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Proactive Medicine in Pediatric Health Management: A DIKWP (Data, Information, Knowledge, Wisdom, and Purpose) Semantic Framework

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Abstract

To shift pediatric care from reactive treatment to proactive health management, this study proposes a purpose-driven semantic framework based on the Data, Information, Knowledge, Wisdom, and Purpose (DIKWP) model. By leveraging artificial intelligence, the framework transforms raw health data into actionable wisdom aligned with each child's specific health goals. We present a system architecture centered on a DIKWP semantic graph and a cognitive reasoning engine to enable early interventions, personalized recommendations, and improved clinician-family collaboration. The framework is formalized using a semantic mathematical model, including a bidirectional cognitive mapping to bridge communication gaps between patients and clinicians. A use case demonstrates the system's ability to anticipate health issues and align decisions with patient-specific purposes. This approach introduces a paradigm for anticipatory and purpose-oriented pediatric care, aiming to improve health outcomes by making healthcare safer, more effective, and transparent.

Categories: Health Informatics, Safe and trustworthy AI in healthcare, Smart health and connected health
Keywords: dikwp framework, modern pediatric, health management, pediatric healthcare, pediatric ai system

Introduction

Pediatric healthcare has traditionally been reactive, addressing problems as they arise. Such reactive care often leads to delayed interventions and missed opportunities for prevention. To improve outcomes, there is a growing movement toward proactive medicine, emphasizing early detection, prevention, and health promotion. For example, the vision of "P4 medicine" (Predictive, Preventive, Personalized, Participatory) seeks to transform healthcare from reacting to diseases into actively maintaining wellness [1]. In pediatrics, a proactive approach means anticipating developmental or health issues and intervening before they escalate. However, achieving truly anticipatory care requires a paradigm shift to purpose-driven medicine - focusing on each patient's long-term health goals rather than only short-term disease management. This purpose-oriented philosophy aligns with patient-centered care, wherein clinicians collaborate with families to define and pursue health outcomes that matter most to the child.

A key enabler of proactive, purpose-driven care is artificial intelligence (AI). AI can continuously analyze health data (clinical records, growth metrics, sensor readings) to predict risks and recommend preventive actions. Unlike humans, AI can monitor numerous parameters in real-time and detect subtle patterns, allowing pediatric care to shift from episodic checkups to continuous oversight. Yet, current AI applications in pediatrics remain largely problem-specific (e.g., diagnosing illness from images) rather than integrated into a holistic, purpose-driven care strategy. Furthermore, many AI systems function as "black boxes", making recommendations without clear reasoning, which can erode clinician and parent trust. To address these gaps, we propose a purpose-driven semantic framework for proactive pediatric health management. This framework extends the classical Data, Information, Knowledge, Wisdom, and Purpose (DIKWP) model [2] - which describes how raw Data become Information, then Knowledge, then Wisdom (actionable insight) - by adding a top dimension of Purpose. The Purpose element explicitly represents the goals and desired outcomes guiding care decisions. By incorporating Purpose, every inference and recommendation made by the AI can be aligned with the child's and family's health objectives (e.g., "improve asthma control to enable school attendance"). This DIKWP model originates from recent research in AI and cognitive informatics [3] and provides a structured semantic approach to link low-level data processing with high-level healthcare goals [4].

Pediatric AI systems

In recent years, numerous AI systems have been developed to assist in pediatric healthcare [5]. These range from diagnostic algorithms (e.g., detecting pediatric pneumonia from chest X-rays) to personalized treatment recommendation engines. AI's ability to analyze vast datasets enables personalized medicine for children by tailoring treatments to individual characteristics like genetics, growth patterns, and medical history. For example, machine learning models can predict potential health issues before they arise by analyzing historical patient data and trends. This proactive analytics capability allows clinicians to implement preventive measures and early interventions, shifting care upstream to avoid serious illness. AI has also improved operational efficiency in pediatric care - automating administrative tasks and continuous patient monitoring - thereby freeing clinicians to spend more time on direct patient interaction. Remote monitoring solutions are particularly impactful in pediatrics: wearable sensors and telehealth platforms powered by AI enable continuous tracking of a child's vital signs and symptoms outside the hospital. This facilitates ongoing care for chronic conditions (like asthma or diabetes) and timely alerts if a concerning pattern (e.g., abnormal heart rate or decreasing peak flow) is detected, often before a family would notice symptoms. Several studies and industry implementations have demonstrated improved outcomes using such AI tools. However, most existing pediatric AI applications focus on specific tasks (diagnosis, risk prediction, etc.) rather than providing an integrated, purpose-driven care continuum. Our work builds on these successes but proposes a unifying semantic framework to orchestrate AI's role toward overarching health goals rather than isolated outputs.

DIKWP theory in healthcare

The DIKW hierarchy (Data → Information → Knowledge → Wisdom) is a foundational model in informatics and knowledge management. It describes how raw data can be processed into meaningful information, then contextualized into knowledge, and finally distilled into wisdom (the insight to make sound decisions). In healthcare, DIKW has informed the design of clinical decision support systems and nursing informatics models, ensuring that data collection ultimately supports clinical wisdom for patient care [1]. Recently, researchers have argued for extending DIKW with a fifth level, Purpose [6], to capture the why behind decisions. Mei and Duan [7] introduced the DIKWP model in the context of artificial general intelligence and cognitive computing research, positing that an AI should not only compute optimal actions (wisdom) but also understand and align with the underlying purpose or goal of those actions [8]. In healthcare, this extension is highly pertinent: treatments and interventions should be evaluated not just on immediate effect but on whether they serve the patient's long-term purpose (health and quality-of-life goals). Some early applications of DIKWP in healthcare include modeling doctor-patient disputes and medical decision processes. These works highlight that many conflicts or errors arise from a lack of shared understanding of the goals or from missing "Purpose" context in communication. By incorporating Purpose as a first-class element in the knowledge framework, clinical systems can ensure that all recommendations explicitly tie back to patient-centered objectives. This approach resonates with the concept of purpose-oriented care in medicine, where patient priorities drive what care is appropriate [4]. Indeed, purpose-oriented care has been shown to catalyze better care integration and patient satisfaction by focusing on outcomes that patients value.

Explainable and trustworthy AI

For AI to be adopted in pediatric practice, transparency and explainability are critical. Clinicians and parents need to trust AI recommendations, especially when children's health is at stake. A lack of transparency in AI systems is often cited as a major barrier to clinical implementation, as healthcare providers must have confidence in the rationale behind the AI's suggestions [9]. Therefore, modern research in medical AI emphasizes Explainable AI - techniques that make AI's decision process interpretable to humans. In pediatric contexts, explainability is tied to ethical obligations: providers must be able to explain to parents why an AI-driven alert or diagnosis was made [10]. Various approaches (e.g., rule-based models, interpretable machine learning, and post-hoc explanation tools) have been explored to enhance trust in AI decisions [11]. Studies have found that when AI systems provide clear and relevant explanations, clinicians' trust and willingness to follow AI advice increase significantly [12]. Our proposed framework embeds explainability by design: the DIKWP semantic graph can be queried to trace how a raw data point (e.g., a sensor reading of nighttime coughing) propagated through information and knowledge layers to result in a wisdom-level recommendation (e.g., adjust asthma medication), and how that recommendation aligns with the patient's purpose (preventing asthma attacks to enable normal school attendance). By providing this trace, the system offers semantic transparency - every suggestion can be linked to supporting data, medical knowledge, and intended outcome.

