracted.
16	If a child's sleep duration is sufficient and he/she is an ambivert, then the child's ability to focus is inconsistent.
17	If a child's sleep duration is high and he/she is extroverted, then the child may be attentive.

Table 2. Sample fuzzy rules.

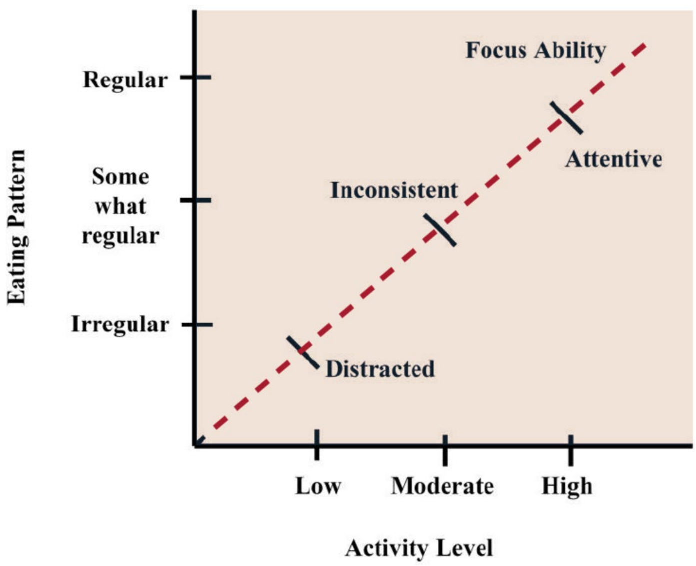


Fig. 5. De-fuzzification process.

$$Inference = \left.\begin{array}{c} \min\left(\mu\ (moderate),\ \mu\ (somewhat\ regular)\right) \\ \min\left(0.33{,}0.33\right) \\ 0.33 \end{array}\right\} \quad (6)$$

Then, the ability to focus is the degree to which the membership function is inconsistent, 0.5. During the computation, the degrees of activity level of the membership and eating pattern values are fed into the AND operation to identify ability-related mental problems. The ability to focus on the final output is estimated by de-fuzzifying and aggregating the rule outputs; Fig. 5 shows the graphical structure of the fuzzy inference process concerning the rule.

Figure 5 depicts the deduction from the given fuzzy rule and membership functions. The rule's degree of membership is highest in the region when the activity level and eating pattern have moderate values. According to the fuzzy output, a positive environment is created for preschoolers by considering various factors such as the ability to focus, the eating pattern, and the activity level.

