applied sciences

Article

The DIKWP (Data, Information, Knowledge, Wisdom, Purpose) Revolution: A New Horizon in Medical Dispute Resolution

Yingtian Mei [1] and Yucong Duan [2,*]

[1] School of Cyberspace Security, Hainan University, Haikou 570228, China; myingtian@126.com
[2] School of Computer Science and Technology, Hainan University, Haikou 570228, China
* Correspondence: duanyucong@hotmail.com

Abstract: The doctor–patient relationship has received widespread attention as a significant global issue affecting people's livelihoods. In clinical practice within the medical field, applying existing artificial intelligence (AI) technology presents issues such as uncontrollability, inconsistency, and lack of self-explanation capabilities, even raising concerns about ethics and morality. To address the problem of doctor–patient interaction differences arising from the doctor–patient diagnosis and treatment, we collected the textual content of doctor–patient dialogues in outpatient clinics of local first-class hospitals. We utilized case scenario analysis, starting from two specific cases: multi-patient visits with the same doctor and multi-doctor interaction differences with the same patient. By capturing the external interactions and the internal thought processes, we unify the external expressions and internal subjective cognition in doctor–patient interactions into interactions between data, information, knowledge, wisdom, and purpose (DIKWP) models. We propose a DIKWP semantic model for the doctor–patient interactions on both sides, including a DIKWP content model and a DIKWP cognitive model, to achieve transparency throughout the entire doctor–patient interaction process. We semantically–bidirectionally map the diagnostic discrepancy space to DIKWP uncertainty and utilize a purpose-driven DIKWP semantic fusion transformation technique to disambiguate the uncertainty problem. Finally, we select four traditional methods for qualitative and quantitative comparison with our proposed method. The results show that our method performs better in content and uncertainty handling. Overall, our proposed DIKWP semantic model for doctor–patient interaction processing breaks through the uncertainty limitations of natural language semantics in terms of interpretability, enhancing the transparency and interpretability of the medical process. It will help bridge the cognitive gap between doctors and patients, easing medical disputes.

Keywords: DIKWP; cognitive computing; semantic processing; formal methods; semantic security

check for updates

Citation: Mei, Y.; Duan, Y. The DIKWP (Data, Information, Knowledge, Wisdom, Purpose) Revolution: A New Horizon in Medical Dispute Resolution. *Appl. Sci.* **2024**, *14*, 3994. https://doi.org/10.3390/app14103994

Academic Editor: Luis Javier Garcia Villalba

Received: 19 March 2024
Revised: 3 May 2024
Accepted: 5 May 2024
Published: 8 May 2024

1. Introduction

The doctor–patient relationship is a significant livelihood issue for each stage of social development, characterized by the different attributes of the times. The gradual tension in the doctor–patient relationship can lead to doctor–patient disputes [1], and the reason for this mainly stems from the cognitive differences between doctors and patients [2]. Therefore, easing the tension in doctor–patient relationships [3] and maintaining the regular order of medical services are questions we need to explore. Fremon et al. [4] conducted a scientific analysis of doctor–patient communication, concluding that a doctor's attitude directly affects the diagnosis and treatment outcome. Weng et al. [5] noted that studies have shown a significant connection between doctors' emotional intelligence, patient trust, and the doctor–patient relationship. The ineffectiveness of communication between doctors and patients is primarily attributed to a lack of transparency throughout the medical consultation process [6] and cognitive distance [7]. Élaina [8] explored the concept of autonomy in the seeker-of-care relationship and reconstructed the doctor–patient relationship based on this understanding. Enhancing understanding and openness is crucial for improving healthcare outcomes. Dean et al. [9] analyzed the communication between several physicians and their patients. They concluded that the ability of physicians to adjust their communication to the cognitive level of their patients could promote mutual understanding. Faiza et al. [10] investigated communication strategies reported by clinical doctors to eliminate differences in medical decision-making with patients. Stewart et al. [11] noted a correlation between effective doctor–patient communication and improved patient health outcomes. Most traditional methods improve the doctor–patient relationship by enhancing and optimizing the doctor's communication skills. However, in reality, doctors often receive more consultations per day than expected, making it challenging to meet patients' individual needs. In recent years, many researchers have leveraged computers to facilitate doctor–patient communication [12,13]. Turing Award winners Bengio, Hinton, and Academician Yao [14] co-authored an article, stating that AI can solve long-standing human problems like disease and poverty. Nassani et al. [15] investigated innovation performance in the healthcare industry through the use of innovation networks and improving people's standard of living. The application of AI in the medical field has evolved from its initial stage of knowledge-driven systems, such as assisting in disease diagnosis and treatment, to a stage driven by data, such as electronic medical records [16] and physiological signals [17]. However, it has also brought about a series of challenges [18,19]. Wang et al. [20] proposed that the data used for training AI may suffer from issues such as incompleteness, inconsistency, and inaccuracy, and considerations should also be given to data accessibility and privacy security. AI sharing patient data without the patient's explicit consent will leave the patient's privacy unprotected [21,22]. Therefore AI techniques are not suitable for application in uncertain, variable, critical, and complex environments [23], and the importance of AI research in healthcare is highlighted [24].

Doctor–patient communication is the key to physician–patient relationship mitigation, and awareness and cognition play a crucial role in doctor–patient communication [25]. Consciousness is our ability to perceive our inner thoughts and the external world, enabling us to understand and interpret our experiences while also recognizing the existence and state of others [26,27]. Cognitive abilities, including understanding, memory, problem-solving, and decision-making, form the basis for processing information, forming opinions, and responding [28,29]. Together, these constitute the framework of human communication, allowing us to understand each other's intentions, emotions, and information, thereby effectively exchanging thoughts, feelings, and knowledge [30,31]. Without the involvement of consciousness and cognition, interactions between people would lack depth and efficiency, making it difficult to establish genuine understanding and connections [32,33]. Thus, consciousness and cognition are internal psychological processes as well as the foundation of interpersonal relationships and social interactions [34]. The exploration of consciousness is a bridge that connects AI's future applications with humans' fundamental cognition. Mudrik et al. [35] suggested that, in exploring the future direction of AI, people need to first understand what consciousness, self, and free will mean to us. Therefore, the development of AI is not just a technological advancement but also involves a deep understanding of the human essence. Lenharo et al. [36] highlighted the scientific community's urgent curiosity about artificial consciousness, with researchers strongly calling for increased funding to explore the boundaries between conscious and unconscious systems. With the emergence and development of large language models (LLMs), more scholars have begun to explore whether machines can have consciousness. Boltuc [37] divides consciousness into three forms and explicitly states that robots already have functional consciousness. Dehaene et al. [38] correlate consciousness and the brain, pointing out the feasibility of developing machine consciousness [39]. Starzyk [40] proposed a physical definition of consciousness and designed a consciousness computational model driven by competing motivations, goals, and attention switching. Shevlin [41] suggested a universal heuristic approach for seeking artificial consciousness to preliminarily assess the potential for consciousness in different artificial systems. Gamez [42] highlighted the progress in measuring intelligence and consciousness research, emphasizing the importance of developing universal intelligence measurement tools and mathematical theories to map physical and conscious states. Baars et al. [43] attribute all natural phenomena to quantum events and emphasize the importance of consciousness. Oriented toward integrating AI with the real economy, Xu et al. [44] explore the relationship between AI cognition and employee depression. In terms of human–computer integration, Paliga [45] pointed out that there is a relationship between human resource intelligence fluency, job performance, and job satisfaction.

The data, information, knowledge, wisdom, and purpose (DIKWP) model conducts a series of explorations at the conscious cognitive level, associating cognitive space, conscious space, semantic space [46], and conceptual space through DIKWP. Cognitive space [47] represents human perceptions, thinking, and thought processes, while conscious space [48] represents human intentions, goals, and subjective experiences. The association between cognitive and conscious spaces will better simulate human conscious activities, allowing intelligent systems to possess more realistic and autonomous cognitive capabilities. By linking and integrating the conceptual space [49] with the cognitive space, the DIKWP model can combine domain knowledge with specific scenarios to analyze and reason problems, thereby providing more accurate and practical solutions. Duan proposed 'relationship defined everything of semantics' (RDXS) to map incomplete, inconsistent, and imprecise subjective–objective hybrid DIKWP resources with the help of the DIKW conceptual system to extend the knowledge graph into an interconnected DIKWP graphical system [50]. Current interdisciplinary and cross-domain research on semantic understanding and fusion represented by natural language processing and related methods assumes that the target DIKWP semantics are objective [51] and the sample DIKWP content is objectively markable. However, in truly universal demand scenarios, the semantic content is mixed subjectively and objectively [52,53]. To overcome this limitation, when dealing with subjective and objective semantic issues [54] in interdisciplinary and cross-domain DIKWP interaction and fusion under uncertainty, Gao et al. proposed a method for the dynamic reconfiguration of service workflows in mobile e-commerce environments based on cloud-edge computing [55]. In industrial applications that largely depend on data generated and collected by various sensors, Li et al. [56] introduced a physical AI solution. In the cutting-edge field of service robots, Song et al. studied service quality and privacy risks in human–machine interactions in a purpose-driven manner [57]. Huang [58] developed an interactive intelligent form-filling system based on DIKWP transformation for semantic recognition and prevention of bias. Based on the DIKWP fusion model, Hu [59] analyzed and processed healthcare and wellness by combining meteorological and depressive diseases. Mei et al. [60] conducted a DIKWP semantic mapping search via intention-driven intelligent case adjudication to narrow the cognitive distance between the parties involved. Liu et al. [61], oriented to the public safety domain, applied the DIKWP model to evaluate and maintain critical public facilities.

