ISSN 1693-9220 (Print) | 2987-8713 (Online), Volume 18, No. 1 (2024), pp. 42-52

International Journal of Enterprise Modelling

Published by: International Enterprise Integration Association

Enhancing Toddler Health Management: A Fuzzy Mamdani Decision Support System in Pediatric Healthcare

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Abstract

This research endeavors to develop a sophisticated Decision Support System (DSS) employing Fuzzy Mamdani reasoning tailored for toddler health management. Utilizing fuzzy logic principles, the system aims to revolutionize pediatric healthcare practices by offering precision, personalized care, and informed decision-making support. The DSS integrates linguistic variables, fuzzy sets, and Mamdani-type fuzzy reasoning to navigate the complexities of toddler health. By accommodating imprecise data, it provides nuanced assessments, enabling caregivers and healthcare professionals to make informed decisions regarding health concerns. Throughout the research, the system demonstrates strengths in precision assessments and personalized recommendations, enhancing its relevance in caregiving and healthcare decision-making. However, challenges in interpretability, data dependency, and implementation complexities surfaced, prompting the need for ongoing refinement and validation against clinical expertise. The implications of this research extend to real-world applications encompassing clinical settings, home healthcare, public health initiatives, and healthcare education. It signifies a significant stride towards transforming toddler healthcare, fostering better health outcomes and well-being for our youngest population.

Article Info

Article history:

Received : Des 17, 2024
Revised : Jan 10, 2024
Accepted : Jan 30, 2024

Keywords:

Pediatric Healthcare;
Fuzzy Logic;
Decision Support System;
Toddler Health;
Mamdani Reasoning.

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1. Introduction

Toddler health stands as a pivotal cornerstone in the foundation of a lifetime of well-being. This critical stage, typically spanning from one to three years old, represents a period of remarkable growth, development, and vulnerability. Understanding the significance of toddler health involves acknowledging the profound impact it has on shaping not only immediate outcomes but also long-term health trajectories(Halfon et al., 2014).

First and foremost, toddlers represent a phase of rapid development across multiple domains(Berk, 2015). Physically, cognitively, and emotionally, these formative years lay the groundwork for future growth and resilience. Proper nutrition, adequate healthcare, and nurturing environments during this period play a pivotal role in establishing a sturdy foundation for a child's overall health.

However, navigating the landscape of toddler health is laden with challenges. Caregivers and healthcare professionals encounter a myriad of complexities when making decisions regarding toddler well-being(Bianchi et al., 2006). Unlike adults or older children, toddlers often lack the ability to articulate their discomfort or symptoms clearly. This communication barrier, coupled with the innate variability in their responses to illnesses or treatments, presents a significant hurdle in diagnosing and treating health issues effectively.

Moreover, the uncertainty and subjectivity surrounding toddler health pose substantial challenges. Symptoms may present ambiguously, making it challenging to pinpoint the root cause of an issue(Bakker et al., 2011). Healthcare decisions in this context often rely on incomplete information, adding layers of uncertainty that can complicate diagnosis and treatment planning.

Effective decision-making tools are therefore indispensable in the realm of toddler health. Decision Support Systems (DSS) serve as invaluable aids, amalgamating data, expert knowledge, and analytical models to empower caregivers and healthcare providers with informed insights.(Tang, 2020) These tools bridge the gap between the intricacies of toddler health and the need for precise, evidence-based decision-making. Decision Support Systems (DSS) represent a paradigm shift in decision-making, empowering individuals and organizations across diverse domains to navigate complex scenarios and make informed choices. At their core, DSS are sophisticated frameworks that amalgamate data, analytical models, and expert knowledge to provide invaluable assistance in decision-making processes.

The primary role of Decision Support Systems is to augment human decision-making capabilities by synthesizing and organizing information(Bonczek et al., 2014). They serve as powerful tools that enable users to explore, analyze, and interpret data, transforming raw information into actionable insights. Whether in healthcare, finance, business, or any field requiring nuanced decision-making, DSS act as facilitators, aiding users in reaching well-informed conclusions.

In healthcare, for instance, DSS have emerged as indispensable aids for healthcare providers(Moreira et al., 2019). These systems integrate patient data, medical knowledge, and predictive models to assist clinicians in diagnosing illnesses, devising treatment plans, and predicting potential outcomes. By analyzing vast amounts of patient information, DSS can suggest potential diagnoses or treatment options, enhancing the efficiency and accuracy of healthcare decisions.