A positive environment for preschoolers

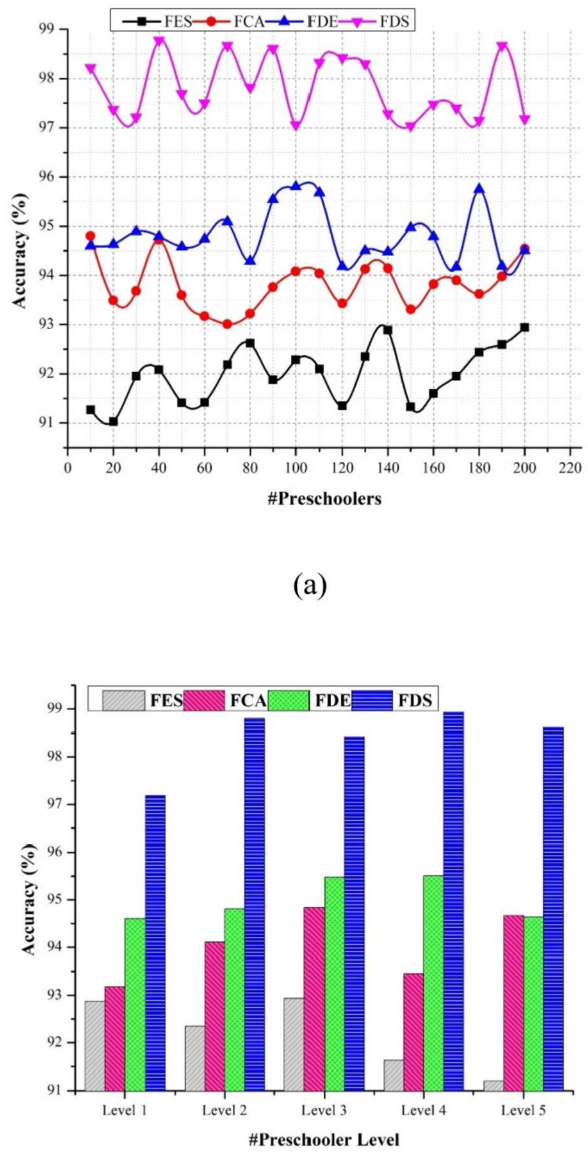
The fuzzy rules are created with the help of expert knowledge, which covers all possible solutions for preschoolers to maintain their mental health. The child's moderate activity level is encouraged by providing physical activities, outdoor activities, movement, encouraged games, and structured playtimes according to the child's age. Then, eating patterns are regularized by creating a structured, consistent mealtime routine. In addition, a social and positive atmosphere and balanced, healthy foods are also provided. Focus is maintained by designing play and learning areas with minimum distraction. Then, activities are broken into acceptable segments that help the preschooler understand and pay attention. The unique variations in activity levels, food habits, and the ability to focus among individuals should be acknowledged and honoured. Activities and routines should be customized to meet every child's distinct requirements and inclinations. Commendation and constructive reinforcement are provided for desired actions, such as sharing, collaboration, and attentiveness. A reward system should be implemented that prioritizes good acts to incentivize and strengthen positive behaviour. The physical environment should be secure, engaging, and favourable for exploration. A feeling of safety and confidence can be developed by upholding regular schedules and explicit standards. A transparent way to communicate with parents should be developed to obtain valuable information about a child's conduct at home. Teachers should cooperate with parents to establish uniformity across domestic and preschool settings. If the child is distracted and cannot focus, the learning environment and schedule should be structured to support attention. A proper routine and break should occur between every activity to improve attention. Then, techniques to calm down, such as quiet reading areas, fidget toys, and breathing processes, should be used to maximize preschoolers' health status. The effective observation and assessment of children's behaviour helps to predict their mental health according to the fuzzy set, membership function, and rules. Thus, the objective of reducing the causes of discomfort while promoting the growth of emotional, behavioural, and social abilities has been successfully established. Implementing a caring, supportive, and customized approach will give preschoolers a sense of security, involvement, and positivity.

Results

This section discusses the efficiency of the FDS system by analyzing preschoolers' mental health. This study collected children's information via various assessments, questionnaires, and surveys. During the analysis, resources from the PPSC were used to evaluate the efficiency of the FDS while exploring preschoolers' mental health. The FDS system uses fuzzification, fuzzy rules, inference systems, and de-fuzzification components to make decisions. The efficiency of the FDS is predicted using different metrics such as accuracy, specificity, sensitivity, and error. These metrics determine how effectively the model classifies preschoolers' mental health. The obtained system performance is compared with that of the FES[20], FCA[21], and an FDE[23], which are described in the literature. According to various studies, compared with other methods, the fuzzy decision-making system improves decision-making accuracy, optimizes resources while analyzing mental health interventions reduces bias and support for non-specialist practitioners, and provides personalized intervention. This study took many steps to reduce the impact of subjectivity and bias during rule construction to allay concerns about the FDS system's expert-defined rules. To begin, a multi-ethnic team of specialists was assembled, including mental health specialists, psychologists, doctors, and early childhood educators. There was less chance of any one position taking over the process because of this varied input, which helped ensure the regulations considered various opinions and experiences. This study employed an iterative method, testing the first rules with a subset of toddlers and then using expert input to make additional refinements. Using actual data from a wide sample of children representing varied socio-economic circumstances, this study undertook a validation phase to verify the rules further and eliminate subjectivity. This validation validated the robustness and generalizability of the rules across various demographics.

Figures 6 (a) and (b) illustrate the accuracy of the analysis of the FDS for exploring preschoolers' mental health. This work intends to maximize the accuracy of predicting mental health issues by observing children's activities and behaviours. The levels of mental illness, disorders, anxiety, and depression were examined using various benchmark data. In this case, the degree of membership value $\mu_A(x) = \begin{cases} \frac{x-\alpha}{m-\alpha} & \alpha < x \leq m \\ \frac{b-x}{b-m} & m < x \leq b \end{cases}$ is computed for every factor to identify the impact on mental health. In addition to the triangular membership function, the trapezoidal membership function $\mu_A(x) = \begin{cases} \frac{x-\alpha}{m-\alpha} & \alpha < x \leq m \\ 1 & m < x \leq n \\ \frac{b-x}{b-m} & m < x \leq b \end{cases}$ is computed to improve the overall prediction of mental health. Thus, mental illness, the level of focus, and positive attitudes are examined using an FDS system with fuzzy rules. The effective generation of fuzzy rules maximizes prediction accuracy. The non-degree membership value is also computed during the computation, which may cause uncertainty. The fuzzy rules cover degree and non-degree membership values, reducing data scarcity and heterogeneity-related certainty. The maximum prediction accuracy is directly proportional to the prediction about the child's mental health and the corresponding recommendations. Thus, the accuracy with the maximum value ensures better improvement, as shown in Fig. 6. The follow-up durations were 1–15 months, 2–24 months, 3–36 months, 4–48 months, and 5–60 months.