Patient-centered and family-centered care

Patient-centered care is especially vital in pediatrics, where healthcare decisions involve not just the patient (child) but also parents or guardians [5]. This approach means treating patients and families as partners and respecting their preferences, needs, and values. In pediatric care models, this often manifests as family-centered care, emphasizing open communication, education, and shared decision-making with families [13]. Research has shown that aligning care with patient/family goals improves adherence and satisfaction [14]. For example, rather than a clinician unilaterally prescribing a treatment, a patient-centered approach would involve discussing the family's goals [15] (such as enabling the child to play sports) and jointly deciding on interventions that support those goals. AI systems must be designed to support, not hinder, such patient-centered interactions [10]. Our framework's explicit Purpose element inherently reinforces patient-centeredness: the Purpose node in the DIKWP graph can encode the family's goals and constraints, ensuring the AI's outputs are filtered or prioritized according to what is most relevant for the patient's life context. Furthermore, by making the AI's reasoning explainable [16], we facilitate shared decision-making - clinicians can convey AI insights to families in understandable terms, and families can provide feedback, thereby maintaining trust and alignment.

Materials And Methods

Methodology

We formalize the DIKWP semantic framework and outline the mathematical underpinnings that enable the system to map between patient and clinician cognitive spaces. We define each component of DIKWP - Data, Information, Knowledge, Wisdom, and Purpose - and describe their representations and transformations using semantic mathematics. We also introduce a model for bidirectional patient-clinician mapping, ensuring that the system mediates understanding between the subjective perspectives of families and clinicians.

DIKWP Component Definitions

Each element of DIKWP is a distinct semantic abstraction with a formal definition, as shown in Figure *1*. This formalization, which distinguishes between entities and the relationships that define their semantics [17], also introduces the concept of artificial consciousness at the higher levels of wisdom and purpose. The notion of consciousness in AI is a subject of active scientific debate [18], and in our framework, it represents the system's capacity for goal-driven self-awareness and ethical alignment.

Problem classification and DIKWP mapping: To address this, we first classify patient-clinician communication challenges into two categories: (1) Standard interpretation issues, which correspond to relatively direct mismatches at the Data and Information levels (e.g., terminology confusion, missing facts). (2) Cognitive misalignment issues, which correspond to higher-order semantic mismatches involving Wisdom and Purpose (e.g., goals, treatment rationales, long-term understanding).

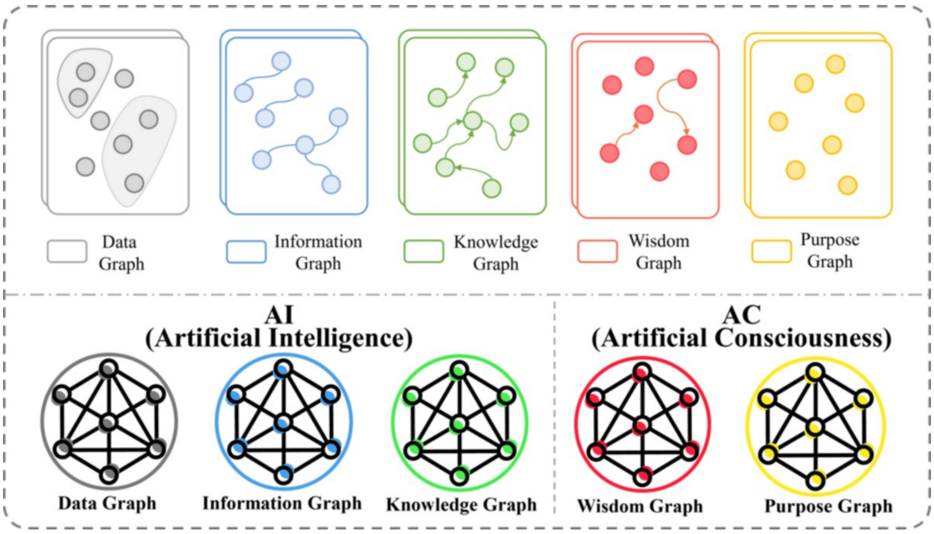

FIGURE 1: A conceptual diagram of the DIKWP model across cognitive spaces

DIKWP, Data, Information, Knowledge, Wisdom, and Purpose

Data represents the raw observations and measurements about the patient, as captured by sensors, medical devices, or manual entry. Formally, we define a Data element as a semantic object D_i that is a concrete manifestation of identical semantics within cognition [8]. This means that even a raw data point (e.g., a temperature reading of 38.2°C) is interpreted in the context of existing concepts ("fever") by the cognitive agent (the system or user). When processing data, we seek and extract the specific identical semantics that define that data. For example, when we see a flock of sheep, we classify them under the "sheep" concept because they share the identical semantics we have for "sheep", even if they differ in size or color. Similarly, a silicone arm might be identified as an 'arm' based on shared semantics like finger count and shape, but determined not to be a real arm due to the lack of a semantic like "the ability to rotate". We represent the set of data concepts as $D = \{d_1, d_2, ...\}$, where each d can be seen as a vector of features in a semantic space. For example, a single data point "cough frequency = 10/night" might have features linking it to the concept cough (sound pattern, frequency) in the system's ontology.

Data in isolation lacks meaning; it becomes meaningful through classification and matching against known concepts. Thus, the system's first step is to semantically tag and integrate data into the Concept Space (e.g., recognize that a pattern of coughing fits the concept of "nocturnal cough"). Mathematization: Each data concept is defined by a set of semantic features $F = \{f_1, f_2, \ldots\}$ that it shares with an ideal concept prototype. We denote a data concept as $d = \langle f_a, f_b, \ldots \rangle$ in a multi-dimensional semantic feature space. A Data Graph is then constructed linking data points that share semantic attributes.

Information is processed data - data imbued with context, relationships, or meaning. In DIKWP, this corresponds to the expression of different semantics [7]. It refers to the generation of new semantic associations by linking cognitive objects (data, information, etc.) based on a specific intent. For instance, combining the data "fever of 38.2°C" and "cough frequency 10/night" with temporal context yields the information "Child has had a high fever and frequent cough over the past 2 nights". This new element highlights the different semantic of a trend or co-occurrence, not just isolated facts. This can also be subjective; a patient's statement of feeling "low" is Information, but its "different semantic" (relative to their baseline) may be unknown to the listener, making it subjective. We formally consider an Information element I_j as a relational tuple or a graph pattern that connects data elements: $I_j : (D_a, D_b, relation)$. The system constructs Information Graphs by linking data nodes with annotated edges (e.g., temporal sequence, causal hint). These Information Graphs answer "what is happening?" in a richer sense than raw data, providing the building blocks for knowledge. In our example, an Information Graph might connect fever, cough, and time to represent a possible symptom cluster.

Knowledge in this framework is the understanding of patterns, rules, or models that explain the information. It corresponds to abstracting at least one complete semantic [8]. A Knowledge element could be a clinical rule, a probabilistic model, or an inferred concept. For example, the system might invoke pediatric medical knowledge that "fever + nocturnal cough is often associated with respiratory infection or asthma exacerbation". This is an abstraction of a complete semantic, similar to the generalized knowledge "all swans are white". We formally define Knowledge as transformations or mappings K:I → I or I → W that apply domain theory to information. Each piece of knowledge is represented in a Knowledge Graph, an ontological network of medical concepts (diseases, symptoms, treatments) and relationships. Our DIKWP graph includes a rich pediatric ontology - e.g., concept nodes for illnesses like "viral bronchitis", "pneumonia", or "asthma", each linked to symptom nodes like "fever", "cough", etc., and treatment nodes. Knowledge processing involves reasoning over this graph: given incoming information graphs, the system searches the Knowledge Graph for matching patterns or applicable rules (using semantic reasoners and probabilistic inference). Mathematically, knowledge can be encoded as logical implication rules (if X and Y then Z) or as learned functions (machine learning models) that map information to likely explanations. A key feature of our semantic mathematics is that knowledge elements carry a truth value or confidence, allowing the system to handle uncertainty (e.g., the association between "fever+cough" and bronchitis might have an 80% confidence).