Therefore, it is of value and significance to use the DIKWP model to address the problems of doctor–patient communication in the doctor–patient relationship and the uneven cognitive level in doctor–patient communication. We take the medical consultation scene as a case prototype and propose constructing a DIKWP semantic model of doctor–patient interactions to visualize the whole process. Meanwhile, the discrepancy space is semantically mapped to DIKWP uncertainty in both directions, and the purpose-driven DIKWP semantic fusion transformation technique handles the discrepancy problem. Finally, the feasibility of the proposed model is explained through comparison. The details will be shown in the following sections: Section 2 briefly introduces the case scenario. Section 3 performs the DIKWP model construction. Section 4 processes the uncertain elements present in the difference space, including inference, computation, and fusion transformation, and Section 5 validates the model and compares it with other methods. Section 6 discusses the model validation process and results. Section 7 summarizes the whole paper and provides an outlook for future work.

2. Case Scenarios

Patients often wonder whom to trust when different doctors provide different diagnoses or question a doctor's professionalism when they offer different diagnoses to different patients. Such thoughts can lead to medical disputes, which often arise from a lack of transparency in the subjective perceptions of both parties during the doctor–patient interaction. These disputes can occur during or after the consultation has ended. We will specifically discuss the issue of medical disputes arising from doctor–patient interactions during the consultation process. The root causes of medical disputes, from the patient's subjective perspective, often stem from the medical services the doctor provides falling short of expectations, such as treatment outcomes or costs being lower than the expected results or higher than anticipated expenses. To this end, we spent half a year collecting hundreds of conversations and audio recordings of patients' visits to the rheumatology and immunology department and the psychology outpatient clinic of a local first-class hospital. We converted the audio into text content while categorizing it into the records of the initial and follow-up visits of 32 patients. Among these, there were patients with only the records of the initial visit or only the records of the follow-up visit. Five cases characterized by doctor–patient conflicts were selected for full-process follow-up, including telephone return visits. In this midst, we will detail two specific cases that tend to cause the most common doctor–patient disputes in the outpatient process.

2.1. Multi-Patient Visits to the Same Doctor

Case 1: Four patients (Tom et al.) chose to visit a hospital after learning online that a doctor there was highly skilled in dealing with psychological and emotional issues. The disease expressions of Alice and Bob were inaccurate and incomplete, leading to diagnostic differences. Communication barriers prevented the doctor from obtaining sufficient information for accurate judgments.

The four patients have diverse living environments and educational backgrounds. Their different communication styles affect how they describe their psychological and emotional issues. These differences may challenge the doctor's understanding and communication during the diagnosis process, affecting diagnostic accuracy and increasing the risk of misdiagnosis and potential medical disputes.

2.2. Multi-Doctor Visits with the Same Patient

Case 2: Tom experienced persistent back pain for two weeks and initially thought it was a sprain. After applying a plaster without relief, he visited Doctor C at a local hospital. Doctor C's final diagnosis was membranous nephropathy, but Tom felt the diagnostic tests prescribed were excessive, indicating overtreatment.

Tom then visited another local hospital, where Doctor B also diagnosed membranous nephropathy and suggested a treatment plan involving a biological agent (rituximab). However, Tom found Doctor B's treatment plan too expensive, costing between CNY 40,000 and CNY 60,000, mostly out-of-pocket since it was not covered by health insurance. Given that his only symptom was back pain, he opted not to proceed with the treatment at that hospital. After these two consultations, Tom sought a third opinion at a top-tier hospital in a significant city. Doctor A also diagnosed him with membranous nephropathy and proposed a treatment plan, combining steroids and immunosuppressants (methylprednisolone plus cyclophosphamide), lasting one year at a cost of around CNY 10,000.

The patient visited three different hospitals and consulted with different doctors. Despite similar consultation processes, issues arose, such as excessive diagnostic testing by doctors and inconsistent treatment plans. These issues undermined the patient's trust in the healthcare system and could also become the root cause of doctor–patient disputes. The main challenges in resolving medical disputes include complex processes, low-resolution efficiency, and the influence of subjective factors. Effectively addressing these real-world problems, optimizing medical processes, and enhancing doctor–patient consultations' transparency are key issues the current healthcare system needs to solve.

We categorize these issues into two types of cognitive differences encountered during the consultation process: the discrepancy caused by the difference between the patient's perception of the doctor and the doctor's self-perception (as part of Figure 1a),and the discrepancy between the patient's expected perception of their symptoms by the doctor and the doctor's actual perception of the patient's condition (as part of Figure 1b).

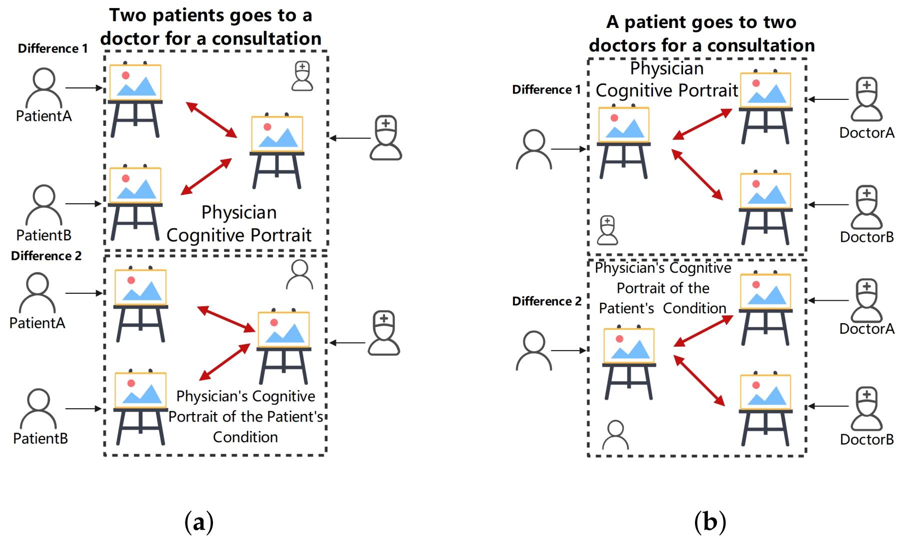


Figure 1. Medical diagnostic differences. (**a**) Patient perceived portrait of doctor vs. doctor's own perceived portrait. (**b**) Patient expectation of dcotor perceived portrait of symptoms vs. dcotor perceived portrait of patient Disease.

3. Model Construction

In the diagnostic and treatment setting, doctor–patient interactions primarily occur through offline consultations, such as initial and follow-up visits at the outpatient department. Doctors create paper or electronic medical records for patients, which are subjectively formatted and recorded by the doctors. When medical disputes arise, these records are often reviewed, but due to the doctors' subjective recording, many DIKWP resources are lost. The missing content often comprises crucial elements needed to resolve disputes. Additionally, the external expressions by the interacting parties (doctors/patients) represent only a part of their internal cognition. To this end, we use the case scenario analysis method to construct an internal cognitive model as well as an external expressive content model for both doctors and patients, starting from two specific cases, namely, multi-patient-same-doctor and multi-patient-multi-doctor interaction differences, to make the doctor–patient interactions transparent. We linked traditional expression systems of randomness, accidental uncertainty, and cognitive uncertainty with DIKWP uncertainty (U), including DIKWP inconsistency (U_{CS}), DIKWP incompleteness (U_{CP}), and DIKWP impreciseness (U_{PR}).

3.1. Definition of Medical Type Resources

3.1.1. Data Type Resource Definition

The data resource (DAT) is stored in a data graph (DG), which is an independent object obtained by direct human observation or sensor collection of real-world objective existences. It is not tied to anyone's intention and is presented in the form of the most straightforward collection. It does not have any substantive content without contextual semantics. Data can be divided into data type (DAT_T) and data entity (DAT_E), according to the definition of meaning, use, and transformation, as shown in Figure 2. Data type represents data with typing ability and is divided into conceptual data (DAT_{T-CN}), collection data (DAT_{T-CL}), and range data (DAT_{T-R}). Data instantiation represents specific people, things, and objects, which can be formalized as follows:

$$\begin{aligned} DAT &::=< DAT_T, DAT_E > \\ &::=< (DAT_{T-CN}, DAT_{T-CL}, DAT_{T-R}), DAT_E > \end{aligned} \tag{1}$$

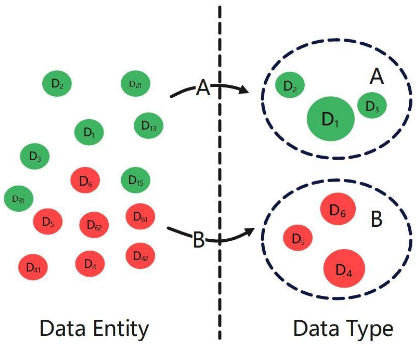


Figure 2. Data type resource.

3.1.2. Information Type Resource Definition

Information resources (INF) are content resources other than data with semantic orientations and values that can be processed independently. Information can also be combined with other data and information to form a chain structure and enhance the semantic value. The combination and transformation of the information chain can express the causal phenomena and dynamic changes between different types of information, as in Figure 3.