Specificity is an important metric used to compute how effectively the FDS approach correctly recognizes true negatives where the approach correctly indicates the non-appearance of particular conditions, such as mental health issues. The results of Fig. 7 (a) and (b) indicate that the method ensures maximum specificity, which is the minimum false-positive value. The effective computation of the degree of membership ensures high accuracy, specificity, and a minimum false-positive rate. $\mu_A(x)$ is the value computed by analyzing the $\alpha < x \leq m$



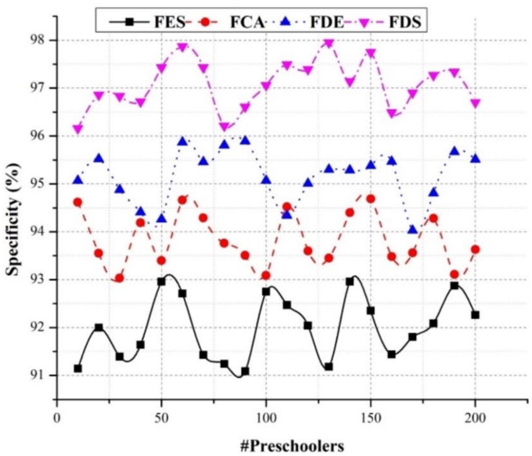
(a)

(b)

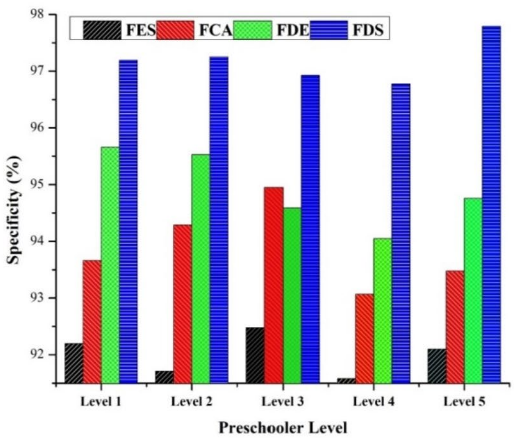
Fig. 6. Accuracy analysis. (**a**) #Preschoolers, (**b**) Preschooler level.

and $m < x \leq b$ conditions. The computed $\mu_A(x)$ identifies the relationship between the linguistic and input variables regarding health parameters like the ability to focus, social engagement, and eating patterns. According to the membership values, fuzzy rules are generated, as seen in Table 2, which portrays the relationships between preschoolers' mental well-being and the input variables. The successful generation of fuzzy rules reduces the false-positive rate and maximizes the overall accuracy of predicting mental health.

The FDS system ensures a high sensitivity when analyzing preschoolers' mental health. The maximum sensitivity value indicates that the system identifies mental health issues involving infected children from the observation. Mental health issues occur at various levels in children and can be recognized effectively at particular intervention times. Regulations that enhance sensitivity should be prioritized, with a focus on identifying possible mental health problems. Rule settings can be altered to boost sensitivity to deviations that suggest early indications of problems while maintaining a balance in the system's overall functioning. Every parameter is considered while classifying the child's behavioural changes during the outcome computation. The computed $\mu_{\mathcal{F}}(x)$ a fuzzy set is explored with fuzzy rules that cover all parameters $\left\{\left(1-\frac{|x_1-x_1^*|}{b_1}\right)\widehat{\mathcal{H}}\ldots\ldots\widehat{\mathcal{H}}\left(1-\frac{|x_n-x_n^*|}{b_n}\right)|x_1-x_1^*|\leq b_i\right.$, which reduces the false-positive rate and maximizes the sensitivity value (Fig. 8 (a) and (b)). The maximum sensitivity, specificity, and accuracy values indicate that the system ensures a minimum error value.