Wisdom is understood as the actionable insight or decision - essentially, a context-aware recommendation or conclusion that directly informs what should be done [3]. Wisdom involves a value judgment step - evaluating what is the best course given multiple knowledge-derived options. This corresponds to integrating information related to ethics, social morals, humanity, and other individual or cultural cognitive values. Wisdom Graphs in the DIKWP graph represent decision pathways, linking a situation to possible actions and outcomes. Wisdom involves a value judgment step - evaluating what is the best course given multiple knowledge-derived options, possibly using patient-specific values (from Purpose) as criteria. We formalize wisdom generation as an optimization or selection function: $W = f_{wisdom}(K_{set}, C_{context})$, where W is the selected Wisdom (actionable insight), f_{wisdom} is the function that evaluates and chooses the best course of action, K_{set} is the set of applicable knowledge elements (e.g., { K_1, K_2,...}), and $C_{context}$ represents the specific constraints of the situation (e.g., patient preferences, resource limitations). This is where explainable AI techniques are crucial: the system might use a rule-based decision tree or an interpretable model to go from knowledge to wisdom, ensuring the rationale can be traced.

Purpose represents the goal or intent that drives decision-making. In our pediatric context, Purpose encodes the child's and family's health objectives (e.g., "maintain normal growth trajectory", "avoid hospitalization"). We formally model Purpose as a binary tuple (Input, Output), where Input captures the stakeholders' understanding of the current situation (a phenomenon or problem) and Goal (as Output) represents the desired outcome. Purpose thus bridges the gap between understanding and action - it frames why an action is chosen by linking it to a goal. Within the Concept Space, Purpose provides a mapping from an abstract need ("child is frequently missing school due to illness") to a concrete goal ("reduce illness frequency so the child can attend >90% school days this term"). We create a Purpose Graph that connects goals with relevant wisdom nodes and knowledge nodes. For example, a goal node "improve asthma control" would connect to wisdom nodes for "medication adherence" and "trigger avoidance strategies", and to knowledge nodes about asthma. The Purpose layer influences all lower layers by weighting and guiding them: data and information that are pertinent to the goals are prioritized, knowledge relevant to the purpose is highlighted, and when multiple wisdom options exist, the one best serving the Purpose is selected. In effect, purpose introduces a feedback loop - it continuously adjusts the system's reasoning so that the evolving understanding remains aligned with the end objectives. This dynamic alignment embodies purpose-driven intelligence in our framework.

Table *1* summarizes the DIKWP components with their roles and examples in a pediatric scenario (an asthma management context).

Component	Role in Framework	Example in Context
Data	Raw observations	Child's temperature is 38.2°C; cough count = 10/night.
Information	Processed data (contextualized)	Fever + frequent nocturnal cough over 2 nights (symptom trend).
Knowledge	Generalized medical understanding	Fever + night cough suggests possible asthma exacerbation or infection.
Wisdom	Actionable insight/decision	Recommend using preventive inhaler tonight and schedule doctor visit.
Purpose	Goal guiding decisions	Keep asthma under control so child can attend school and sleep well.

TABLE 1: DIKWP components in pediatric health management

DIKWP, Data, Information, Knowledge, Wisdom, and Purpose

Each component is rigorously defined within three cognitive spaces, as proposed by our semantic modeling approach: the Cognitive Space (the agent's internal conceptual state), the Concept Space (the abstract representation of concepts and categories), and the Semantic Space (the relationships between semantic units). A full formal treatment is beyond the scope of this paper, but intuitively: when new data arrive, the system interprets them through the Concept Space (matching to known concepts) and the Semantic Space (understanding relationships), updates the DIKWP graph, and then derives wisdom (actionable insight) guided by Purpose. The mathematical representations (e.g., vectors for concepts, graphs for ontologies, logic formulas for rules) ensure that this process follows a reproducible semantic structure. In particular, the inclusion of Purpose in the formal model forces a continuous check: Does this inference or action serve the intended goal? By design, any output that does not align with a defined Purpose node is flagged and either adjusted or explained as a necessary trade-off.

The DIKWP semantic model can be viewed as a mesh of interrelated elements rather than a simple hierarchy [8]. In fact, a 5×5 DIKWP transformation matrix provides a systematic framework for analyzing and understanding the possible interconversions and relationships among the five cognitive elements: Data (D), Information (I), Knowledge (K), Wisdom (W), and Purpose (P). This matrix structure enumerates all possible transformation relationships between each element and each of the others, as shown in Table *2*. Each entry in the matrix represents a potential conversion from the row element to the column element (for example, D→I denotes transforming raw data into information; W→P denotes using a recommended action to fulfill a goal).

	D	I	K	W	P
D	D→D	D→I	D→K	D→W	D→P
I	I→D	I→I	I→K	I→W	I→P
K	K→D	K→I	K→K	K→W	K→P
W	W→D	W→I	W→K	W→W	W→P
P	P→D	P→I	P→K	P→W	P→P

TABLE 2: DIKWP 5×5 transformation matrix

This matrix illustrates all types of semantic transformations among the five DIKWP elements. As seen above, our framework allows not only the "classic" upward flow (D→I→K→W→P) but also lateral and downward flows. For example, the "classic" upward flow is represented by the diagonal entries D→I, I→K, K→W, and W→P. However, the other cells represent crucial feedback loops. A W→K (Wisdom to Knowledge) transformation represents learning new, generalized knowledge from the outcome of a specific decision (e.g., learning that a particular intervention was effective). A P→D (Purpose to Data) transformation shows how a high-level goal (e.g., "prevent asthma attacks") actively guides the system to seek specific data (e.g., "increase monitoring of nocturnal cough data"). For instance, W→K might represent learning new knowledge from a decision outcome, and P→D could represent how a goal influences what data to collect. This meshed design contrasts with a strictly layered hierarchy, enabling rich interconnectivity and feedback among all five elements.

DIKWP, Data, Information, Knowledge, Wisdom, and Purpose

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Patient-Clinician Bidirectional Mapping

A core methodological challenge in pediatric care is bridging the cognitive gap between patients (and their families) and clinicians [19,20]. They often have different perspectives and terminologies: a parent might describe "my child looks very tired and cranky", where as a clinician frames it as "patient exhibits fatigue and irritability, possibly due to poor oxygenation". Misalignment in these cognitive frames can lead to misunderstandings, reduced trust, or suboptimal decisions. Our framework addresses this through a bidirectional mapping in the semantic model. We explicitly model two viewpoints within the DIKWP graph: the patient/family's perspective and the clinician's perspective (see Figure *2*). Each perspective has its own representation in Cognitive Space, which is then mapped via shared Concept and Semantic Spaces so that the underlying meaning is aligned.