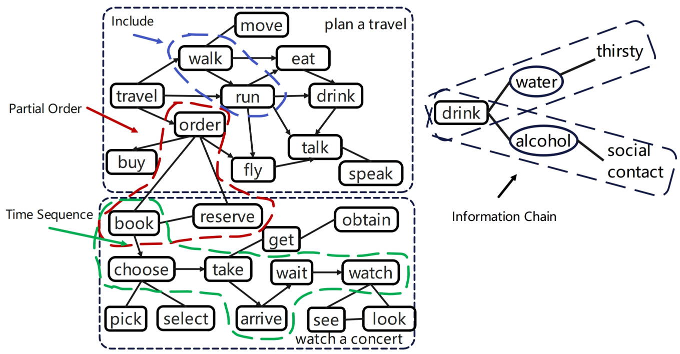


Figure 3. Information type resource.

The information partial order (INF_P) relationship refers to the comparison and state change among information nodes with similar semantics or the unidirectional semantics and logical deduction exhibited by information resources when describing the development process of things. For example, the verb "order/book/reserve" has the same meaning in this context but is represented in multiple ways. The information temporal (INF_T) relationship indicates that some information nodes do not have a direct semantic relationship but show a temporal connection in the sentence. For instance, verbs like "choose", "take", and "arrive" are temporally related in this context. The information include (INF_I) relationship refers to grouping overly lengthy semantic information or information chains to obtain information nodes with a smaller semantic coverage range. For example, "walk" includes "run" since walking encompasses running. In the information chain, the action "drink" can be associated with "water" or "alcohol", where drinking water implies the purpose of thirst, and drinking alcohol implies the purpose of socializing. This can be formalized as follows:

$$\begin{aligned} &INF ::=< INF_P, INF_T, INF_I > \\ &INF_P ::= ep\{order_I < order_I < order_I\} \\ &INF_T ::= ep\{choose_I \rightarrow take_I \rightarrow arrive_I\} \\ &INF_I ::= ep\{walk_I \vee run_I\} \end{aligned} \tag{2}$$

3.1.3. Knowledge Type Resource Definition

Knowledge resources (KNG) can be obtained from DAT and INF after structured and formalized correlation, statistics, and inference, describing the integrity abstraction relationships between content at the type/class level, and conclusions can be deduced from conditions. There is an inclusion and conduction relationship between knowledge. The inclusion relationship (KNG_I) means that parent knowledge (KNG_F) completely contains child knowledge (KNG_S), or child knowledge belongs to parent knowledge, which can be formalized as follows:

$$\begin{aligned} &KNG ::=< KNG_I, KNG_C > \\ &KNG_I ::=< KNG_F, KNG_S > \end{aligned} \tag{3}$$

Knowledge conduction (KNG_C) refers to the transmissibility of knowledge, which we represent as a triad. It includes the knowledge condition (major premise (KNG_{MAR}), minor premise (KNG_{MIN})), and conclusion (knowledge conclusion, KNG_{CLS}). Any trinomial contains three different lexical items: major, minor, and intermediate, and the lexical item that serves as the predicate in the concluding judgment is called the major item, which is usually denoted by "MAR". The word item that is the main item in the conclusion judgment is called the minor item, which is usually denoted by "MIN". In this case, a premise that contains a major term is called a major premise, a premise that contains a minor term is called a minor premise, and a judgment that contains both a major and a minor term is called a conclusion.

$$\begin{aligned} &KNG_C ::=< KNG_{MAR}, KNG_{MIN}, KNG_{CLS} > \\ &KNG_{MAR} ::=< (DAT \cup INF)_{MID} \rightarrow (DAT \cup INF)_{MAR} >_{MAR} \\ &KNG_{MIN} ::=< (DAT \cup INF)_{MIN} \rightarrow (DAT \cup INF)_{MID} >_{MIN} \\ &KNG_{CLS} ::=< (DAT \cup INF)_{MIN} \rightarrow (DAT \cup INF)_{MAR} >_{CLS} \end{aligned} \tag{4}$$

3.1.4. Wisdom Type Resource Definition

Wisdom (WIS) resources are generally difficult to obtain by direct mapping of healthcare-type resources and need to be obtained by reasoning. We can regard them as the value judgment (VAL) of DIKW-type resources based on PUP in a particular case scenario, which has the same and different points with knowledge; the same point is that both need to reason, and the different point is that wisdom resources are more subjective, formally represented as follows:

$$WIS ::=< DAT|INF|KNG +_{DIKWP} PUP \Leftrightarrow DAT|INF|KNG >_{VAL} \tag{5}$$

3.1.5. Purpose Type Resource Definition

Purpose (PUP) resources are some hidden or obvious purposes that humans have for a particular thing and are explicit representations of human beings' efforts to solve a particular problem or satisfy a certain need. We can interpret them as function PUPs that take DIKW resources as input and obtain the output of DIKW resources. The input and output DIKW resources can be specific to DAT, INF, KNG, or WIS nodes. We consider whether the input nodes between intents have purpose relevance (PUP_R), purpose consistency (PUP_{CS}), purpose partial order (PUP_P), and purpose conflict (PUP_{CF}), formally represented as follows:

$$\begin{aligned} &\{DAT|INF|KNG|WIS\}_{OUTPUT} = pup(\{DAT, INF, KNG, WIS\}_{INPUT}) \\ &PUP ::=< PUP_R, PUP_{CS}, PUP_P, PUP_{CF} > \end{aligned} \tag{6}$$

We assume that the input node is $node_{IN}$ and the output node is $node_{OUT}$, PUP_R means that multiple purposes have the same $node_{IN}$ node but different $node_{OUT}$ nodes. PUP_{CS} means that multiple purposes have different $node_{IN}$ nodes but the same $node_{OUT}$ node. PUP_P means that the $node_{IN}/node_{OUT}$ node becomes a $node_{OUT}/node_{IN}$ node of another purpose. PUP_{CF} is the existence of inconsistent or antagonistic $node_{OUT}$ nodes due to differences in content bias and dominant nature, as in Figure 4.

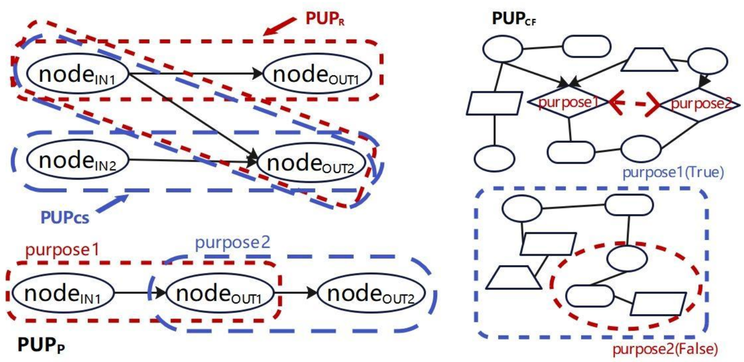


Figure 4. Purpose type resource.

3.2. Classification of Differences in Uncertain Medical Type Resources

In response to the issue of DIKWP uncertainty among different types of medical resources, we map these uncertainties to the DIKWP difference space for detailed classification and processing. Differences in medical resources ($DIFF_{MR}$) are divided into differences in medical resource data ($DIFF_{DAT\_MR}$), differences in medical resource information ($DIFF_{INF\_MR}$), differences in medical resource knowledge ($DIFF_{KNG\_MR}$), differences in medical resource wisdom ($DIFF_{WIS\_MR}$), and differences in medical resource purpose ($DIFF_{PUP\_MR}$). $DIFF_{MR}$ is interrelated with U, which can be formalized as follows:

$$\begin{aligned} &DIFF_{MR} ::=< DIFF_{DAT\_MR}, DIFF_{INF\_MR}, DIFF_{KNG\_MR}, DIFF_{WIS\_MR}, DIFF_{PUP\_MR} > \\ &U ::=< U_{CS}, U_{CP}, U_{PR} > \\ &DIFF_{MR} \leftrightarrow U \end{aligned} \tag{7}$$

We provide a specific example to demonstrate the relationship between DIKWP uncertainty and difference space and an example of its resolution. Below, we present Text A in a definite scenario, with "Sherlock" as the subject and the current purpose being "What is Sherlock?". We randomly add, delete, and modify Text A to produce Text B, representing an uncertain scenario.

Text A: Sherlock is mysterious. In September 2011, Sherlock walked to the shop, bought a knife, and killed a doctor. He eluded the police for three years by relying on his keen insight. What is Sherlock?

Text B: Sherlock is ? In 2011, Sherlock walked to the restaurant, bought a knife and killed a ? He eluded the police for four years by relying on his keen ?? is Sherlock?

We map the content of the text to the DIKWP graph, forming a schematic for identifying and marking the DIKWP graph difference space under uncertain scenarios. as shown in Figure 5.