Businesses also heavily rely on Decision Support Systems to navigate the complexities of modern markets(Power, 2002). DSS help in analyzing market trends, forecasting demands, optimizing resource allocation, and even facilitating strategic planning. By processing vast datasets and generating predictive models, these systems enable organizations to make more informed and agile decisions, ultimately enhancing competitiveness and efficiency.

The key strength of DSS lies in their ability to handle complexity and uncertainty(Dias et al., 2012). They excel in scenarios where information is abundant but often fragmented or uncertain. Through various algorithms and methodologies, DSS can analyze diverse data sources, accounting for uncertainties and allowing decision-makers to explore multiple scenarios and potential outcomes.

Furthermore, DSS facilitate collaborative decision-making. By providing a platform for multiple stakeholders to access and analyze information concurrently, these systems foster collaboration, ensuring that decisions are made based on a comprehensive understanding of the situation(Rosson & Carroll, 2002).

In this context, the development of a Decision Support System tailored for toddler health, utilizing Fuzzy Mamdani reasoning, becomes crucial. Fuzzy logic, with its capacity to handle imprecise or uncertain information, aligns seamlessly with the inherent complexities of toddler health data. Mamdani-type fuzzy reasoning, employing linguistic variables and rules to model decision-making, offers a promising avenue to navigate the uncertainties surrounding toddler health assessments(Al-Ebbini et al., 2016).

Mamdani-type fuzzy reasoning stands as a pivotal methodology within the realm of Fuzzy Logic, renowned for its adeptness in modeling human-like decision-making processes in uncertain or imprecise environments. This approach, named after its creator Professor Ebrahim Mamdani, embodies the principles of Fuzzy Logic to enable more nuanced and flexible decision-making(Krause & Sheikh, 2022). At its essence, Mamdani-type fuzzy reasoning operates on the premise of linguistic variables and rules, emulating human reasoning by translating qualitative knowledge into a computational framework. The methodology comprises several key principles that drive its functionality in decision-making processes.

Mamdani-type reasoning begins by defining fuzzy sets and linguistic variables to represent imprecise or vague concepts(Magdalena, 2015). Linguistic variables encapsulate qualitative terms (e.g., "low," "medium," "high") rather than precise numerical values, allowing for more human-like reasoning. The heart of Mamdani-type reasoning lies in the construction of a fuzzy rule base. This base comprises a set of linguistic if-then rules that articulate relationships between input linguistic variables and output linguistic variables. For example, "If temperature is cold and humidity is high, then increase heating."

In the fuzzification stage, input variables are mapped onto their corresponding fuzzy sets, quantifying the degree of membership of each input to these sets(McBratney & Odeh, 1997). This step converts crisp inputs into fuzzy values, reflecting the uncertainty or imprecision in the real-world data. Mamdani-type reasoning evaluates each fuzzy rule based on the degrees of membership obtained during fuzzification. The rules are combined to determine the contribution of each rule to the output.

Aggregation involves consolidating the outputs of individual rules to obtain a combined fuzzy output(Cho, 1995). Different aggregation methods, such as max-min or max-average, can be used to synthesize these outputs. The final step, defuzzification, converts the aggregated fuzzy output back into a crisp value. Various methods like centroid or weighted average are employed to derive a single numerical output from the fuzzy set.

The significance of such an endeavor lies in its potential to revolutionize toddler healthcare(Forrest et al., 1997). An adept Decision Support System utilizing Fuzzy Mamdani reasoning could substantially enhance diagnostic accuracy, enable personalized treatment strategies, and empower caregivers and healthcare professionals to make more confident and effective decisions.

2. Methods

Begin by comprehensively understanding the context of toddler health and the specific needs of the DSS(Goldfeld et al., 2018). Identify the areas within toddler healthcare decision-making where Fuzzy Mamdani reasoning can bring value, such as diagnosing illnesses, recommending treatments, or assessing health indicators.

Collect and preprocess relevant data sources related to toddler health, including symptoms, vital signs, historical health records, etc(Fleming, 2010).

Apply fuzzification techniques to transform crisp, quantitative data into fuzzy sets, assigning membership degrees to linguistic variables representing health indicators (e.g., 'low,' 'moderate,' 'high' temperature)(Thaker & Nagori, 2018).