(a)



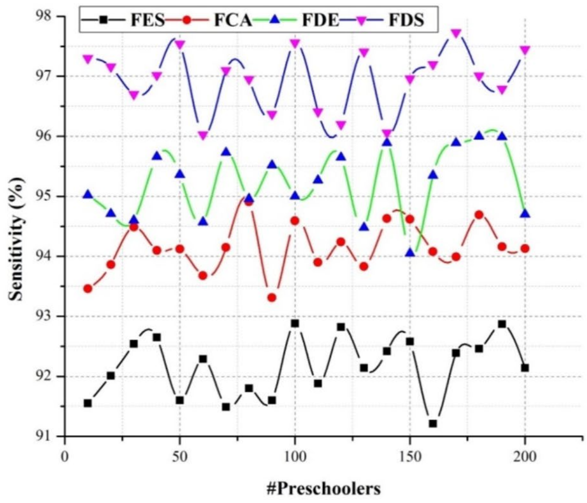
(b)

Fig. 7. Specificity analysis. (a) #Preschoolers, (b) Preschooler level.

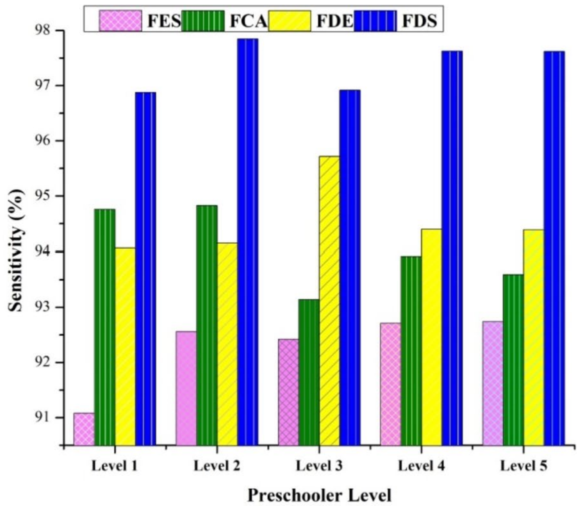
Figure 9 (a) and (b) illustrate the error rate analysis of various numbers of preschoolers and different levels of children. The minimum error rate indicates that the FDS system recognizes the child's mental health with maximum accuracy. In this case, the fuzzy set variable is constructed from crisp inputs of attention, activity, and eating habits. Children's mental states are calculated after creating fuzzy rules and degrees of membership values. Computing the degree of membership allows for the youngster's most accurate mental health assessment. A fuzzy decision support system (DSS) reduces user mistakes using fuzzy logic's flexibility and adaptation to handle uncertainties and imprecise information. Fuzzy sets, membership functions, and rules that account for data changes and complexity enable this. Fuzzy logic enables presenting inaccurate or confusing facts so the system can make well-informed judgments even with incomplete or uncertain input. The system's design balances precision and accuracy to reduce false positives and negatives. Optimizing membership functions and rule bases and thoroughly validating and testing may reduce errors.

This Fuzzy Decision Support (FDS) System relies on qualitative input, which may change based on the cultural and contextual setting in which it is evaluated. The system's accuracy and usefulness may be affected by this heterogeneity, especially in preschool settings. The system might overcome this issue using fuzzy logic and powerful machine learning. With this upgrade, the algorithm might learn from larger datasets, adapt to different cultural norms, and increase its predicting accuracy. Real-time educator and caregiver input may enhance the system's suggestions, making them contextually relevant and readily applicable.

Continuous learning processes, feedback loops, and adaptability help the system reduce mistakes over time. The FDS system uses fuzzy logic to produce efficient and trustworthy decisions in complicated and ever-changing situations. As decided, a positive environment is created for youngsters to improve their social skills, conduct, and involvement.



(a)



(b)

Fig. 8. Sensitivity analysis. (**a**) #Preschoolers, (**b**) Preschooler level.

Fuzzy Decision Support (FDS) outperforms neural networks and random forests in preschooler mental health assessment. Non-experts struggle to grasp decision-making because neural networks cannot be explained. Neural networks excel in non-linear pattern recognition and complicated dataset processing. Random forests are durable and interpretable, but they may struggle with erroneous or insufficient data, which is typical in mental health examinations. Despite their effectiveness in handling uncertainty and imprecision, typical fuzzy logic systems may have adaptability and scalability issues. Fuzzy logic and machine learning let the FDS system manage ambiguous and unexpected input while giving transparency and flexibility.