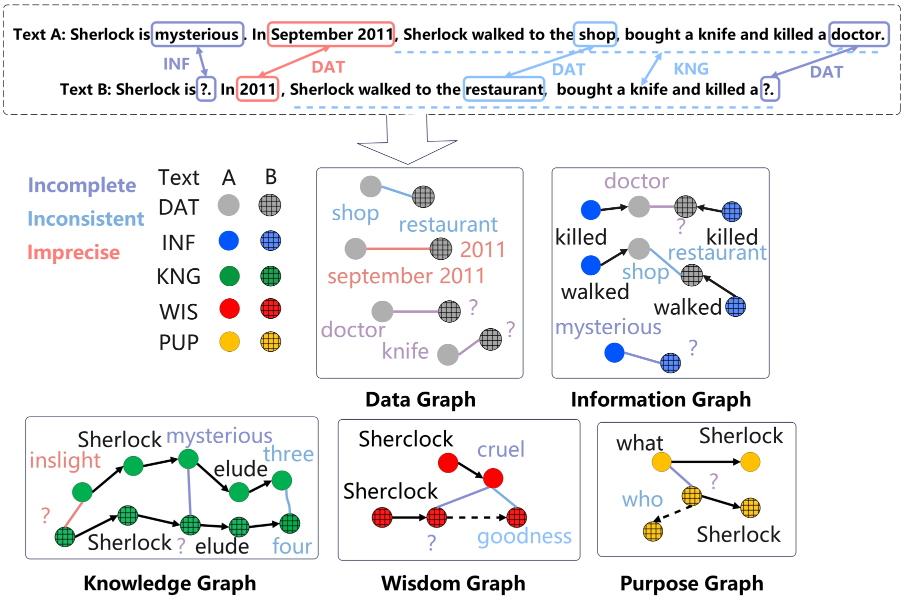


Figure 5. DIKWP differential spatial labeling and identification schematic under uncertainty—Text A and B.

We match DIKWP-incomplete resources to different space processing based on data, knowledge, wisdom, and purpose, as single types or in missing combinations. DIKWP-imprecise resources are matched to different space processing where the precision of data, knowledge, wisdom, and purpose, whether as single types or in combinations, is insufficient. DIKWP-inconsistent resources are matched to different space processing, where conflicts or imbalances exist in data, knowledge, wisdom, and purpose as single types or combinations. The DIKWP uncertainty difference processing framework is shown in Figure 6.

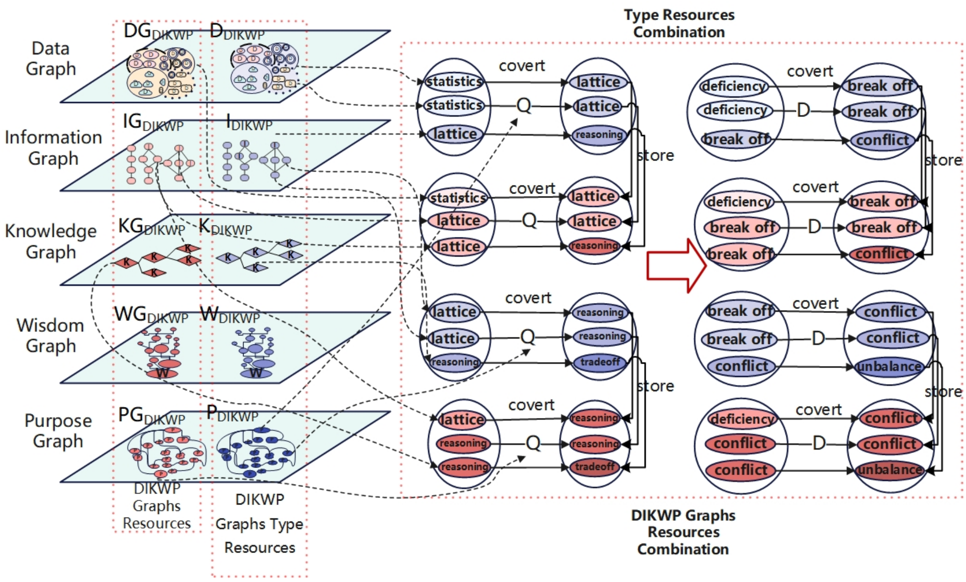


Figure 6. DIKWP uncertainty variance processing framework.

3.3. Processing of Uncertain Medical Type Resources

We classify the two cases in the "Case Scenarios" into scenarios of multiple patients with the same doctors, and doctors with the same patient for detailed analysis and processing. Initially, we map the resources of both cases into the DIKWP graph. Based on the recipient of the target content and the content expected to be understood, we match these to the subjective DIKWP cognition graph of the interpreter and the DIKWP content graph of the concepts or language faced by the interpreter, respectively, for formal definition.

$$
\begin{aligned}
&DIKWP\ Graph\colon DIKWP ::=< DG, IG, KG, WG, PG > \\
&DIKWP\ Content\ Graph\colon DIKWP_{CT} ::=< DG_{CT}, IG_{CT}, KG_{CT}, WG_{CT}, PG_{CT} > \\
&DIKWP\ Cognition\ Graphs\colon DIKWP_{CG} ::=< DG_{CG}, IG_{CG}, KG_{CG}, WG_{CG}, PG_{CG} >
\end{aligned} \tag{8}
$$

3.3.1. Treatment of Multi-Patient Same-Doctor Diagnostic Discrepancies

When multiple patients with suspected similar conditions consult the same doctor, each patient will develop their cognitive space model. This includes the patient's DIKWP cognition graph, their disease, and their perception of the doctor's DIKWP. The expected DIKWP cognition graph regarding the doctor's understanding of symptoms also forms part of this. The DIKWP (disease text description) content graph, representing the patient's subjective expression, can be constructed from the patient's perceived doctor's DIKWP cognition graph and the expected DIKWP cognition graph of the doctor's understanding of symptoms. Setting aside diagnostic differences due to the doctor's fatigue or workload, the doctor creates a DIKWP cognition graph for the patient's conditions based on their own DIKWP cognition graph after interacting with multiple patients. The doctor diagnoses by integrating their cognition and symptom knowledge, resulting in the final DIKWP diagnostic content graph.

In addressing such issues, we consider using DIKWP reasoning computation to solve the problem. Assume two patients (A and B) visit the same doctor and face diagnostic differences. Identifying the root cause is necessary to solve this issue, and we attempt to trace its origin. The diagnostic difference is due to differences between Patient A's diagnostic DIKWP content graph and Patient B's diagnostic DIKWP content graph, which can be traced back to differences in Patient A's disease description DIKWP content graph. The reason can be found in the differences between the DIKWP cognition graph of Patient A and the DIKWP cognition graph of Patient B; that is, there exists a cognitive gap between Patient A and Patient B. In the DIKWP graph, this is manifested as inconsistencies, inaccuracies, and incompleteness between the DIKWP semantic graph of Patient A and the semantic graph of Patient B, with the specific processing procedure shown in Figure 7.

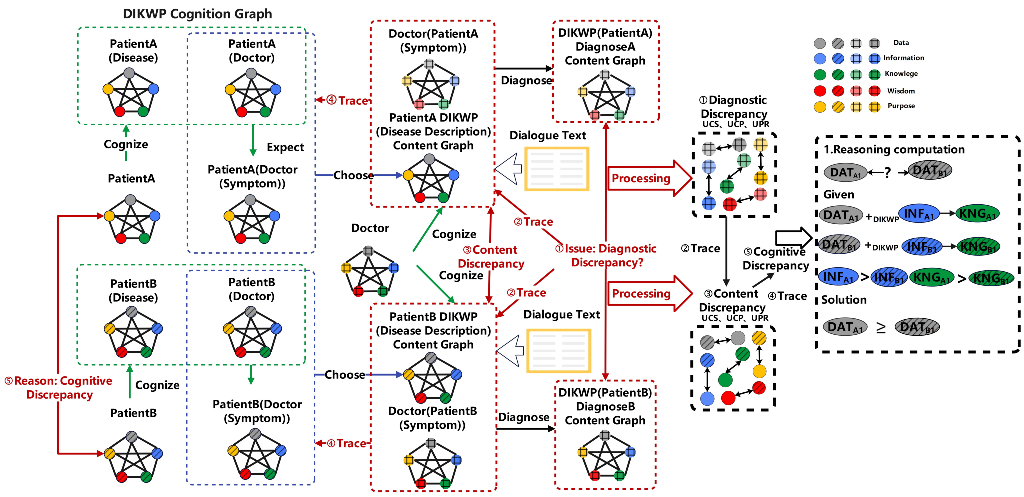


Figure 7. Processing of multi-patient same-doctor diagnostic discrepancies.

The reasoning process is as follows:

$$
\begin{aligned}
&\textbf{Request: } DAT_{A1} \; ? \; DAT_{B1} \\
&\textbf{Solutions:} \\
&\quad Given\ DAT_{A1} +_{DIKWP} INF_{A1} \rightarrow KNG_{A1} \\
&\quad DAT_{B1} +_{DIKWP} INF_{B1} \rightarrow KNG_{B1} \\
&\quad INF_{A1} > INF_{B1}, KNG_{A1} > KNG_{B1}
\end{aligned} \tag{9}
$$

It can be derived that:

$$DAT_{A1} \geq DAT_{B1} \tag{10}$$

We define Case 1 as subjective expression content text (SubExText) and store it in the (condition, conclusion) key–value pair structure as in Table 1 below.

Table 1. Splitting the text of subjective expressions.

SubExText	Condition	Conclusion
SubExText-T	I often felt guilty and blamed myself for my words and actions, I had mood swings, which occurred frequently, and my appetite and sleep received a great deal of disruption.	The patient had no history of diseases, no family history of depression or other psychiatric disorders, a preliminary diagnosis of moderate depression with a 60% tendency, and psychotherapy was recommended.
SubExText-J	I felt constant guilt and shame for my words and actions, and an overall feeling of emotional despair. I often have doubts about my abilities and values, feel helpless and confused, and my appetite and sleep have been greatly affected.	The patient had no history of diseases, no family history of depression or other psychiatric disorders, a preliminary diagnosis of moderate depression with a 70% tendency.
SubExText-A	I occasionally felt guilty and blamed for my words and actions, and my emotions occasionally felt desperate. I often have doubts about my abilities and values, feel helpless and confused, and my appetite and sleep have been greatly affected.	The patient had no history of diseases, no family history of depression or other psychiatric disorders, a preliminary diagnosis of ?
SubExText-B	I am sometimes embarrassed by my words and actions, and my emotions often feel ?. Sometimes feel lonely, especially when relationships are challenging or when facing discomfort.	The patient had no history of specific illnesses, no family history of depression or other psychiatric disorders, and a preliminary diagnosis of no depressive tendencies.