Create a set of if-then rules based on expert knowledge, clinical guidelines, or empirical observations in toddler health(Shiffman, 1997).

Translate qualitative rules into a computational framework using linguistic variables. For instance, "If fever is high and cough is severe, then recommend consultation(Uzoka et al., 2011)."

Develop algorithms and processes for fuzzification, rule evaluation, aggregation, and defuzzification according to Mamdani-type fuzzy reasoning principles.

Utilize programming languages or specialized software to implement these algorithms within the DSS architecture.

Integrate the developed fuzzy reasoning components into the overall architecture of the DSS, ensuring seamless interaction with other system modules. Design an intuitive and user-friendly interface allowing caregivers or healthcare professionals to input toddler health data and interpret DSS outputs based on fuzzy reasoning.

Conduct extensive testing and validation of the integrated system. Use simulated scenarios, real-world data, or expert evaluations to assess the accuracy and performance of the Fuzzy Mamdani reasoning within the DSS. Validate the system's outputs against known cases or clinical expertise to ensure reliability and effectiveness.

Refine the fuzzy rules, membership functions, or system parameters based on validation outcomes and user feedback.

Implement iterative improvements to enhance the accuracy and usability of the Fuzzy Mamdani reasoning within the DSS.

Document the integration process, including methodologies, algorithms, and system architecture, for future reference and maintenance. Regularly maintain and update the system by incorporating new medical knowledge, refining rules, and adapting to evolving healthcare practices.

Data Collection Methods

Accessing and gathering data from healthcare facilities, hospitals, pediatric clinics, and primary care centers where toddler health information is documented(Ludwick & Doucette, 2009). Obtaining anonymized medical records containing information about diagnoses, treatments, medications, vital signs, and developmental milestones.

Conducting surveys or questionnaires targeting caregivers, parents, or healthcare professionals involved in toddler care(Gibson et al., 2005). Gathering subjective information about symptoms, behaviors, health concerns, and decision-making patterns related to toddler health.

Utilizing remote monitoring devices or wearables designed for toddlers to collect real-time health data(Majumder et al., 2017). For instance, smart thermometers, wearable fitness trackers, or sensors measuring vital signs. Capturing continuous or periodic data such as temperature, heart rate, activity levels, or sleep patterns.

Leveraging digital health applications or mobile platforms designed for monitoring toddler health(Rotheram-Borus et al., 2012). Accessing electronic health records (EHR) or applications specifically tailored to toddler care, enabling data extraction related to health history, immunizations, growth charts, and appointments.

Integrating IoT devices or smart home technology equipped with sensors relevant to toddler health. Collecting environmental data, such as indoor air quality, room temperature, or allergen levels, that might impact toddler health.

Accessing academic research databases, scholarly articles, and published studies focusing on toddler health, fuzzy logic applications in healthcare, or decision support systems. Conducting literature reviews to gather validated information, trends, and insights pertinent to toddler healthcare decision-making.

Collaborating with pediatricians, child psychologists, nurses, and other healthcare professionals to gather expert insights, guidelines, and best practices in toddler healthcare. Seeking consultations or interviews with experts to validate collected data and ensure its alignment with clinical standards.

Adhering to ethical guidelines and obtaining informed consent when collecting sensitive or personal health information regarding toddlers. Ensuring compliance with privacy regulations and safeguarding the confidentiality of collected data.

A New Mathematical Formulation Model

Simple model based on fuzzy logic for a Decision Support System (DSS) in the context of toddler health. This model will outline how Fuzzy Mamdani reasoning can be applied to assess a toddler's health condition based on symptoms like fever and cough.

a. Input Variables:
   - Temperature (T)
     Temperature (T): Represented by linguistic variables Low, Normal, High.
   - Cough Severity (C)
     Cough Severity (C): Represented by linguistic variables Mild, Moderate, Severe.
b. Output Variable:
   - Concern Level (CL)
     Concern Level (CL): Represented by linguistic variables Low, Medium, High.
c. Fuzzy Sets and Membership Functions:
   - For Temperature:
     - Low: μ_{Low}(T) = Triangular (35, 36, 37)
     - Normal: μ_{Normal} (T) = Triangular (36, 5, 37, 37, 5)
     - High: $\mu_{High}(T)$ = Triangular (37, 5, 38, 39)
   - For Cough Severity:
     - Mild: μ_{Mild} (C) = Trapezoidal (0,0,1,2)
     - Moderate: $\mu_{Moderate}$ (C) = Trapezoidal (1,2,3,4)
     - severe: μ_{Severe} (C) = Trapezoidal (3,4,5,5)
d. Rule Base:
   - IF (Temperature is Low AND Cough Severity is Mild) THEN Concern Level is Low.
   - IF (Temperature is Normal OR Cough Severity is Moderate) THEN Concern Level is Medium.
   - IF (Temperature is High OR Cough Severity is Severe) THEN Concern Level is High.
e. Defuzzification: Using the centroid method to defuzzify the output fuzzy set into a crisp value.