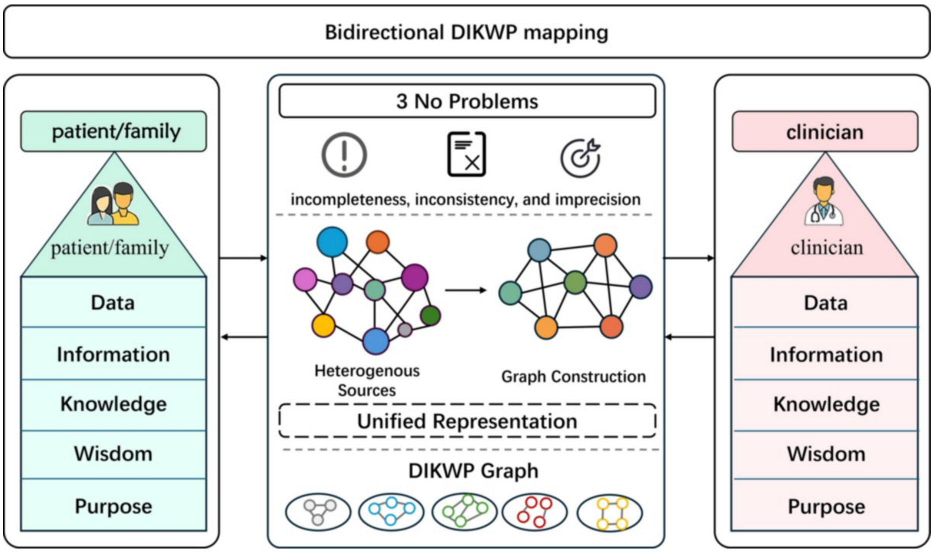

FIGURE 2: Bidirectional DIKWP mapping between patient and clinician perspectives

DIKWP, Data, Information, Knowledge, Wisdom, and Purpose

Problem classification and DIKWP mapping: To address this, we first classify patient-clinician communication challenges into two categories: Standard interpretation issues, which correspond to relatively direct mismatches at the Data and Information levels (e.g., terminology confusion, missing facts). Cognitive misalignment issues, which correspond to higher-order semantic mismatches involving Wisdom and Purpose (e.g., goals, treatment rationales, long-term understanding).

Let the total set of patient-clinician communication issues be denoted as *P*, with standard issues $P_S \subseteq P$, and higher-level cognitive misalignments $P_H \subseteq P$, where $P_H = P \setminus P_S$. For the higher-order issues, the system applies DIKWP semantic decomposition, breaking each misalignment instance $p \in P_H$ into a structured semantic representation via:

$$M = T^{PC}_{\mathrm{DIKWP}}(P_H)$$

where T^{PC}_{DIKWP} is a transformation function encoding patient-clinician cognitive mappings across DIKWP layers. $M = \{m_1, m_2, \ldots, m_k\}$ represents modules of misunderstanding (e.g., misaligned purpose, incomplete clinical explanation), where *k* is domain-dependent (e.g., 75 modules in our pediatric dataset).

5×5 Transformation of patients and clinician: To formalize this mapping process, we define 5×5 transformation matrices that represent the semantic alignment between DIKWP layers across the patient and clinician perspectives. $T^{\mathrm{DIKWP}}_{\mathrm{Patient}\to\mathrm{Clinician}}$ represent the transformation from patient/family cognitive states to clinician cognitive representations. $T^{\mathrm{DIKWP}}_{\mathrm{Clinician}\to\mathrm{Patient}}$ represent the inverse transformation, facilitating clinical output into patient-understandable language.

These matrices are structured as:

$$T^{\mathrm{Patient}\to\mathrm{Clinician}} = \begin{bmatrix} T_{DD} & T_{DI} & T_{DK} & T_{DW} & T_{DP} \\ T_{ID} & T_{II} & T_{IK} & T_{IW} & T_{IP} \\ T_{KD} & T_{KI} & T_{KK} & T_{KW} & T_{KP} \\ T_{WD} & T_{WI} & T_{WK} & T_{WW} & T_{WP} \\ T_{PD} & T_{PI} & T_{PK} & T_{PW} & T_{PP} \end{bmatrix}$$

$$T^{\text{Clinician}\to\text{Patient}} = \begin{bmatrix} T'_{DD} & T'_{DI} & T'_{DK} & T'_{DW} & T'_{DP} \\ T'_{ID} & T'_{II} & T'_{IK} & T'_{IW} & T'_{IP} \\ T'_{KD} & T'_{KI} & T'_{KK} & T'_{KW} & T'_{KP} \\ T'_{WD} & T'_{WI} & T'_{WK} & T'_{WW} & T'_{WP} \\ T'_{PD} & T'_{PI} & T'_{PK} & T'_{PW} & T'_{PP} \end{bmatrix}$$

Each matrix entry T_{XY} (or T'_{XY}) quantifies the semantic strength of transformation from DIKWP element *X* to element *Y* across perspectives (e.g., from patient-level Information to clinician-level Knowledge). These values can be learned from annotated corpora or defined via ontological mappings.

Concretely, the system maintains a set of nodes in the DIKWP graph that are tagged as "patient-reported" versus "clinician-observed". For example, a parent's observation "child is not eating well" becomes a Data/Information node in patient terms, which the system maps to the medical concept "appetite loss" in clinician terms. This corresponds to a transformation like T_{DI} or T_{II} in the patient-to-clinician matrix. This mapping uses a combination of natural language processing (for narrative inputs) and ontology alignment. We leverage a pediatric ontology that includes layman terms and medical terms as synonyms or related concepts (drawing from sources like SNOMED CT for clinical terms and consumer health vocabularies for lay terms). The Semantic Space is critical here: it captures relationships and equivalences between different expressions of the same underlying semantic content. Thus, the phrase "cranky and fussy" in parent language is linked to "irritability" in clinical language within the semantic network - an instance of a T_{II} transformation.

Using bidirectional semantic mapping, the system can translate a clinician's Wisdom (e.g., "initiate bronchodilator therapy") into an explanation a parent understands (e.g., "use the inhaler to help open up his lungs so he can breathe easier"), modeled as T_{WW} or T_{WI}. Likewise, it can convey a parent's Purpose (e.g., "I want my child to sleep through the night") into a formal Purpose representation that clinicians see as well (e.g., "improve nocturnal symptom control"), corresponding to T_{PP}.

Formally, we implement this as a two-part algorithm:

Encoding, which maps user inputs from either party into a structured DIKWP vector representation (i.e., locating the input in the joint semantic graph), denoted as:

Decoding, which maps the system's DIKWP-based internal reasoning back into a form understandable to the target party:

$$\text{DIKWP}_{\text{output}} = T_{\text{mapping}} \cdot \text{DIKWP}_{\text{input}}$$

Here, T_{mapping} is either $T^{\text{DIKWP}}_{\text{Patient}\to\text{Clinician}}$ for clinician-facing output or $T^{\text{DIKWP}}_{\text{Patient}\to\text{Clinician}}$ for patient-facing explanation.

In the decoding step, the system uses the semantic relations in the ontology to generate explanations appropriate for the audience - for instance, the system knows that "school attendance" (a family-stated goal) relates to "asthma control" (a clinical goal) and can thus frame an outcome in terms of "keeping the child in school" for the family, versus "preventing asthma exacerbations" for the clinician. Through these mechanisms, our framework ensures that both families and clinicians are kept "on the same page", each receiving information and recommendations in terms they understand, yet grounded in a shared semantic model.

System architecture

The proposed system architecture is designed to operationalize the DIKWP framework in a practical healthcare setting. It consists of several key components organized in a modular fashion, as depicted in Figure 3. The architecture seamlessly integrates data ingestion, semantic processing, reasoning, and user interaction layers to create a continuous feedback loop for proactive pediatric health management.

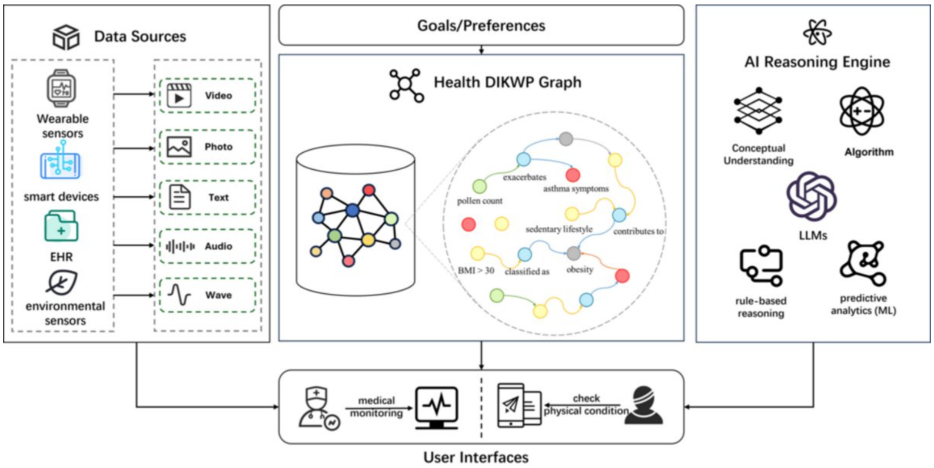

FIGURE 3: DIKWP-based pediatric health management system architecture

The system ingests multi-source data, feeds it through the DIKWP semantic layers via the reasoning engine, and provides outputs through clinician and patient interfaces. The Purpose layer influences all stages, creating a closed-loop feedback for continuous learning.