We use inference for such SubExText problems when the content of the subjective expression of the two subjects is different. We pick out the known (condition, conclusion), map the content of SubExText to DIKWP, compare them one by one, and reason about the text with the least uncertainty of the problem's existence first to obtain a basic objective result, which is then stored in the reasoning new resource base (NRB). This provides doctors with diagnostic references before diagnosis, thereby reducing diagnostic errors. It can be formalized as follows:

$$Result ::=< DAT|INF|KNG|WIS|PUP > \tag{11}$$

Finally, the SubExText that needs to be solved is reasoned through the NRB to obtain the final target.

3.3.2. Treatment of Multi-Doctor Same-Patient Diagnostic Discrepancies

In a single patient visiting multiple doctors, the patient, based on their own DIKWP cognition graph, forms a perception of the disease and the doctors. This leads to an expected DIKWP cognition graph regarding how the doctors understand the symptoms. These four cognition graphs make up the patient's cognitive space model. A subjective DIKWP (disease text description) content graph is obtained through the patient's subjectively expected cognitive model of the doctor. After the interactions between the two doctors and the patient, each doctor forms their own DIKWP cognition graph of the patient's condition. They arrive at a diagnosis by integrating their cognition and understanding of symptoms, resulting in the final DIKWP diagnostic content graph.

To address such issues, we consider DIKWP fusion and transformation to solve the problem, assuming the same patient visits doctors (A, B) at different hospitals and encounters diagnostic differences. Similarly, we can trace back from the differences in the DIKWP content graphs between Doctor A and Doctor B to find the root cause, which lies in the differences in the DIKWP cognition graphs of Doctor A and Doctor B, indicating a cognitive gap between them. In the DIKWP graph, this is reflected as inconsistencies, impreciseness, and incompleteness between Doctor A's DIKWP semantic graph and Doctor B's semantic graph, with the specific processing procedure illustrated in Figure 8.

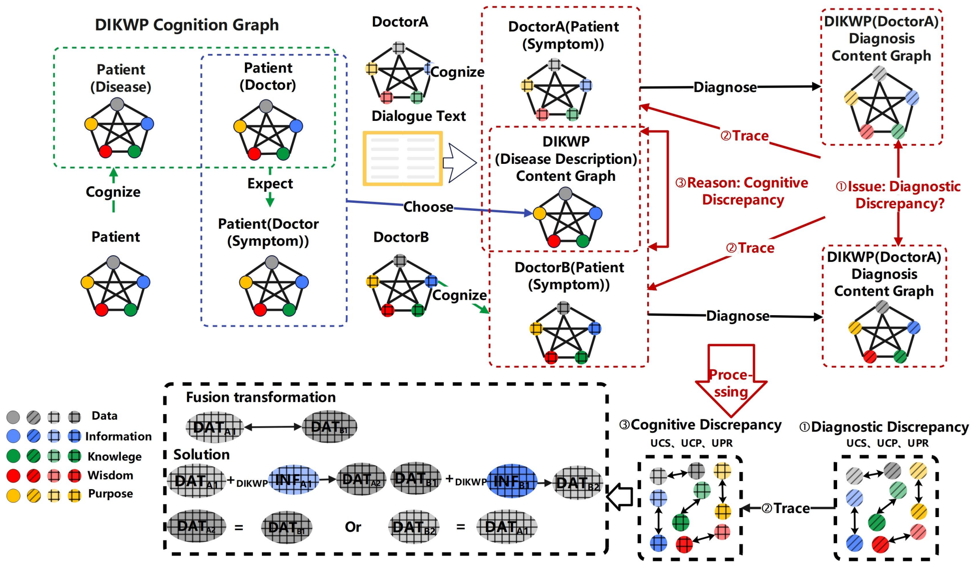


Figure 8. Processing of multi-doctor same-patient diagnostic discrepancies.

The reasoning process is as follows:

$$\begin{aligned} &\textbf{Request: } DAT_{A1} \leftrightarrow DAT_{B1} \\ &\textbf{Solutions:} \\ &\quad DAT_{A1} +_{DIKWP} INF_{A1} \rightarrow DAT_{A2} \\ &\quad DAT_{B1} +_{DIKWP} INF_{B1} \rightarrow DAT_{B2} \\ &\quad DAT_{A2} = DAT_{B1} \vee DAT_{B2} = DAT_{A1} \end{aligned} \tag{12}$$

To address the diagnostic differences between doctors, intra-modal and cross-modal transformations and reasoning are performed. This ensures that the transformed resources can satisfy the outputs of PUP, DAT, INF, KNG, and WIS. This approach aims to reduce the diagnostic errors that doctors make for different patients with the same condition and to resolve uncertainty issues, as shown in Table 2.

Table 2. Type resource conversion.

Class	Type	Formalized	Computing
Homo-modal	DAT → DAT	$< U_{CS}, U_{CP}, U_{PR} >_{DAT} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{DAT}$	$DAT_{exist} +_{DIKWP} (DAT\|INF\|KNG\|WIS) +_{DIKWP} PUP = DAT_{new}$
	INF → INF	$< U_{CS}, U_{CP}, U_{PR} >_{INF} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{INF}$	$INF_{exist} +_{DIKWP} (DAT\|INF\|KNG\|WIS) +_{DIKWP} PUP = INF_{new}$
	KNG → KNG	$< U_{CS}, U_{CP}, U_{PR} >_{KNG} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{KNG}$	$KNG_{exist} +_{DIKWP} (DAT\|INF\|KNG\|WIS) +_{DIKWP} PUP = KNG_{new}$
	WIS → WIS	$< U_{CS}, U_{CP}, U_{PR} >_{WIS} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{WIS}$	$WIS_{exist} +_{DIKWP} (DAT\|INF\|KNG\|WIS) +_{DIKWP} PUP = WIS_{new}$
	PUP → PUP	$< U_{CS}, U_{CP}, U_{PR} >_{PUP} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{PUP}$	$PUP_{exist} +_{DIKWP} (DAT\|INF\|KNG\|WIS) +_{DIKWP} PUP = PUP_{new}$
Cross-modal	DAT → INF	$< U_{CS}, U_{CP}, U_{PR} >_{DAT} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{INF}$	$DAT_{exist} +_{DIKWP} (DAT\|INF_{exist}\|KNG\|WIS) +_{DIKWP} PUP = INF_{new}$
	DAT → KNG	$< U_{CS}, U_{CP}, U_{PR} >_{DAT} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{KNG}$	$DAT_{exist} +_{DIKWP} (DAT\|INF\|KNG_{exist}\|WIS) +_{DIKWP} PUP = KNG_{new}$
	DAT → WIS	$< U_{CS}, U_{CP}, U_{PR} >_{DAT} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{WIS}$	$DAT_{exist} +_{DIKWP} (DAT\|INF\|KNG\|WIS_{exist}) +_{DIKWP} PUP = WIS_{new}$
	DAT → PUP	$< U_{CS}, U_{CP}, U_{PR} >_{DAT} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{PUP}$	$DAT_{exist} +_{DIKWP} (DAT\|INF\|KNG\|WIS_{exist}) +_{DIKWP} PUP_{exist} = PUP_{new}$
	INF → DAT	$< U_{CS}, U_{CP}, U_{PR} >_{INF} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{DAT}$	$INF_{exist} +_{DIKWP} (DAT_{exist}\|INF\|KNG\|WIS) +_{DIKWP} PUP = DAT_{new}$
	INF → KNG	$< U_{CS}, U_{CP}, U_{PR} >_{INF} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{KNG}$	$INF_{exist} +_{DIKWP} (DAT\|INF\|KNG_{exist}\|WIS) +_{DIKWP} PUP = KNG_{new}$
	INF → WIS	$< U_{CS}, U_{CP}, U_{PR} >_{INF} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{WIS}$	$INF_{exist} +_{DIKWP} (DAT\|INF\|KNG\|WIS_{exist}) +_{DIKWP} PUP = WIS_{new}$
	INF → PUP	$< U_{CS}, U_{CP}, U_{PR} >_{INF} \rightarrow < U_{CS}, U_{CP}, U_{PR} >_{PUP}$	$INF_{exist} +_{DIKWP} (DAT\|INF\|KNG\|WIS) +_{DIKWP} PUP_{exist} = PUP_{new}$

4. Model Reasoning and Difference Processing

We conduct reasoning and verification on the two scenarios encountered during the medical consultation process, specifically addressing the $DIFF_{MR}$ issue in Case 1 and 2.

4.1. Processing Diagnostic Differences Caused by Multiple Patients with the Same Doctor

To tackle the diagnostic difference problem caused by multiple patients consulting the same doctor, we first use purpose-driven data, information, knowledge, and wisdom fusion technology to formally analyze the dispute's causes before addressing specific case differences.