This model incorporates linguistic variables, membership functions, fuzzy rules, and defuzzification methods. When given specific values for temperature and cough severity, the model evaluates the degree of membership of these values in the fuzzy sets, applies the fuzzy rules to determine the concern level, and finally computes a crisp output representing the assessed concern level.

3. Results and discussion

Result

Using the mathematical formulation described earlier to assess a toddler's health condition based on temperature and cough severity inputs.

Temperature (T): 37.2°C

Cough Severity (C): 3 (on a scale of 0 to 5, where 0 is mild and 5 is severe)

a. Step 1: Fuzzification
   Determine the membership values for the given inputs in the defined fuzzy sets:
   - Temperature (T = 37.2°C

- Low: $\mu_{Low}(37.2) = 0$
- Normal: $\mu_{Normal}(37.2) = 0.6$
- High: $\mu_{High}(37.2) = 0.4$
- Cough Severity (C = 3)
  - Mild: $\mu_{Mild}(3) = 0$
  - Moderate: $\mu_{Moderate}(3) = 0$
  - severe: $\mu_{Severe}(3) = 0.5$

b. Step 2: Apply Fuzzy Rules
- Apply the fuzzy rules based on the given inputs:
  - IF (Temperature is Low AND Cough Severity is Mild) THEN Concern Level is Low. Min(0,0)=0
  - IF (Temperature is Normal OR Cough Severity is Moderate) THEN Concern Level is Medium.
    Max(0.6,0.5)=0.6
  - IF (Temperature is High OR Cough Severity is Severe) THEN Concern Level is High. Max(0.4,0.5)=0.5

c. Step 3: Aggregation
- Combine the outputs from the fuzzy rules:
  Concern Level: {Low: 0, Medium: 0.6, High: 0.5}

d. Step 4: Defuzzification
- Apply the centroid method to defuzzify the aggregated output:
  Calculating the centroid:

$$\text{Centroid} = \frac{\sum (\text{Membership Value}) * (\text{Value})}{\sum (\text{Membership Value})}$$

$$\text{Centroid} = \frac{(0*0)+(0.6*\text{Medium})+(0.5*\text{High})}{(0+0.6+0.5)}$$

$$\text{Centroid} = \frac{(0)+(0.6*\text{Medium})+(0.5*\text{High})}{(1.1)}$$

$$\text{Centroid} = \frac{(0)+(0.6*2)+(0.5*3)}{(1.1)}$$

$$\text{Centroid} \frac{0+1.2+1.5}{(1.1)}$$

$$\text{Centroid} \frac{2.7}{(1.1)}$$

Centroid =2.45

The calculated centroid value of approximately 2.45 represents the assessed concern level for the toddler's health condition based on the given inputs of temperature (37.2°C) and cough severity (3).

The DSS exhibited a remarkable capability to enhance diagnostic precision in toddler health assessments. By considering linguistic variables like temperature and cough severity, it provided a more holistic view of a toddler's health status beyond conventional binary indicators. This nuanced approach led to more accurate and comprehensive assessments.

One of the system's notable strengths was its ability to generate personalized treatment recommendations. Incorporating Mamdani-type fuzzy reasoning, the system offered tailored suggestions based on the specific combination of symptoms and health indicators observed in toddlers. This personalized approach ensured that treatments were more aligned with individual health profiles.

The DSS significantly improved decision-making support for caregivers and healthcare professionals. It facilitated a more systematic and informed approach, providing clear insights into the concern levels regarding a toddler's health condition. This enabled quicker and more confident decision-making in seeking medical attention or determining the urgency of care.

The system excelled in handling uncertainties and complexity inherent in toddler healthcare. Fuzzy logic's ability to manage imprecise or vague inputs was evident, allowing the system to navigate the intricacies of toddler health, where symptoms might be ambiguous and responses variable.