DIKWP, Data, Information, Knowledge, Wisdom, and Purpose; EHR, Electronic Health Records; LLMs, Large Language Models; ML, Machine Learning

Data Sources and Ingestion

At the foundation of the system are diverse data sources capturing the child's health state. These include (1) Electronic Health Records (EHR) - clinical data like diagnoses, medications, lab results; (2) Wearable and IoT Sensors - e.g., smartwatch tracking activity and sleep, smart inhaler recording usage, home air quality monitors; (3) Patient-Reported Data - symptom diaries or surveys entered by parents (e.g., appetite logs, mood observations); (4) Imaging and Labs - if applicable, such as radiographs or blood test results; and (5) Population Health Data - relevant epidemiological data (e.g., flu outbreaks in the area) that provide context.

We formalize these as a multimodal time-indexed set:

$$D(t) = \{D_1(t),\ D_2(t),\ D_3(t),\ D_4(t),\ D_5(t)\}$$

where each $D_i(t)$ represents one data stream (e.g., D_1 for EHR, D_2 for sensors, etc.).

A Data Ingestion Module interfaces with these sources in real-time or at regular intervals. It performs preprocessing like timestamp alignment T, cleaning C (handling missing or noisy readings), and standardization S (converting units, coding variables consistently), expressed as:

$$I(D(t)) = \left\{S \circ C \circ T\big(D_i(t)\big)\right\}_{i=1}^{5}$$

For example, temperature readings from a home thermometer are converted to a standard format and verified for plausibility. The ingestion layer uses secure application programming interfaces to ensure privacy and integrates with hospital systems (for EHR data) using standards like HL7 FHIR for interoperability.

DIKWP Semantic Graph Database

At the core of the architecture lies the DIKWP graph, a semantic knowledge base that stores and organizes information across the Data, Information, Knowledge, Wisdom, and Purpose elements.

This is formalized as a labeled directed graph:

$$G_{\text{DIKWP}} = (V, E), \quad V = V_D \cup V_I \cup V_K \cup V_W \cup V_P$$

with node types corresponding to each DIKWP layer and typed semantic edges $(v_i, v_j, r_{ij}) \in E$.

As raw data is ingested, it is added as Data nodes V_D and linked to relevant ontology concepts. Information nodes V_I are created when the system detects meaningful patterns (e.g., symptom episodes). Knowledge nodes V_K represent structured medical knowledge (e.g., clinical guidelines and ontological relationships), while Wisdom nodes V_W emerge from evaluative reasoning over interventions. Purpose nodes V_P are either explicitly provided or inferred from user behavior.

The graph updates dynamically as new data arrives, and every element includes contextual traceability via semantic paths, ensuring explainability. This traceability is formalized as:

$$\text{trace}\left(v_m^{(W)}\right) = \text{Path}\left(v_m^{(W)} \leftarrow \cdots \leftarrow v_i^{(D)}\right)$$

Here, trace is the function that retrieves the full reasoning path for a given node. The input $v_m^{(W)}$ is a specific Wisdom node (a recommendation), and the function returns the Path, which is the sequence of nodes and edges connecting the Wisdom node back to its originating Data node(s), such as $v_i^{(D)}$. This allows the system to answer "why" a particular recommendation was made by exposing the entire chain of inferences.

Reasoning Engine

The system's intelligence resides in the Reasoning Engine, which operates continuously on the DIKWP graph. It has multiple components: a rule-based inference engine and a machine learning prediction module, working in tandem.

The rule-based engine uses symbolic rules derived from clinical guidelines, represented as:

$$\rho : \textbf{IF} \quad \text{fever} \wedge \text{cough} \wedge \text{age} < 3 \ \Rightarrow \uparrow P(\text{bronchiolitis})$$

Here, ρ represents a specific inference rule. The antecedent (the IF clause) consists of conditions (e.g., fever, cough) that are checked against nodes in the DIKWP graph. The consequent (the THEN clause) specifies an outcome, such as an increased probability, P, of a certain condition (e.g., bronchiolitis). When the DIKWP graph contains matching antecedent nodes, the engine triggers the rule, adding a new inference node v_{inf} with an associated confidence score $\alpha\epsilon\ [0,1]$.

The machine learning module detects complex temporal or multivariate patterns that are difficult to capture with symbolic rules. It applies predictive models, formalized as:

$$f_{\text{ML}} : X_{\text{context}} \mapsto y \in [0,1]$$

In this function, f_{ML} is the machine learning model. While the framework is model-agnostic - a key feature for ensuring adaptability to new technologies like modern large language models - typical models for this type of risk-stratification task would include traditional machine learning (e.g., logistic regression for interpretability or recurrent neural networks/long short-term memory for processing time-series sensor data). For validation, any chosen model would be trained on a historical dataset, tested on a hold-out set, and validated for clinical utility based on metrics like area under a receiver operating characteristic curve for risk prediction and precision/recall for alerts. X_{context} is the input feature vector containing contextual data (such as a time-series of sensor readings and patient-reported symptoms), and y is the predicted output, typically a risk score or probability. These outputs are then added to the DIKWP graph as new Knowledge $v^{(K)}$ or Wisdom $v^{(W)}$ nodes.

Ontology and Semantic Mapper

Supporting the reasoning and graph is the Ontology Service, which houses the formal definitions of all medical concepts, symptoms, and their interrelations. The ontology serves as the schema and vocabulary that the DIKWP graph uses. It includes synonym mappings (linking patient lay language to medical terminology, as discussed in Section Patient-Clinician Bidirectional Mapping), hierarchical relationships (e.g., asthma is a type of chronic respiratory disease), and part-whole relationships (e.g., wheeze is a symptom of asthma). The Semantic Mapper component uses this ontology to label incoming data and to help the reasoning engine generalize across concepts. For instance, if a new symptom appears in data ("child complains of chest tightness"), the mapper recognizes this as related to "breathing difficulty" and links it to the known concept of "asthma symptom". This component is key to explainability: by grounding all events in a well-defined ontology, the system can generate explanations like "We detected X, which is an early sign of Y, and given goal Z, we suggest W". The ontology is maintained and updated by knowledge engineers and can be customized to institutional protocols. As medical knowledge evolves, new concepts or updated guidelines can be incorporated into the ontology to keep the system current.

Supporting the reasoning and graph is the Ontology Service, modeled as:

$$O = (C, R_O)$$

where C is the set of medical concepts and R_O includes semantic relations. The Semantic Mapper uses this ontology to label incoming data, a process represented by the function:

$$M_{\text{semmap}} : X \to C$$

Here, X represents the raw incoming data (e.g., a text string or sensor reading), C is the set of formal medical concepts from the ontology, and M_{semmap} is the mapping function that assigns a concept from C to the input data X.