Privacy issues are a big barrier to using the FDS system since it handles sensitive information on children's mental health. Parents and guardians may be worried about the storage, access, and use of their children's data, which poses possible difficulties in assuring compliance with privacy laws like COPPA and the General Data Protection Regulation (GDPR). The need to provide training to caregivers is another obstacle. Providers and teachers need proper training to understand and use the FDS system's results for it to work. This can be particularly difficult because caregivers in low-resource areas do not have the means or time to get extensive training. Another major obstacle is the absence of sufficient resources. The system may not be adoptable, implementable, or maintainable by many schools or daycare facilities due to a lack of funding, personnel, or resources. This is especially important in areas with lesser incomes since their infrastructure may not be able to handle sophisticated technology.

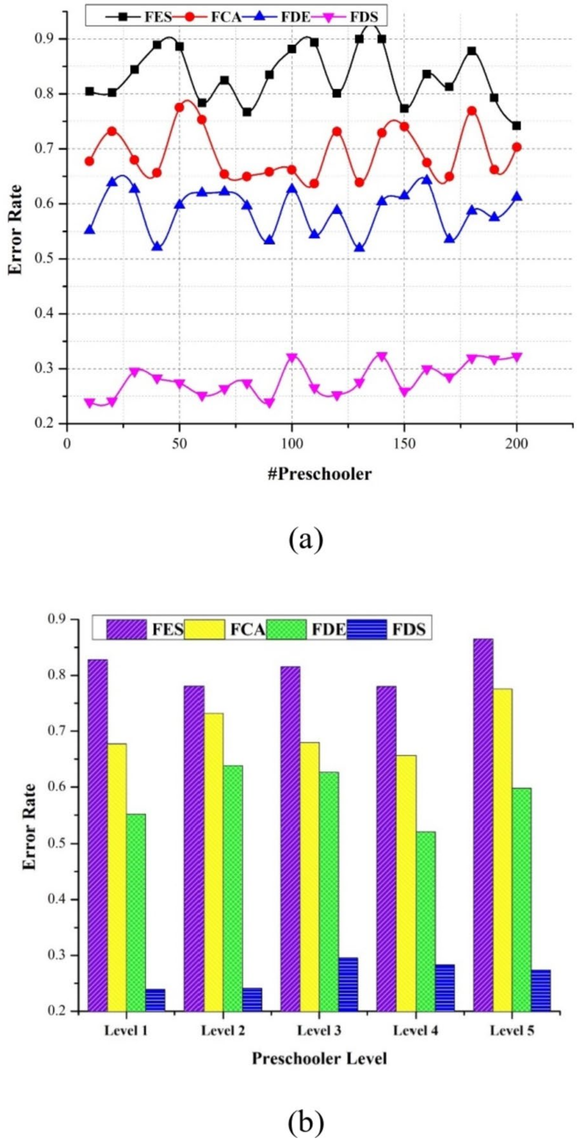


Fig. 9. Error rate analysis. (**a**) #Preschoolers, (**b**) Preschooler level.

A solution to the data privacy problem might be for the FDS system to adhere to applicable privacy standards while simultaneously implementing robust privacy-preserving measures such as encrypting sensitive data and anonymizing identifying information. Collecting parental or guardian permission and disseminating accurate and transparent information about the intended use of such data is of the utmost importance. Giving people the choice to opt out of collecting non-essential data in a way that respects their privacy may help even more. A scalable and adaptable training program that combines online modules for convenience with in-person workshops for practical instruction might be designed to meet the needs of caregivers. These programs must highlight the system's suggestions and how caregivers may incorporate them into everyday life. Additional measures to lessen the training load include making the FDS system's user interface more intuitive and providing clear, concise instructions. Lastly, limited technological infrastructure and low-cost gadgets may be included in the system's architecture to tackle resource limits. Underprivileged communities can afford preschools and schools if they work with nonprofits, the public sector, or private sector partners. To further ensure the system's accessibility and sustainability, grant funds and sponsorship programs might be used to assist its adoption in settings with limited resources.