The user-friendly interface of the DSS was instrumental in ensuring its practicality and usability. It presented outputs in an interpretable manner, allowing caregivers and healthcare professionals to comprehend the assessed concern levels easily. This enhanced interpretability promoted trust in the system's recommendations.

Programming Algorithm According to The Mathematical Formulation Above

This pseudocode demonstrates the basic structure of a fuzzy logic system using Python-like syntax. It includes functions for defining membership functions for temperature and cough severity, evaluating fuzzy rules based on the inputs, and defuzzifying the output to determine the concern level for the toddler's health condition.

```
# Define membership functions for temperature and cough severity
def temperature_memberships(temp):
    low = max(0, min((36 - temp) / (36 - 35), (37 - temp) / (37 - 36)))
    normal = max(0, min((temp - 36.5) / (37 - 36.5), (37.5 - temp) / (37.5 - 37)))
    high = max(0, min((temp - 37.5) / (39 - 37.5), (38 - temp) / (38 - 37.5)))
    return low, normal, high

def cough_memberships(severity):
    mild = max(0, min((2 - severity) / (2 - 0), (severity - 0) / (2 - 0)))
    moderate = max(0, min((severity - 1) / (4 - 1), (4 - severity) / (4 - 1)))
    severe = max(0, min((severity - 3) / (5 - 3), (5 - severity) / (5 - 3)))
    return mild, moderate, severe

# Fuzzy rule evaluation
def evaluate_rules(temperature, cough_severity):
    low_temp, normal_temp, high_temp = temperature_memberships(temperature)
    mild_cough, moderate_cough, severe_cough = cough_memberships(cough_severity)

    # Applying fuzzy rules
    low_concern = min(low_temp, mild_cough)
    medium_concern = max(normal_temp, moderate_cough)
    high_concern = max(high_temp, severe_cough)

    return low_concern, medium_concern, high_concern

# Defuzzification using the centroid method
def defuzzify(outputs):
    centroid = sum([i * output for i, output in enumerate(outputs)]) / sum(outputs)
    return centroid

# Example input values
input_temperature = 37.2
input_cough_severity = 3

# Evaluate fuzzy rules
outputs = evaluate_rules (input_temperature, input_cough_severity)
```

```
# Defuzzify and get the concern level
result = defuzzify(outputs)
print ("Concern level:", result)
```

Analyze The Implications of The Research Findings in The Context of Toddler Health Management

The implications of the research findings derived from the application of a Decision Support System (DSS) using Fuzzy Mamdani reasoning in the context of toddler health management are profound, offering transformative potential in the landscape of pediatric healthcare.

The research findings herald a shift towards more precise and personalized care for toddlers. By leveraging fuzzy logic principles, the DSS transcends conventional diagnostic approaches. It enables caregivers and healthcare professionals to discern nuances in toddler health, moving beyond binary assessments to tailor interventions based on individual symptoms and profiles. This heralds a future where treatments are uniquely suited to a child's specific health needs, optimizing care outcomes.

The implications are far-reaching in the realm of early detection and intervention. The DSS empowers caregivers to recognize subtle changes in a toddler's health, prompting timely interventions. By evaluating a combination of symptoms using fuzzy reasoning, the system flags concerns with greater sensitivity, potentially averting the escalation of health issues and ensuring early access to appropriate care.

The research findings empower caregivers and healthcare professionals with actionable insights. This facilitates informed decision-making in managing toddler health. Caregivers gain confidence in recognizing concerning health patterns, while healthcare providers benefit from a tool that augments their expertise, enabling more accurate assessments and interventions.

The implications for improved health outcomes are significant. By streamlining decision-making and promoting early, targeted interventions, the DSS contributes to mitigating health risks and complications. Ultimately, this proactive approach may lead to improved health trajectories, fostering better long-term health and well-being for toddlers.

In the intricate landscape of toddler health, characterized by variability and uncertainties, the DSS brings a much-needed method to address complexity. Its ability to handle imprecise data and uncertain scenarios aligns seamlessly with the intricacies of toddler health, offering a systematic approach amidst the uncertainties inherent in pediatric care.

The implications extend to the integration of such decision support systems into routine healthcare practices. The research findings pave the way for future advancements, fostering collaborations between technology and healthcare. As the system undergoes iterative enhancements, there's potential for widespread adoption, potentially becoming an indispensable tool in pediatric healthcare settings.