User Interfaces (Clinician and Patient)

The system provides tailored interfaces for clinicians and for patients/families, ensuring that each user group interacts optimally with the AI. The Clinician Dashboard is integrated into the clinical workflow (e.g., as part of the EHR interface). It presents a concise summary of the child's status (trends, alerts, predictions) and any AI-generated recommendations. Importantly, it also provides explanations and evidence: a clinician can click on a recommendation to see which data and knowledge nodes led to it. The dashboard allows the clinician to give feedback (approve, adjust, or reject a recommendation), which is fed back into the system for learning and refinement. The Family App/Portal is a mobile or web application for parents (and older pediatric patients when appropriate). It translates the system's outputs into lay-friendly language, focusing on actionable information and education. For example, if the system detects a risk, it might send a gentle alert: "Your child's readings suggest asthma might flare up; consider using the preventive inhaler tonight. Tap for tips on improving bedroom air quality". The portal also allows parents to input data (symptoms, concerns) and to set their goals and priorities, which update the Purpose element in the DIKWP graph. Both interfaces are designed with transparency in mind - families can see explanations appropriate to their level (e.g., visualizations of how the child's current measurements compare to healthy ranges, rather than technical rule traces), and clinicians can see detailed decision logic. Additionally, both interfaces support communication and shared decision-making: for instance, a summary view of the AI's assessment can be shared or discussed during a clinic visit, keeping the family and clinician aligned on the care plan.

The architecture is a multilayered system (data → semantic graph → reasoning → interface) all guided by Purpose. This design ensures that as soon as data is acquired, it flows through semantic understanding to actionable output, and user feedback flows back in, achieving a continuous cycle of proactive care.

Results And Discussion

Case scenario

We now illustrate the proposed system in action through a representative use case scenario. This example demonstrates how the DIKWP-based proactive system functions in a real pediatric context, highlighting how data, reasoning, and human stakeholders (clinicians and families) interact through a dynamic knowledge graph.

Background: Emma is a 10-year-old girl with moderate persistent asthma. Traditional care has been reactive - she typically visits the clinic after flare-ups. In our system, her Purpose node is defined as maintaining asthma control so she can attend school and play soccer without interruption.

Scenario: Emma's family enrolls in the AI-driven proactive care program. She begins wearing a smartwatch and uses a connected peak-flow meter and inhaler sensor. These devices stream daily data to the system, including peak expiratory flow (PEF), nighttime cough frequency (detected via a sound-analysis app), rescue inhaler usage, physical activity levels, and parent-reported data (like cold symptoms). These inputs are ingested into the system's Data layer, where they are standardized and stored as structured Data nodes (e.g., $v_1^{(D)}$ representing PEF, $v_2^{(D)}$ representing nighttime cough, $v_3^{(D)}$ representing inhaler usage, $v_4^{(D)}$ representing activity, $v_5^{(D)}$ representing cold symptoms, and $v_6^{(D)}$ for other data), which form the set $v_1^{(D)}$ through $v_6^{(D)}$. Over the course of a week, the system detects a gradual decline in peak flow, frequent nighttime coughing, and increased reliance on rescue medication. These observations are semantically aggregated into Information nodes, such as $v_7^{(I)}$: "PEF dropped by 15%", $v_8^{(I)}$: "Nighttime coughing occurred on 5 nights", and $v_9^{(I)}$: "3 additional albuterol puffs used".

The reasoning engine then applies symbolic inference over these Information nodes, generating Knowledge-level interpretations. These include $v_{10}^{(K)}$: “Asthma control is poor”, inferred from the peak flow trend; $v_{11}^{(K)}$: “Impending exacerbation suspected”, based on cough patterns; and $v_{12}^{(K)}$: “Insufficient control”, triggered by medication overuse. Additional contextual knowledge is derived directly from raw data, including $v_{13}^{(K)}$: “Infection-triggered flare possible”, based on cold symptoms reported by parents, and $v_{14}^{(K)}$ and $v_{15}^{(K)}$, which capture recovery indicators like reduced coughing and improved peak flow, respectively. In parallel, the system's machine learning module processes the same data triplet $\{v_1, v_2, v_3\}^{(D)}$, and infers a high short-term risk of deterioration, represented as $v_{10}^{(K)}$.

These knowledge interpretations activate Wisdom-layer recommendations. For instance, $v_{16}^{(W)}$: “Recommend step-up therapy” is generated from poor control, while $v_{17}^{(W)}$: “Consider increasing steroid dose” reflects predicted flare risk. A further planning node $v_{18}^{(W)}$: “Preventive action to avoid ER” links this medical reasoning with real-world goal prioritization. Before finalizing these actions, the system checks each recommendation for alignment with Purpose-layer goals defined by clinicians or families. In Emma's case, these include $v_{19}^{(P)}$: “Ensure school participation”, $v_{20}^{(P)}$: “Enable physical activity”, and $v_{21}^{(P)}$: “Prevent emergency care”. Once an action is confirmed as aligned - e.g., $v_{16}^{(W)} \rightarrow v_{19}^{(P)}$ - the system monitors outcomes. If, for example, Emma experiences no missed school days and her peak flow improves, the Purpose node activates a feedback loop resulting in $v_{22}^{(W)}$: “Maintain treatment”.

All nodes participating in this reasoning process are listed in Table 3, which organizes the full set of DIKWP entities by semantic layer, from raw observations through to feedback-informed planning.

Type	Node ID	Meaning	Semantic Meaning	Inferred from
Data (V_D)	$v_1^{(D)}$–$v_6^{(D)}$	Peak flow, cough, inhaler use, cold symptom, etc.	Devices, parent-reported	Observed
Information (V_I)	$v_7^{(I)}$–$v_9^{(I)}$	Aggregated symptom trends	ρ_1–ρ_3	Aggregated
Knowledge (V_K)	$v_{10}^{(K)}$–$v_{15}^{(K)}$	Clinical interpretations and outcomes	ρ_4–ρ_9	Symbolic/Machine Learning
Wisdom (V_W)	$v_{16}^{(W)}$–$v_{18}^{(W)}$, $v_{22}^{(W)}$	Recommendations and feedback	ρ_{10}–ρ_{12}, ρ_{16}	Decision
Purpose (V_P)	$v_{19}^{(P)}$–$v_{21}^{(P)}$	Patient-centered goals	Linked from Wisdom	Goal

TABLE 3: Structured DIKWP node table

DIKWP, Data, Information, Knowledge, Wisdom, and Purpose

The rules governing these transitions are shown in Table 4, which lists each symbolic inference rule $_i$, its antecedent and consequent, associated confidence score, and corresponding DIKWP transition.

Rule ID	Antecedent (If...)	Consequent (Then...)	Score	Element Transition
ρ_1–ρ_3	Raw sensor readings ↓/↑	Aggregated symptom summaries	0.84–0.95	D → I
ρ_4–ρ_6	Symptom summaries	Knowledge: Poor control, flare, dependence	0.86–0.97	I → K
ρ_7–ρ_9	Cold symptoms, improvement data	Infection trigger, recovery confirmation	0.80–0.83	D → K
ρ_{10}–ρ_{12}	Knowledge assessments	Wisdom recommendations	0.91–0.98	K → W
ρ_{13}–ρ_{15}	Wisdom recommendations	Purpose alignment	0.92–0.96	W → P
ρ_{16}	Goal satisfaction feedback	Maintain treatment	0.87	P → W (loop)

TABLE 4: Inference rules ρ_i used in DIKWP reasoning chain

DIKWP, Data, Information, Knowledge, Wisdom, and Purpose

This reasoning path is shown in Figure 4, which illustrates how structured inputs are progressively transformed across the DIKWP elements through both symbolic and statistical inference.