4.1.1. Reasoning on Diagnostic Differences

Diagnostic differences arising in doctor–patient interactions can lead to medical disputes. The patient's intent during the consultation can be segmented from "describing the condition" to "receiving a diagnosis". In Case 1, with four patients (P_T, P_J, P_A, P_B)

consulting, diagnostic differences occur due to varying expressions, hence the cause of the dispute can be formally deduced as follows:

$$\begin{aligned}
&DIKWP_{CG}(P_A) ::=< DG_{CG}(P_A), IG_{CG}(P_A), KG_{CG}(P_A), WG_{CG}(P_A), PG_{CG}(P_A) > \\
&DG_{CG}(P_A) ::= DAT_{CG_1}(P_A), \ldots, DAT_{CG_N}(P_A), N \geq 1 \\
&DG_{CG}(P_A) = \{word, action, emotion, ?, relationship, discomfort\} \rightarrow U_{CP} \\
&PUP_{CG_1}(P_A) ::= Disease\ conditions \\
&Search\ PUP_{CG_1}(P_A)\ in\ DIKWP_{CG}(P_A) \\
&INF_{CG_1}(P_A) \rightarrow Disease\ Basic\ Condition\ Description\ Information \\
&INF_{CG_1}(P_A) = \{sometimes, embarrassed \ldots\} \\
&DIKWP_{CG}(P_B) ::=< DG_{CG}(P_B), IG_{CG}(P_B), KG_{CG}(P_B), WG_{CG}(P_B), PG_{CG}(P_B) > \\
&DG_{CG}(P_B) ::= DAT_{CG_1}(P_B), \ldots, DAT_{CG_N}(P_B), N \geq 1 \\
&PUP_{CG_1}(P_B) ::= Disease\ conditions \\
&Search\ PUP_{CG_1}(P_B)\ in\ DIKWP_{CG}(P_B) \\
&INF_{CG_1}(P_B) \rightarrow Disease\ Basic\ Condition\ Description\ Information \\
&INF_{CG_1}(P_B) = \{occasionally, blamed, \ldots\} \\
&\{sometimes, embarrassed \ldots\}_{INF} \neq \{occasionally, blamed, \ldots\}_{INF} \\
&\rightarrow U_{CP}\ and\ U_{PR}
\end{aligned} \tag{13}$$

4.1.2. Processing on Diagnostic Differences

In Case 1, P_A's unclear expression led to diagnostic differences. We map the (condition, conclusion) in SubExText to DIKWP, one by one, to find out the two main body expression texts (SubExText-T, SubExText-J) with the least $DIFF_{MR}$. We first map SubExText-T, SubExText-J, SubExText-A, and SubExText-B(Condition, Conclusion) to DIKWP, respectively, and the "?" part that needs to be solved can be set as an x-band solver. The "?" part can be set to x for solving, and the specific process is as follows:

The Basic Objective Result is Stored in the NRB for Reasoning

We first transform SubExText-T and SubExText-J formally, which can be obtained as follows:

SubExText-T

$$\begin{aligned}
&[INF_{T1} \wedge INF_{T2} \wedge INF_{T3} \wedge INF_{T4}]((T, DAT_{T1}), (T, DAT_{T2}), (DAT_{T3}, DAT_{T4}))\wedge \\
&[INF_{T5} \wedge INF_{T6} \wedge INF_{T7} \wedge INF_{T8}](DAT_{T5}, DAT_{T6})\wedge \\
&[INF_{T9} \wedge INF_{T10} \wedge INF_{T11}]((DAT_{T7}, DAT_{T8}), (T, DAT_{T9})) \rightarrow \\
&[INF_{T11} \wedge INF_{T12} \wedge INF_{T13} \wedge INF_{T14}]((DAT_{T10}, DAT_{T11}), (DAT_{T10}, DAT_{T12}))\wedge \\
&[INF_{T13} \wedge INF_{T14} \wedge INF_{T15} \wedge INF_{T16} \wedge INF_{T17}]((DAT_{T13}, DAT_{T14}), (DAT_{T14}, DAT_{T15}))\wedge \\
&[INF_{T18} \wedge INF_{T19} \wedge INF_{T14} \wedge INF_{T20} \wedge INF_{T21}]((DAT_{T16}, DAT_{T14}), (DAT_{T17}, DAT_{T18}))\wedge \\
&[INF_{T22} \wedge INF_{T23} \wedge INF_{T24}]DAT_{T19}
\end{aligned} \tag{14}$$

SubExText-J

$$\begin{aligned}
&[INF_{J1} \wedge INF_{J2} \wedge INF_{J3} \wedge INF_{J4}]((J, DAT_{J1}), (J, DAT_{J2}), (DAT_{J3}, DAT_{J4}))\wedge \\
&[INF_{J5} \wedge INF_{J6} \wedge INF_{J7}](DAT_{J5}, DAT_{J6})\wedge \\
&[INF_{J8} \wedge INF_{J9} \wedge INF_{J10} \wedge INF_{J3}]((J, DAT_{J7}), (DAT_{J8}, DAT_{J9})) \rightarrow \\
&[INF_{J11} \wedge INF_{J13}]((DAT_{J10}, DAT_{J11}))\wedge \\
&[INF_{J3} \wedge INF_{J9} \wedge INF_{J12} \wedge INF_{J13} \wedge INF_{J14}](DAT_{J12}, DAT_{J13})\wedge \\
&[INF_{J15} \wedge INF_{J16} \wedge INF_{J17} \wedge INF_{J18}]((DAT_{J13}, DAT_{J14}), (DAT_{J14}, DAT_{J15}))\wedge \\
&[INF_{J17} \wedge INF_{J18} \wedge INF_{J19} \wedge INF_{J20} \wedge INF_{J21}]((DAT_{J16}, DAT_{J14}), (DAT_{J14}.DAT_{J17}), \\
&(DAT_{J14}, DAT_{J18})) \wedge [INF_{J22} \wedge INF_{J23} \wedge INF_{J18} \wedge INF_{J24} \wedge INF_{J25}] \\
&((DAT_{J19}, DAT_{J17}), (DAT_{J20}, DAT_{J21}))
\end{aligned} \tag{15}$$

We introduce relevant conditions, specifically the following:

- Known condition

$$\begin{aligned}
&DAT : DAT_{T1} = DAT_{J1}, DAT_{T2} = DAT_{J2}, DAT_{T3} = DAT_{J3}, DAT_{T4} = DAT_{J4}, \\
&DAT_{T7} = DAT_{J12}, DAT_{T8} = DAT_{J13} \\
&INF : INF_{T2} = INF_{J1}, INF_{T3} = INF_{J3}, INF_{T4} = INF_{J4}
\end{aligned} \tag{16}$$

- Comparison of frequency and extent
  Moments are in the frequency to a greater extent than the hourly rate, so we can consider moments > hourly rate. Therefore, it can be obtained as follows:

$$INF_{T1} < INF_{J2} \tag{17}$$

- Disambiguation
  Some words have different lexical meanings to express the same meaning and some words have the same meaning but different expressions. Then, we need to disambiguate. We define the disambiguation function as EL, including lexical disambiguation (EL_{POS}) and lexical disambiguation (EL_{MEAN}), as follows:

$$\begin{aligned}
&EL ::=< EL_{POS}, EL_{MEAN} > \\
&< DAT_{T1}, DAT_{J1} >::= EL_{POS}(DAT_{T1}, DAT_{J1}) \\
&< DAT_{T5}, DAT_{J5} >::= EL_{MEAN}(DAT_{T5}, DAT_{J5})
\end{aligned} \tag{18}$$

- Emotional vocabulary
  Depression and despair, both volatility and despair, are negative emotions in the emotional vocabulary but differ in degrees. Generally speaking, volatility is more likely to describe a mild, temporary depression or emotional upset. At the same time, despair more strongly expresses an emotional state of hopelessness and despair to a deeper degree, so despair > swings. Therefore, the following can be obtained:

$$DAT_{T6} < DAT_{J6} \tag{19}$$

- The rule of common sense
  KNG_1(Moderately depressed people may doubt their own abilities and values, as well as feel helpless and confused); KNG_2(moderately depressed patients have large mood swings); we formalize these three knowledge rules as follows:

$$
\begin{aligned}
&KNG_1: \\
&[INF_{T18} \wedge INF_{T19} \wedge INF_{T20} \wedge INF_{T21}]((DAT_{T15}, DAT_{T14}), (DAT_{J8}, DAT_{J9})) \\
&\rightarrow [INF_{J8} \wedge INF_{J9} \wedge INF_{J10} \wedge INF_{J3}]((J, DAT_{J7}), (DAT_{J8}, DAT_{J9})) \wedge \\
&[INF_{J11} \wedge INF_{J13}](DAT_{J10}, DAT_{J11}) \\
&KNG_2: \\
&[INF_{J22} \wedge INF_{J23} \wedge INF_{J18} \wedge INF_{J24} \wedge INF_{J25}]((DAT_{J9}, DAT_{J17}), \\
&(DAT_{J20}, DAT_{J21})) \rightarrow [INF_{T5} \wedge INF_{T6} \wedge INF_{T7} \wedge INF_{T8}](DAT_{T5}, DAT_{T6})
\end{aligned} \tag{20}
$$

Due to

$$
\begin{aligned}
&SubExText - T(Conclusion) \leq SubExText - J(Conclusion) \\
&\rightarrow SubExText - T(Condition) \leq SubExText - J(Condition)
\end{aligned} \tag{21}
$$

The following can be obtained:

$$
Result ::= ep\{DAT_{T3} \leq DAT_{J3}\} \tag{22}
$$

Ultimately, blamed is less than or equal to shame and can be obtained and stored in the NRB. The result inference validation diagram is shown in Figure 9.