Discussion

The variety and quantity of the dataset is a major drawback of this research. The results of the FDS system can only be applied to a small subset of the population since the sample size of preschoolers is so small. When training on a limited dataset, overfitting occurs, and the model becomes too specialized to the training data and may not be able to handle new, unknown data. Another issue is a possible bias in the system's fuzzy rule definitions. Experts probably developed the standards; therefore, the classification of some actions or symptoms might be skewed by subjective interpretations or a lack of diversity in expert viewpoints. As a result, there is a chance that mental health evaluations may be skewed since the fuzzy system would give more weight to certain behaviours than others. Expanding the dataset to include a more diverse sample of children from different socio-economic, cultural, and geographic origins and validating fuzzy rules using a larger variety of expert input and empirical data will help alleviate these constraints.

Fuzzy Decision Support (FDS) holds great promise for use in real-world preschool settings, where it might aid teachers and caregivers in the early detection of mental health issues. The FDS may analyze children's behavioural and emotional data to provide real-time assessments. It might then provide targeted suggestions for treatments or further exams. This has the potential to be particularly helpful in areas with few resources since having access to mental health practitioners may be challenging. Making such a system work, however, isn't without its challenges. For example, caregivers may need more training to use the FDS system. Concerns over the protection of sensitive mental health data may also slow its adoption. It is recommended that caregivers get specialized training on understanding and using FDS results to address these issues. Integrating privacy-preserving mechanisms within the system, such as data encryption and anonymization, is also important for keeping sensitive information secret.

Future research might gain a lot by using bigger and more varied datasets that include a wider range of cultural, geographical, and socioeconomic factors. As a result, the FDS system would be more adaptable to meet the diverse and complicated demands of preschoolers in various settings. To learn more about the developmental trajectory of preschoolers' mental health and the effects of early treatments informed by the FDS on their long-term consequences, longitudinal studies would be very helpful. Researchers may compare the FDS system's predictions and suggestions for children's mental health over time to see whether they are consistent and if the recommendations work. In the long run, these planned improvements to the FDS system's accuracy, robustness, and practicality would help preschool-aged children's mental health.

Conclusion

This paper analyzed preschoolers' mental health using the FDS. This system relied on the PPSC to track children's activities, and scores were computed according to the child's response. According to the crisp inputs, the fuzzification process is performed by applying the degree of membership value, which creates low, moderate, and high sets. The rules are developed for input combinations that identify the variables' relationships. This process reduces uncertainty while identifying a child's mental health status. After that, the de-fuzzification process is performed to generate recommendations concerning input. The system's excellence was analyzed using different metrics in which the system ensured 96.79% specificity, 97.98% accuracy, a 0.28% error rate, and 97.08% sensitivity. This process helps to improve preschoolers' mental efficiency and provides recommendations that maximize overall performance in the education system. However, the system requires training to improve the accuracy of recommendations for analyzing large data. In the future, optimization techniques will be incorporated to improve the efficiency of data analysis. Future research will concentrate on increasing the number and variety of participants to overcome the shortcomings of the present dataset and enhance the FDS system's generalizability. To ensure the sample represents the population, we will seek out people from low-income families, rural locations, and varied cultural backgrounds. This addition may better capture particular behavioural patterns, parenting techniques, and socio-environmental variables that impact preschoolers' mental health. Future research can rectify these shortcomings by using stratified sample methods to guarantee inclusiveness, utilizing longitudinal designs to monitor developmental trajectories, and engaging with various populations to understand preschoolers' mental health better.

Data availability

The data used and/or analysed during the current study available from the corresponding author on reasonable request.

Annexure

Q. No.	Questions	Answer options
1	Is complains of aches and pains	a) Never (b) Sometimes (C) Often
2	Is child spending more time alone	a) Never (b) Sometimes (C) Often
3	Tires easily has little energy	a) Never (b) Sometimes (C) Often
4	Fidgety, unable to sit still	a) Never (b) Sometimes (C) Often
5	Has problem with teacher	a) Never (b) Sometimes (C) Often
6	Less interested in school	a) Never (b) Sometimes (C) Often
7	Act as if driven by a motor	a) Never (b) Sometimes (C) Often
8	Daydreams too much	a) Never (b) Sometimes (C) Often
9	Distracted easily	a) Never (b) Sometimes (C) Often
10	Is afraid of new situations	a) Never (b) Sometimes (C) Often
11	Feels sad and unhappy	a) Never (b) Sometimes (C) Often
12	Is irritable and angry	a) Never (b) Sometimes (C) Often
13	Feels hopeless	a) Never (b) Sometimes (C) Often
14	Has trouble concentrating	a) Never (b) Sometimes (C) Often