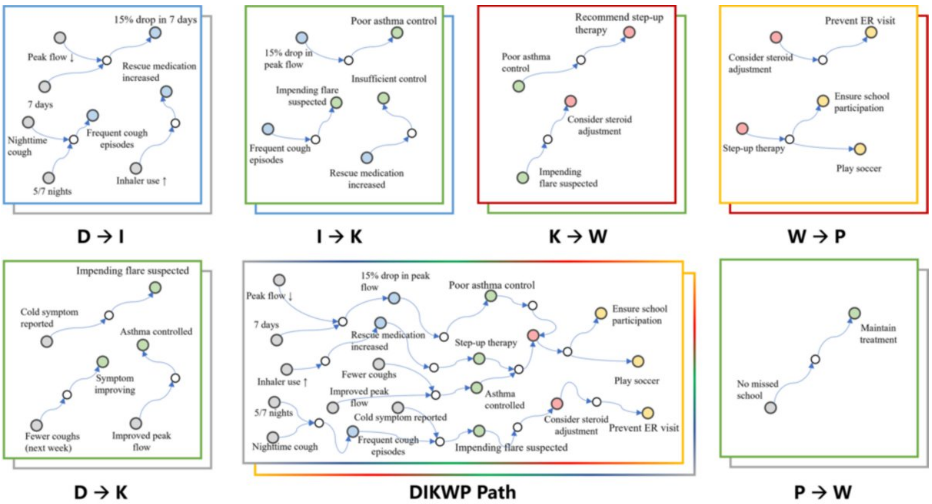

FIGURE 4: DIKWP inference chain for Emma's asthma scenario

This figure illustrates the full reasoning path. The D →I (Data to Information) panel shows raw data (e.g., “Peak flow”, “Nighttime cough”) being aggregated into trends (e.g., “15% drop”). The I →K (Information to Knowledge) panel shows these trends being interpreted as clinical concepts (e.g., “Poor asthma control”). The K →W (Knowledge to Wisdom) panel shows these concepts leading to actionable recommendations (e.g., “Recommend step-up therapy”). Finally, W →P (Wisdom to Purpose) shows the action being validated against the patient's goals (e.g., “Ensure school participation”). The D →K and P →W loops show direct inferences and feedback, respectively.

DIKWP, Data, Information, Knowledge, Wisdom, and Purpose

We present a heat map that summarizes the semantic transition intensity across the DIKWP layers during this process, as shown in Figure 5. It highlights frequent transitions between Data-Information and Information-Knowledge, reflecting high reasoning activity within the system.

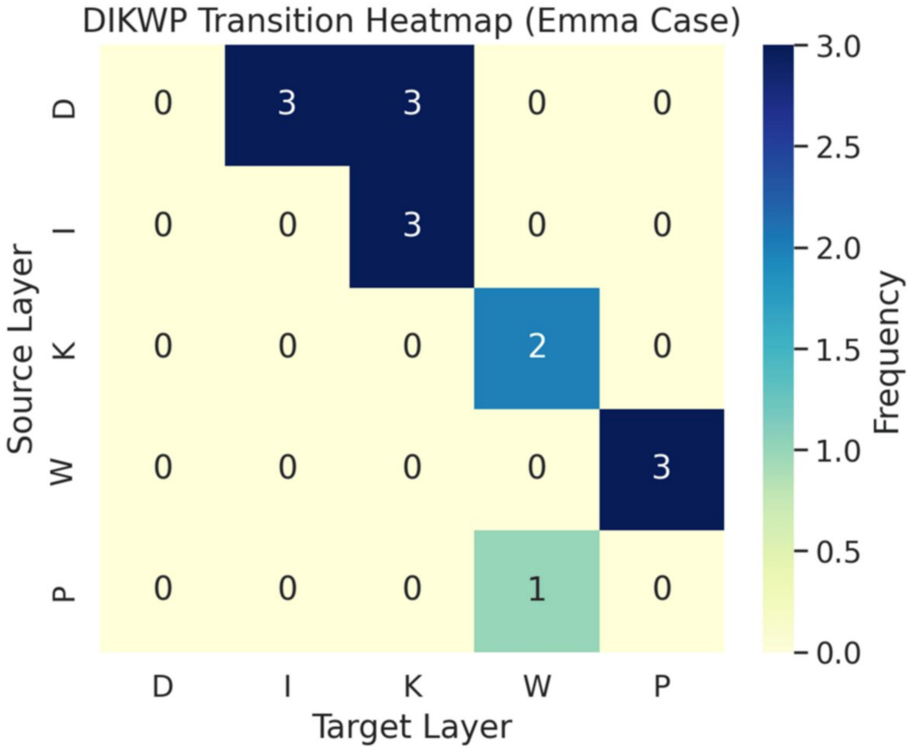

FIGURE 5: Heat map of DIKWP semantic leap frequency generated by reasoning paths based on the Emma's case

The values indicate the number of distinct inference rules that perform a given transformation. The high-frequency transitions, specifically D→I (three instances), D→K (three instances), and I→K (three instances), reflect the system's core data processing and interpretation activities, converting raw observations into clinical knowledge. It also shows strong activity in decision-making (K→W, two instances) and purpose-alignment (W→P, three instances), as well as the feedback loop (P→W, one instance), visualizing the system's complete, purpose-driven reasoning cycle.

DIKWP, Data, Information, Knowledge, Wisdom, and Purpose

We evaluate the complete reasoning path using metrics such as alignment with clinical guidelines, coherence with the user's Purpose goals, and the overall confidence of inference edges, as shown in Figure 6. These results demonstrate our system's ability to proactively support asthma management with transparency and real-time personalization.

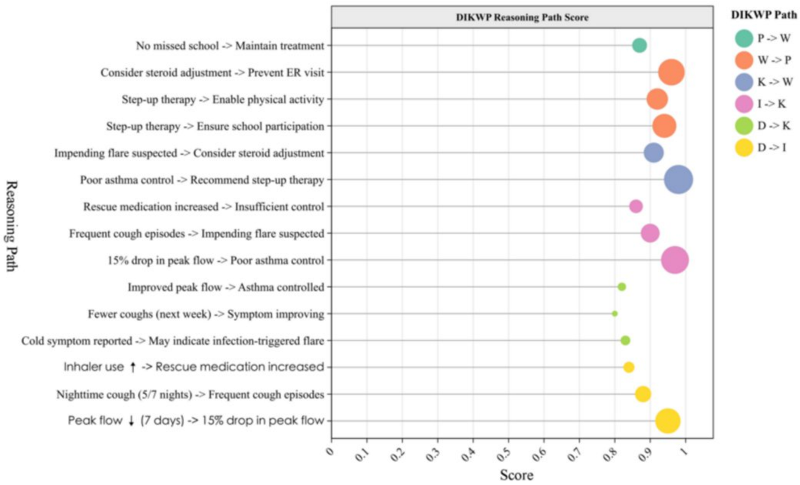

FIGURE 6: DIKWP reasoning path evaluation based on the Emma's case

This figure displays each step in the reasoning chain plotted against its associated confidence "Score" (0.0 to 1.0). The size of the bubble also corresponds to the score, providing a visual guide to the system's certainty at each step. The color-coding (legend) maps each path to its DIKWP transformation type (e.g., D→I, I→K). This visualization allows for a quick audit of the inference chain's overall reliability.

DIKWP, Data, Information, Knowledge, Wisdom, and Purpose

This scenario illustrates the core strength of our DIKWP framework: a graph-structured AI that continuously integrates real-world sensor data, clinical knowledge, and human-defined goals to drive explainable, Purpose-aligned, and adaptive healthcare decisions.

Discussion

The proposed purpose-driven pediatric health management framework offers significant advantages over conventional reactive models, yet also raises several challenges that must be addressed for successful real-world adoption. In this section, we discuss the benefits of our approach, potential hurdles (technical, ethical, and practical), and how we ensure semantic safety and system transparency to maintain trust among users.