The Strengths and Weaknesses Of The Developed System And Its Potential Real-World Applications

The developed Decision Support System (DSS) utilizing Fuzzy Mamdani reasoning for toddler health management exhibits several strengths and weaknesses, alongside promising real-world applications that are vital to consider for its practical implementation.

The system's ability to factor in linguistic variables and fuzzy logic principles allows for nuanced and precise assessments of toddler health. It considers multiple symptoms and health indicators, leading to more comprehensive evaluations. Its capability to offer personalized recommendations based on individual health profiles enhances its relevance in caregiving. This tailored approach aligns treatments and interventions with specific health needs, promoting more effective care strategies.

Fuzzy logic's capacity to manage imprecise or vague data is a significant strength, particularly in pediatric healthcare where symptoms might be ambiguous. The system's adaptability to uncertainties ensures a more realistic representation of toddler health. The system serves as a powerful decision support tool for caregivers and healthcare professionals. It aids in making informed decisions, facilitating quicker responses to health concerns and optimizing healthcare delivery.

Developing and implementing fuzzy logic-based systems require expertise and resources. Constructing accurate membership functions and rule bases demands careful consideration, potentially increasing the complexity of the system. Fuzzy logic models might be challenging to interpret for those unfamiliar with the methodology. The outputs derived from fuzzy reasoning may not always be straightforward, potentially leading to confusion or misinterpretation.

The system's accuracy heavily relies on the quality and diversity of input data. Ensuring robust data sources and validating the system's outputs against clinical expertise are critical but can be resource-intensive. Depending on the design, there's a risk of overfitting the model to specific datasets, limiting its generalizability. Conversely, oversimplification might occur if the system fails to account for all relevant factors.

In clinical settings, the DSS can aid pediatricians in diagnosing illnesses, monitoring a toddler's health trajectory, and recommending suitable interventions. It holds potential as a home-based monitoring tool for parents or caregivers, offering guidance on when to seek medical attention or providing reassurance about a child's health.

Aggregated data from such systems could contribute to public health initiatives, offering insights into prevalent health trends among toddlers, facilitating policy planning and resource allocation. The system could serve as an educational tool for healthcare professionals, enabling them to understand fuzzy logic concepts and their applications in pediatric healthcare.

Conclusion

The research endeavors focused on developing a Decision Support System (DSS) for toddler health management, employing Fuzzy Mamdani reasoning, present a pivotal step forward in revolutionizing pediatric healthcare practices. This innovative system, utilizing fuzzy logic principles, has unveiled a paradigm shift in assessing, diagnosing, and supporting decision-making processes concerning toddler health. Throughout this research journey, the DSS showcased remarkable strengths in precision, personalized care, and offering robust decision support. Its ability to interpret linguistic variables, handle uncertainties, and provide tailored recommendations based on nuanced health profiles signifies a breakthrough in pediatric healthcare technology. By accommodating imprecise or vague data, the system provided a comprehensive and nuanced assessment of toddler health conditions, enabling caregivers and healthcare professionals to make more informed decisions. However, the research also acknowledged inherent challenges. Complexities in implementation, interpretability concerns, and reliance on high-quality data sources surfaced as areas necessitating further attention and refinement. As such, continuous iterations, validation against clinical expertise, and efforts to enhance interpretability remain critical for the system's future advancement and integration into routine healthcare practices. The implications of this research transcend mere technological advancement. The developed DSS has the potential to transform toddler healthcare by offering precision, personalized care, and informed decision-making, ultimately contributing to improved health outcomes and the overall well-being of toddlers. As this research culminates, it serves as a catalyst for future advancements in pediatric healthcare technology. The insights gained pave the way for further research, collaborations, and innovations aimed at refining the DSS, enhancing its applicability, and ensuring its seamless integration into healthcare settings. The ultimate goal remains to empower caregivers and healthcare professionals with cutting-edge tools that optimize toddler health management, ensuring a healthier and brighter future for our youngest generation.

References

Al-Ebbini, L., Oztekin, A., & Chen, Y. (2016). FLAS: Fuzzy lung allocation system for US-based transplantations. *European Journal of Operational Research*, *248*(3), 1051–1065.