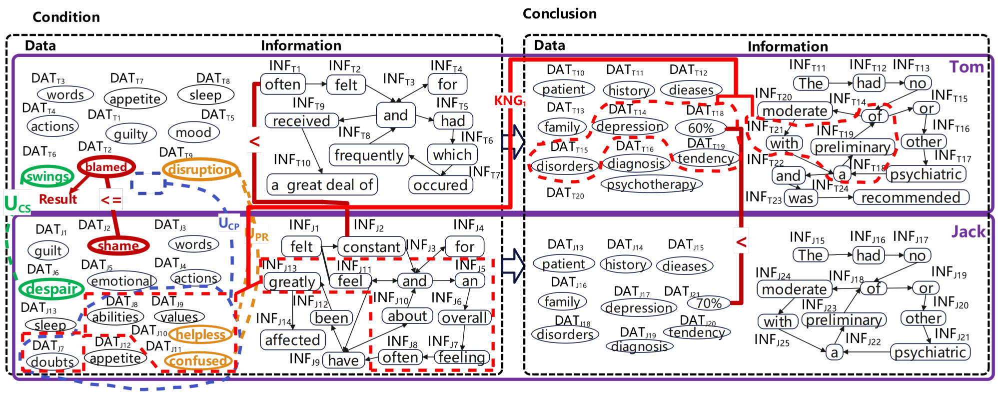


Figure 9. Case 1-Result deposited in NRB.

Search the NRB and Solve for the Target

We first set SubExText-A(Conclusion) with "?" as $Target_1$, and SubExText-B(Condition) with "?" as $Target_2$, and the specific solution is as follows:

- Solving for $Target_1$
  This can be seen by the relevant conditions in the result's reasoning above:

$$
\begin{aligned}
&SubExText - T(Condition) < SubExText - A(Condition) \leq \\
&SubExText - J(Condition) \rightarrow SubExText - T(Conclusion) < \\
&SubExText - A(Conclusion) \leq SubExText - J(Conclusion)
\end{aligned} \tag{23}
$$

Formalize SubExText-A(Conclusion) as follows:

$$
\begin{aligned}
&[INF_{A12} \wedge INF_{A13} \wedge INF_{A14} \wedge INF_{A15}]((DAT_{A14}, DAT_{15}), (DAT_{14}, DAT_{16})) \wedge \\
&[INF_{A14} \wedge INF_{A15} \wedge INF_{A16} \wedge INF_{A17} \wedge INF_{A18}]((DAT_{A17}, DAT_{A18}), \\
&(DAT_{A18}, DAT_{A19})) \wedge Target_1
\end{aligned} \tag{24}
$$

The following is known:

$$
\begin{aligned}
&DAT:\\
&DAT_{T10} = DAT_{A14} = DAT_{J13}, DAT_{T11} = DAT_{A15} = DAT_{J14},\\
&DAT_{T12} = DAT_{A17} = DAT_{J16}, DAT_{T14} = DAT_{A18} = DAT_{J17},\\
&DAT_{T15} = DAT_{A19} = DAT_{J18}, DAT_{T16} = DAT_{A20} = DAT_{J13}\\
&INF:\\
&INF_{T11} = INF_{A12} = INF_{J15}, INF_{T12} = INF_{A13} = INF_{J17},\\
&INF_{T13} = INF_{A14} = INF_{J17}, INF_{T14} = INF_{A15} = INF_{J18},\\
&INF_{T15} = INF_{A16} = INF_{J19}, INF_{T16} = INF_{A17} = INF_{J20},\\
&INF_{T15} = INF_{A16} = INF_{J19}, INF_{T16} = INF_{A17} = INF_{J20},\\
&INF_{T17} = INF_{A18} = INF_{J21}, INF_{T18} = INF_{A20} = INF_{J23}
\end{aligned}
\tag{25}
$$

Therefore:

$$
\begin{aligned}
&[INF_{T18} \wedge INF_{T19} \wedge INF_{T14} \wedge INF_{T20} \wedge INF_{T21}]((DAT_{T16}, DAT_{T14}),\\
&(DAT_{T17}, DAT_{T18})) \wedge [INF_{T22} \wedge INF_{T23} \wedge INF_{T24}]DAT_{T19} < Target_1\\
&\leq [INF_{J22} \wedge INF_{J23} \wedge INF_{J18} \wedge INF_{J24} \wedge INF_{J25}]\\
&((DAT_{J19}, DAT_{J17}), (DAT_{J20}, DAT_{J21}))
\end{aligned}
\tag{26}
$$

That is, $Target_1$'s initial diagnosis for Alice is moderate depression with a depressive tendency of 60% to 70%, and $Target_1$'s inference validation diagram is shown in Figure 10.

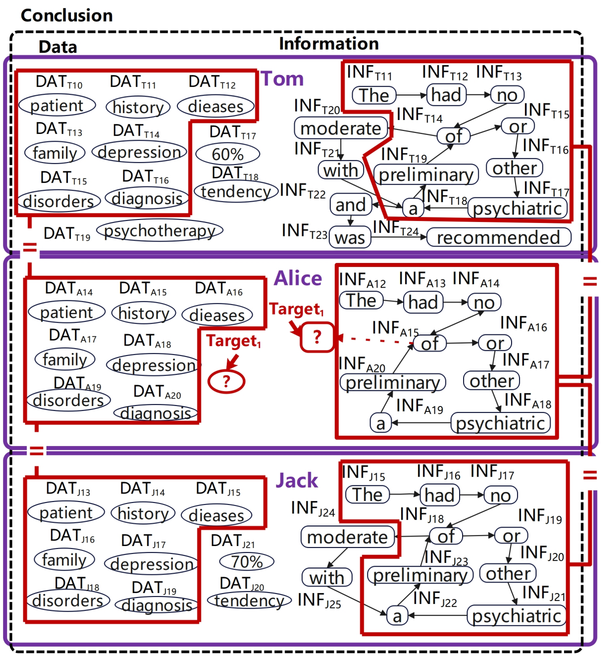


Figure 10. Case 1- Search for the NRB and solve for Target.

- Solving for $Target_2$ We require $Target_2$ in SubExText-B(Condition), according to the following condition:

$$\begin{aligned}&SubExText-B(Conclusion)<SubExText-T(Conclusion)\leq\\&SubExText-J(Conclusion)\rightarrow SubExText-B(Condition)<\\&SubExText-T(Condition)\leq SubExText-J(Condition)\end{aligned} \tag{27}$$

We formalize SubExText-B(Condition) to obtain the following:

$$\begin{aligned}&[INF_{B1}\wedge INF_{B2}\wedge INF_{B3}]((B,DAT_{B1}),(DAT_{B2},DAT_{B3}))\wedge\\&[INF_{B3}\wedge INF_{B4}\wedge INF_{B5}\wedge Target_2](DAT_{B4},Target_2)\wedge\\&[INF_{B7}\wedge INF_{B8}\wedge INF_{B9}\wedge INF_{B10}\wedge INF_{B11}]((DAT_{B4},DAT_{B7}),(B,DAT_{B8}))\end{aligned} \tag{28}$$

We are known:

$$\begin{aligned}&DAT:\\&DAT_{B2}=DAT_{T3}=DAT_{J3},DAT_{B3}=DAT_{T4}=DAT_{J4}\\&INF:\\&INF_{B3}=INF_{T3}=INF_{J3},INF_{B4}=INF_{T1}\end{aligned} \tag{29}$$

Comparison between frequency and extent:

$$INF_{B1}<INF_{J2}<INF_{T1} \tag{30}$$

Disambiguation:

$$\begin{aligned}&<DAT_{B4},DAT_{J5}>=EL_{POS}(DAT_{B4},DAT_{J5})\\&<INF_{B5},INF_{T2}>EL_{POS}(DAT_{B5},DAT_{T2})\end{aligned} \tag{31}$$

Emotional vocabulary:

$$DAT_{B1}<DAT_{T2}\leq DAT_{J2} \tag{32}$$

The rule of common sense: KNG (frequent doubts about one's abilities and worth, feeling helpless and confused, and appetite and sleep have been greatly affected, and the emotional level is greater than the feeling of loneliness at times, especially when relationships are challenging or when facing discomfort), formalizes the knowledge rule, as follows:

$$\begin{aligned}&[INF_{B1}\wedge INF_{B5}](B,DAT_{B5})\wedge[INF_{B7}\wedge INF_{B8}\wedge INF_{B9}\wedge INF_{B10}\wedge INF_{B11}]\\&((DAT_{B6},DAT_{B7})(B,DAT_{B8}))<[INF_{J8}\wedge INF_{J9}\wedge INF_{J10}\wedge INF_{J13}]((J,DAT_{J7}),\\&(DAT_{J8},DAT_{J9}))\wedge[INF_{J11}\wedge INF_{J13}](DAT_{J10},DAT_{J11})\wedge\\&[INF_{J3}\wedge INF_{J9}\wedge INF_{J12}\wedge INF_{J13}\wedge INF_{J14}](DAT_{J12},DAT_{J13})\end{aligned} \tag{33}$$

Therefore:

$$[Target_2]Target_2\leq DAT_{J6} \tag{34}$$

That is, $Target_2$ as a whole is less than desperate.

4.2. Processing Diagnostic Differences Caused by the Same Patient Consulting Multiple Doctors

To address the diagnostic differences caused by the same patient consulting multiple doctors, we first use purpose-driven data, information, knowledge, and wisdom fusion technology to formally analyze the dispute's causes before handling the differences in Case 2.