Q. No.	Questions	Answer options
15	Less interested in friends	a) Never (b) Sometimes (C) Often
16	Fights with other children	a) Never (b) Sometimes (C) Often
17	Absent from school	a) Never (b) Sometimes (C) Often
18	School grades dropping	a) Never (b) Sometimes (C) Often
19	Is down on him or herself	a) Never (b) Sometimes (C) Often
20	Visits the doctor with doctor finding nothing wrong	a) Never (b) Sometimes (C) Often
21	Has trouble in sleeping	a) Never (b) Sometimes (C) Often
22	Worries a lot	a) Never (b) Sometimes (C) Often
23	Wants to be with you more than before	a) Never (b) Sometimes (C) Often
24	Feels he or she is bad	a) Never (b) Sometimes (C) Often
25	Take unnecessary risk	a) Never (b) Sometimes (C) Often
26	Get hurt frequently	a) Never (b) Sometimes (C) Often
27	Seems to be having less fun	a) Never (b) Sometimes (C) Often
28	Act younger than children his or her age	a) Never (b) Sometimes (C) Often
29	Does not listen to rules	a) Never (b) Sometimes (C) Often
30	Does not show feelings	a) Never (b) Sometimes (C) Often
31	Does not understand other peoples feeling	a) Never (b) Sometimes (C) Often
32	Teases other	a) Never (b) Sometimes (C) Often
33	Blames other for his or her troubles	a) Never (b) Sometimes (C) Often
34	Takes things that do not belong to him or her	a) Never (b) Sometimes (C) Often
35	Refuse to share	a) Never (b) Sometimes (C) Often

Note: The above questionaries are collected from “Paediatric Symptom Checklist (PPSC)” that used to understand the child mental health on various situation.

Received: 26 September 2024; Accepted: 28 March 2025
Published online: 10 April 2025

References

1. Malti, T. Children and violence: nurturing social-emotional development to promote mental health. *Social Policy Rep.* **33** (2), 1–27 (2020).
2. LaBelle, B. Positive outcomes of a social-emotional learning program to promote student resiliency and address mental health. *Contemp. School Psychol.* **27** (1), 1–7 (2023).
3. Thongseiratch, T., Leijten, P. & Melendez-Torres, G. J. Online parent programs for children’s behavioral problems: A meta-analytic review. *Eur. Child Adolesc. Psychiatry*. **29**, 1555–1568 (2020).
4. Chaidi, I. & Drigas, A. Parents’ views questionnaire for the education of emotions in autism spectrum disorder in a Greek context and the role of ICTs. *Technium Soc. Sci. J.* **33**, 73 (2022).
5. Ye, J. Pediatric mental and behavioral health in the period of quarantine and social distancing with COVID-19. *JMIR Pediatr. Parent.*, **3**(2), e19867. (2020).
6. Pelaez, M. & Novak, G. Returning to school: separation problems and anxiety in the age of pandemics. *Behav. Anal. Pract.* **13**, 521–526 (2020).
7. Agnafors, S., Torgerson, J., Rusner, M. & Kjellström, A. N. Injuries in children and adolescents with psychiatric disorders. *BMC Public. Health*. **20** (1), 1–10 (2020).
8. Muris, P. & Ollendick, T. H. Selective mutism and its relations to social anxiety disorder and autism spectrum disorder. *Clin. Child Fam. Psychol. Rev.* **24**, 294–325 (2021).
9. Abdivalievna, A. N. Psychodiagnostics of children with attention deficiency syndrome and hyperactivity. *ACADEMICIA: Int. Multidisciplinary Res. J.* **11** (3), 2352–2355 (2021).
10. Chevance, A. et al. Ensuring mental health care during the SARS-CoV-2 epidemic in France: A narrative review. *L’encephale* **46** (3), 193–201 (2020).
11. Creswell, C., Waite, P. & Hudson, J. Practitioner review: anxiety disorders in children and young people - assessment and treatment. *J. Child Psychol. Psychiatry*. **61** (6), 628–643 (2020).
12. Vasileva, M., Graf, R. K., Reinelt, T., Petermann, U. & Petermann, F. Research review: A meta-analysis of the international prevalence and comorbidity of mental disorders in children between 1 and 7 years. *J. Child Psychol. Psychiatry*. **62** (4), 372–381 (2021).
13. Tate, A. E. et al. Predicting mental health problems in adolescence using machine learning techniques. *PloS One*, **15**(4), e0230389. (2020).
14. Aleem, S. et al. Machine learning algorithms for depression: diagnosis, insights, and research directions. *Electronics* **11** (7), 1111 (2022).
15. Ntakolia, C. et al. An explainable machine learning approach for COVID-19’s impact on mood States of children and adolescents during the first lockdown in Greece. *Healthcare* **10** (1), 149 (2022, January).
16. Rasheduzzaman, M., Al Mamun, F., Faruk, M. O., Hosen, I. & Mamun, M. A. Depression in Bangladeshi university students: the role of sociodemographic, personal, and Familial psychopathological factors. *Perspect. Psychiatr. Care.* **57** (4), 1585–1594 (2021).
17. Zhuang, W., Chen, C. & Lyu, L. When foundation model Meets federated learning: motivations, challenges, and future directions. *ArXiv Preprint arXiv*. **23** (6), 15546 (2023).
18. Hassan, M. M. & Mokhtar, H. M. AutismOnt: an ontology-driven decision support for autism diagnosis and treatment. *Egypt. Inf. J.* **23** (1), 95–103 (2022).