Advantages of the Proactive Purpose-Driven Approach

A key advantage of our system is its ability to anticipate and prevent health issues, rather than only responding after problems worsen. By continually analyzing data streams and trends, the system enables early interventions - as seen in the asthma scenario where an exacerbation was prevented. Proactive care can improve clinical outcomes (e.g., fewer hospitalizations, better chronic disease control) and enhance quality of life for children (less missed school, more consistent development). The integration of the Purpose element ensures that all recommendations are patient-centered and aligned with individualized goals. This stands in contrast to many AI systems that might optimize for a generic metric (like risk reduction) without considering whether the action is desirable or appropriate for the patient's life context. By explicitly modeling Purpose, our framework personalizes care plans in a meaningful way - for instance, tailoring interventions to a family's priorities or a teen's personal aspirations.

Another advantage is improved coordination and communication. The DIKWP system acts as a mediator between families and clinicians. It can translate and relay concerns, remind each party of the other's perspective, and keep both informed in real-time. This bidirectional flow of information can strengthen the therapeutic alliance: families feel heard and continuously supported (not just during clinic visits), and clinicians receive synthesized, relevant updates rather than unfiltered raw data. This provides a mechanism for continuous, automated monitoring and support, augmenting the care team's capacity. By bridging the patient-clinician perspective gap, the system helps avoid misunderstandings and ensures that care decisions take into account both medical expertise and the family's context and values.

Our approach inherently provides a high degree of explainability and transparency. Owing to the semantic framework, the reasoning process is not a black-box but can be traced through the DIKWP graph (data → information → knowledge → wisdom → purpose). This traceability is crucial in healthcare - doctors need to justify decisions, and patients/families deserve to understand why something is recommended. By design, any stakeholder can inquire “Why did the system suggest this?” and receive a logical explanation path, satisfying the need for clarity and trust. This transparency is tied to what we term semantic safety: the system's recommendations can be audited for semantic coherence and correctness before action is taken. For example, a clinician can inspect whether the system perhaps mis-labeled a symptom or made a faulty inference; any such issue is easier to catch and correct with an explainable, graph-based system than it would be with an opaque predictive model.

From a systems perspective, another benefit is continuous learning and improvement. Traditional medical guidelines update slowly and individual clinician knowledge has practical limits, but our AI can quickly learn from each new case, refining its knowledge base and predictive models. Over time, this could lead to discovery of subtle patterns (for instance, identifying environmental triggers of certain conditions or early warning signs of rare complications) that might not be evident in static guidelines. By operating as a constantly learning system (with human oversight), the framework can adapt to emerging evidence and the specific characteristics of the patient population it serves.

Challenges and Limitations

Despite its advantages, the framework faces technical and practical challenges. One challenge is scalability and performance. Semantic reasoning with a large, complex ontology and many concurrent patient streams can be computationally intensive. Real-time inference across a broad DIKWP graph may strain computing resources if not engineered efficiently. We need to optimize database queries and possibly prune the search space using context (for example, focusing reasoning on the relevant subset of the graph for a given patient's current issues, rather than the entire knowledge base). We have to carefully architect the system to scale horizontally (adding computing nodes as the number of patients grows) and possibly use edge computing for some initial data processing (e.g., performing preliminary analysis on a wearable device or a phone to reduce data transmission loads). These measures can help ensure that the system remains responsive even as data volume and user numbers increase.

Another challenge is data quality and integration. Pediatric data can be noisy, incomplete, or heterogeneous (coming from different devices and sources). If the data feeding into the system are inaccurate or biased, the outputs will suffer (“garbage in, garbage out”). We address this by implementing rigorous data validation and cleaning in the ingestion phase and by encoding uncertainty in the DIKWP graph (so the system can flag low-confidence data or conclusions). Integrating data from many sources (clinical records, personal devices, etc.) also requires interoperability standards and careful mapping to the ontology, which is an ongoing engineering effort.

There are also challenges around user experience and adoption. Busy clinicians might experience alert fatigue if the system generates too many alerts or false alarms. We mitigate this by tuning the alert thresholds and by tiering notifications (for example, non-urgent suggestions are bundled into summaries rather than interruptive alerts). Families might vary in their comfort with technology; thus, the app interface must be intuitive and supportive (co-designed with input from parents). Trust in the AI is crucial: if either clinicians or families find the system unreliable or too opaque, they may disregard its recommendations. This is why our emphasis on explainability and human-in-the-loop control is so important - users must feel that the AI is a helpful assistant, not an unaccountable authority.

Semantic Safety and Error Mitigation

Semantic safety refers to ensuring the system's understanding and reasoning remain correct and meaningful, avoiding incorrect actions due to misinterpretation. We have multiple layers of semantic safety: the ontology provides formal definitions to reduce ambiguity; the BUG detection catches when the system's semantics go awry (like conflicting interpretations); and the human-in-the-loop design means a clinician can veto any recommendation that “doesn't make sense”. We also incorporate conservative defaults - if the system is not reasonably confident or if the situation is novel (outside its training/knowledge), it errs on the side of caution (maybe default to recommending seeing a doctor rather than some novel AI-derived intervention).

An example of semantic safety in action: suppose the system encounters a combination of symptoms it hasn't seen (rare disease). Instead of confidently giving a wrong recommendation, it would flag this as a high uncertainty scenario (no matching rule with high confidence, ML model low probability outputs) - and the safe action might be, “uncertain diagnosis - refer to specialist”, which is aligned with do no harm principle. This way, the system doesn't operate outside its validated knowledge boundaries without human oversight.

We maintain transparency logs as mentioned: every inference and its justification can be reviewed. If a harm ever occurs or a near-miss, these logs allow an immediate root cause analysis (was it a data issue? A reasoning flaw? etc.), and then we fix the semantic model accordingly, hence continuously improving safety.

Limitations and Future Directions

Despite its promise, the framework has limitations that guide our future work. The current validation relies on an illustrative scenario; a key next step is to pilot the framework in a controlled clinical setting to rigorously evaluate its impact on health outcomes, such as reductions in emergency visits and improvements in chronic disease metrics. The knowledge base, while robust for asthma, needs expansion to cover more pediatric subspecialties like cardiology and neurology to enhance its comprehensiveness.

Future research will focus on integrating a wider array of data, including genomic data and social determinants of health, to enrich the Purpose layer and improve predictive accuracy for developmental or mental health conditions. We also plan to explore advanced meta-cognitive mechanisms, such as a “BUG theory” for detecting and learning from semantic errors in reasoning, to further bolster the system's safety and reliability. Continuous co-design with pediatricians, nurses, and families will remain central to ensuring the tool is both user-friendly and clinically valuable. Ultimately, our vision is for this purpose-driven framework to evolve into a new standard for intelligent pediatric care, making healthcare a more anticipatory, precise, and compassionate endeavor.

Conclusions

This paper introduced a proactive pediatric health management framework by extending the DIKW model with an explicit Purpose layer (DIKWP). Our primary contribution is the formalization and application of this purpose-driven semantic model to pediatric care, enabling AI systems to move beyond reactive problem-solving to anticipatory, goal-aligned health support. We presented a system architecture, grounded in a DIKWP semantic graph, that facilitates explainable reasoning, personalized interventions, and a shared understanding between families and clinicians. The illustrative case study confirmed the framework's potential to translate real-time data into actionable wisdom that directly serves the patient's long-term well-being. By placing purpose at the forefront of AI-driven healthcare, this work lays a foundational step toward creating more transparent, personalized, and effective pediatric care systems.

Appendices

Data Availability

All data generated or analyzed during this study are either included in this article or are available from the corresponding author on reasonable request for any data not explicitly presented in the paper.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Disclosures

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The case scenario presented in this study is illustrative and uses synthetic data generated to reflect typical clinical patterns in pediatric asthma management. For specific details of the DIKWP semantic framework developed in this study, please contact the corresponding author.

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