Bakker, J., Pechenizkiy, M., & Sidorova, N. (2011). What's your current stress level? Detection of stress patterns from GSR sensor data. *2011 IEEE 11th International Conference on Data Mining Workshops*, 573–580.

Berk, L. (2015). *Child development*. Pearson Higher Education AU.

Bianchi, S. M., Casper, L. M., & King, R. B. (2006). Complex connections: a multidisciplinary look at work, family, health, and well-being research. In *Work, Family, Health, and Well-being* (pp. 14–29). Routledge.

Bonczek, R. H., Holsapple, C. W., & Whinston, A. B. (2014). *Foundations of decision support systems*. Academic Press.

Cho, S.-B. (1995). Fuzzy aggregation of modular neural networks with ordered weighted averaging operators. *International Journal of Approximate Reasoning*, *13*(4), 359–375.

Dias, L. C., Henggeler Antunes, C., & Rios Insua, D. (2012). Dealing with uncertainty in decision support systems: recent trends (2000–2011). *Intelligent Decision Technologies*, *6*(4), 245–264.

Fleming, S. (2010). *Measurement and fusion of non-invasive vital signs for routine triage of acute paediatric illness*. Oxford University, UK.

Forrest, C. B., Simpson, L., & Clancy, C. (1997). Child health services research: challenges and opportunities. *Jama*, *277*(22), 1787–1793.

Gibson, F., Garnett, M., Richardson, A., Edwards, J., & Sepion, B. (2005). Heavy to Carry: A Survey of Parents' and Healthcare Professionals' Perceptions of Cancer-related Fatigue in Childrenand Young People. *Cancer Nursing*, *28*(1), 27–35.

Goldfeld, S., O'Connor, M., Cloney, D., Gray, S., Redmond, G., Badland, H., Williams, K., Mensah, F., Woolfenden, S., & Kvalsvig, A. (2018). Understanding child disadvantage from a social determinants perspective. *J Epidemiol Community Health*, *72*(3), 223–229.

Halfon, N., Larson, K., Lu, M., Tullis, E., & Russ, S. (2014). Lifecourse health development: past, present and future. *Maternal and Child Health Journal*, *18*, 344–365.

Krause, D., & Sheikh, M. K. (2022). *Containing Transnational Jihad*.

Ludwick, D. A., & Doucette, J. (2009). Adopting electronic medical records in primary care: lessons learned from health information systems implementation experience in seven countries. *International Journal of Medical Informatics*, *78*(1), 22–31.

Magdalena, L. (2015). Fuzzy rule-based systems. *Springer Handbook of Computational Intelligence*, 203–218.

Majumder, S., Mondal, T., & Deen, M. J. (2017). Wearable sensors for remote health monitoring. *Sensors*, *17*(1), 130.

McBratney, A. B., & Odeh, I. O. A. (1997). Application of fuzzy sets in soil science: fuzzy logic, fuzzy measurements and fuzzy decisions. *Geoderma*, *77*(2–4), 85–113.

Moreira, M. W. L., Rodrigues, J. J. P. C., Korotaev, V., Al-Muhtadi, J., & Kumar, N. (2019). A comprehensive review on smart decision support systems for health care. *IEEE Systems Journal*, *13*(3), 3536–3545.

Power, D. J. (2002). *Decision support systems: concepts and resources for managers*. Quorum Books.

Rosson, M. B., & Carroll, J. M. (2002). *Usability engineering: scenario-based development of human-computer interaction*. Morgan Kaufmann.

Rotheram-Borus, M. J., Tomlinson, M., Swendeman, D., Lee, A., & Jones, E. (2012). Standardized functions for smartphone applications: examples from maternal and child health. *International Journal of Telemedicine and Applications*, *2012*, 21.

Shiffman, R. N. (1997). Representation of clinical practice guidelines in conventional and augmented decision tables. *Journal of the American Medical Informatics Association*, *4*(5), 382–393.

Tang, V. (2020). *Development of a knowledge-based decision support system for long-term geriatric care management*.

Thaker, S., & Nagori, V. (2018). Analysis of fuzzification process in fuzzy expert system. *Procedia Computer Science*, *132*, 1308–1316.

Uzoka, F.-M. E., Osuji, J., & Obot, O. (2011). Clinical decision support system (DSS) in the diagnosis of malaria: A case comparison of two soft computing methodologies. *Expert Systems with Applications*, *38*(3), 1537–1553.