19. Andermo, S. et al. School-related physical activity interventions and mental health among children: a systematic review and meta-analysis. *Sports Medicine-Open*. **6** (1), 1–27 (2020).
20. Dehghandar, M., Ahmadi, G. & AghebatbeenMonfared, H. Designing a fuzzy expert system for diagnosis and prediction of metabolic syndrome in children and adolescents. *Health Manage. Inform. Sci.* **8** (2), 79–89 (2021).
21. Gui, J. & Suh, J. Analysis of graphic perception education for young children based on fuzzy clustering analysis. *Computational Intelligence and Neuroscience*, 2022. (2022).
22. Liu, J. Research on the model of children's health assessment based on behavioral characteristics. *Highlights Sci. Eng. Technol.* **2**, 30–36 (2022).
23. Liu, Y., Chen, C., Alotaibi, R. & Shorman, S. M. Study on audio-visual family restoration of children with mental disorders based on the mathematical model of fuzzy comprehensive evaluation of differential equation. *Appl. Math. Non-linear Sci.* **7** (2), 307–314 (2021).
24. Qasrawi, R., Polo, S. P. V., Al-Halawa, D. A., Hallaq, S. & Abdeen, Z. Assessment and prediction of depression and anxiety risk factors in schoolchildren: machine learning techniques performance analysis. *JMIR Formative Res.*, **6**(8), e32736. (2022).
25. Al-shami, T. M. (2, 1)-Fuzzy sets: properties, weighted aggregated operators and their applications to multi-criteria decision-making methods. *Complex. Intell. Syst.* **9** (2), 1687–1705 (2023).
26. Al-shami, T. M., Alcantud, J. C. R. & Mhemdi, A. New generalization of fuzzy soft sets:(a, b)-Fuzzy soft sets. *Aims Math.* **8** (2), 2995–3025 (2023).
27. Ibrahim, H. Z., Al-shami, T. M., Arar, M. & Hosny, M. kmn-Rung picture fuzzy information in a modern approach to multi-attribute group decision-making. *Complex. Intell. Syst.*, 1–21. (2023).
28. Khabbaz, A., Fateh, M., Pouyan, A. & Rezvani, M. Designing a serious game for children with autism using reinforcement learning and fuzzy logic. *J. AI Data Min.* **11** (3), 375–390 (2023).
29. Giveki, D. Human action recognition using an optical flow-gated recurrent neural network. *Int. J. Multimedia Inform. Retr.* **13** (3), 29 (2024).
30. Fard, M. G., Montazer, G. A. & Giveki, D. A novel fuzzy logic-based method for modeling and recognizing Yoga pose. In *2023 9th International Conference on Web Research (ICWR)* (pp. 1–6). IEEE. (2023), May.
31. Sheldrick, R. C. et al. The preschool pediatric symptom checklist (PPSC): development and initial validation of a new social/emotional screening instrument. *Acad. Pediatr.* **12** (5), 456–467 (2012).

Author contributions
Xinyue Li wrote and revised this manuscript.

Funding
This study has no funding.

Declarations

Competing interests
The authors declare no competing interests.

Ethics approval and consent to participate
This study complies with ethical standards and is approved by the Scientific Research Ethics Committee of Graduate School in Philippine Women's University (approval number: PWU-G- 2022 - 114). It was performed in accordance with relevant guidelines and regulations. It obtained the informed consent of all human participants. For children, the permission of the guardian was obtained.

Additional information
Correspondence and requests for materials should be addressed to X.L.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.