4.2.1. Diagnostic Differences Reasoning

Diagnostic differences in doctor–patient interactions can lead to medical disputes. The intent during a doctor's consultation process can be segmented from "ordering tests" to "receiving a diagnosis" and ultimately to "formulating a treatment plan". In Case 2, where doctors (D_A, D_B, D_C) diagnose a patient, driven by the purpose of "order tests", differences in the tests ordered by D_A and D_C could lead to diagnostic differences. C_A indicates the patient's objective content text. The reason can then be formally deduced as follows:

$$\begin{aligned}
DIKWP_{CG}(D_A(C_A)) ::= &< DG_{CG}(D_A(C_A)), IG_{CG}(D_A(C_A)), KG_{CG}(D_A(C_A)),\\
&WG_{CG}(D_A(C_A)), PG_{CG}(D_A(C_A)) >\\
DIKWP_{CG}(D_C(C_A)) ::= &< DG_{CG}(D_C(C_A)), IG_{CG}(D_C(C_A)), KG_{CG}(D_C(C_A)),\\
&WG_{CG}(D_C(C_A)), PG_{CG}(D_C(C_A)) >\\
DG_{CG}(D_A(C_A)) ::= &DAT_{CG_1}(D_A(C_A)), \ldots, DAT_{CG_N}(D_A(C_A)), N \geq 1\\
DG_{CG}(D_C(C_A)) ::= &DAT_{CG_1}(D_C(C_A)), \ldots, DAT_{CG_N}(D_C(C_A)), N \geq 1\\
DG_{CG}(D_A(C_A)) = &\{location, pain, activity, fever, weight\}\\
DG_{CG}(D_C(C_A)) = &\{foamy, cloudy\}\\
Search\ DG_{CG}((D_A(C_A)\ in\ DIKWP_{CG}((D_A(C_A)) &\rightarrow NOT\ FOUND\ U_{CP}\\
Search IG_{CG}((D_A(C_A)\ in\ DIKWP_{CG}((D_A(C_A)) &\rightarrow NOT\ FOUND\ U_{CP}\\
PUP_{CG_1}((D_A(C_A) ::= &\ open\ test\ item\\
Search\ PUP_{CG_1}((D_A(C_A)\ in\ &DIKWP_{CG}(D_A(C_A))\\
DG_{CG}(D_A(C_A)) = &\{urine\ routine, urine\ proteinquantification, blood\ routine,\\
&serum\ creatinine, blood\ urea\ nitrogen\}\\
IG_{CG}(D_A(C_A)) = &\{renal\}\\
PUP_{CG_1}((D_C(C_A) ::= &\ open\ test\ item\\
Search\ PUP_{CG_1}((D_C(C_A)\ in\ &DIKWP_{CG}(D_C(C_A))\\
DG_{CG}(D_C(C_A)) = &\{kidney\ stones, X-Rays, blood\ tests\}\\
IG_{CG}(D_C(C_A)) = &\{infections\}\\
DG_{CG}(D_A(C_A)) \neq &DG_{CG}(D_C(C_A))\\
&\rightarrow U_{CS} and U_{PR}\\
IG_{CG}(D_C(C_A)) = &\{infections\}\\
IG_{CG}(D_A(C_A)) \neq &IG_{CG}(D_C(C_A))\\
&\rightarrow U_{CS} and U_{PR}
\end{aligned} \tag{35}$$

Similarly, driven by the purpose of "formulate a treatment plan", differences in the treatment plans between D_A and D_B could lead to diagnostic differences. This is reflected in the issues of uncertainty in data, information, knowledge, wisdom, and purpose, as shown in Table 3.

Table 3. Uncertainty issues in multi-doctor cases with the same patient.

		U_{CS}	U_{CP}	U_{PR}
Data	Doctor$_A$ and Doctor$_B$	{hormones,immunosuppressants, Methylprednisolone, Cyclophosphamide}$_{DAT_A}$ $\neq$ {biological agents,rituximab}$_{DAT_B}$	{Methylprednisolone, Cyclophosphamide}$_{DAT_A}$ AND {rituximab}$_{DAT_B}$	{Methylprednisolone, Cyclophosphamide}$_{DAT_A}$ $\leftrightarrow$ {rituximab}$_{DAT_B}$
	Doctor$_A$ and Doctor$_C$	{urine routine, 24-h urine protein, biochemistry}$_{DAT_A}$ $\neq$ {CT scan, bones,infection}$_{DAT_C}$	{color,texture}$_{DAT_A}$ AND {kidney stones}$_{DAT_C}$	{blood routine, serum creatinine, blood urea nitrogen}$_{DAT_A}$ $\leftrightarrow$ {blood tests}$_{DAT_C}$
Information	Doctor$_A$ and Doctor$_B$	{starting}$_{INF_A}$ $\neq$ {inject}$_{INF_B}$	{inflammatory}$_{INF_A}$ AND {damage}$_{INF_B}$	{side,such as}$_{INF_A}$ $\leftrightarrow$ {side,include,increased}$_{INF_B}$
	Doctor$_A$ and Doctor$_C$	{understand,renal}$_{INF_A}$ $\neq$ {look for}$_{INF_C}$	{foamy,cloudy}$_{INF_A}$ AND {specific,worse}$_{INF_C}$	{includes,understand}$_{INF_A}$ $\leftrightarrow$ {rule out,common}$_{INF_C}$
Knowledge	Doctor$_A$ and Doctor$_B$	{starting(Methylprednisolone) $\rightarrow$ reduce(kidneys)}$_{KNG_A}$ $\neq$ {inject(rituximb) $\rightarrow$ reduce(proteinuria)}$_{KNG_B}$	{side(effect) $\rightarrow$ gain(weight) increase(blood pressure ˆ risks)}$_{KNG_A}$ AND {include(biologics, side(effect)) $\rightarrow$ increase(risks)}$_{KNG_B}$	{side(effect) $\rightarrow$ gain(weight) increase(blood pressure, risks)}$_{KNG_A}$ $\leftrightarrow$ {include(biologics, side(effect)) $\rightarrow$ increase(risks)}$_{KNG_B}$
	Doctor$_A$ and Doctor$_C$	{understand(renal status) $\rightarrow$ start(urine routine, 24-h urine protein,biochemistry)}$_{KNG_A}$ $\neq$ {kidney stones $\rightarrow$ start(CT scan, blood tests)}$_{KNG_C}$	{foamy ˆ cloudy(urine) $\rightarrow$ understand(renal status)}$_{KNG_A}$ AND {no(fever) ˆ stable(weight) ˆ worse (activity)ˆspecific(pain location) $\rightarrow$ kidney stones}$_{KNG_C}$	{understand(renal status) $\rightarrow$ start(urine routine, 24-h urine protein,biochemistry)}$_{KNG_A}$ $\leftrightarrow$ {kidney stones $\rightarrow$ start(CT scan, blood tests)}$_{KNG_C}$
Wisdom	Doctor$_A$ and Doctor$_B$	{hormones ˆ immuno suppressants}$_{WIS_A}$ $\neq$ {biological agents}$_{WIS_B}$	{considering(health ˆ condition)}$_{WIS_A}$ AND {fast(treatment)}$_{WIS_B}$	{considering(health ˆ condition)}$_{WIS_A}$ $\leftrightarrow$ {fast(treatment)}$_{WIS_B}$
	Doctor$_A$ and Doctor$_C$	{renal(status)}$_{WIS_A}$ $\neq$ {kidney stones}$_{WIS_C}$	{understand(renal status)}$_{WIS_A}$ AND {rule out(problem)}$_{WIS_C}$	{understand(renal status)}$_{WIS_A}$ $\leftrightarrow$ {rule out(problem)}$_{WIS_C}$
Purpose	Doctor$_A$ and Doctor$_B$	{starting(Methylprednisolone Cyclophosphamide)}$_{PUP_A}$ $\neq$ {ject(rituximab)}$_{PUP_B}$	{reduce(kidneys)}$_{PUP_A}$ AND {reduce(proteinuria)}$_{PUP_B}$	{reduce(kidneys)}$_{PUP_A}$ $\leftrightarrow$ {reduce(proteinuria)}$_{PUP_B}$
	Doctor$_A$ and Doctor$_C$	{start(urine routine, 24-h urine protein,biochemistry)}$_{PUP_A}$ $\neq$ {CT scan}$_{PUP_C}$	{understand(renal status)}$_{PUP_A}$ AND {look for(bones, infections)}$_{PUP_C}$	{understand(renal status)}$_{PUP_A}$ $\leftrightarrow$ {look for(bones,infections)}$_{PUP_C}$

4.2.2. Diagnostic Differences Processing

We map the interactive dialogues from Case 2 into the DIKWP model, where the patient's main complaint is "two weeks of back pain with a sensation of fatigue". In the doctor–patient interaction, the doctors' cognition graphs are continually updated, particularly their cognition graphs regarding the patient and their DIKWP cognition graphs related to the patient's condition. There are differences in treatment plans between D_A and D_B, and differences in the tests ordered by D_A and D_C, indicating variances in the doctors' cognition graphs about the patient and their DIKWP cognition graphs of the patient's condition. When combined with Table 3, the specific differences in the DIKWP graphs of D_A, D_B, and D_C are depicted in Figure 11.

To address the issue of differences, we propose a fusion solution that approaches the uncertainty caused by diagnostic differences from both intra-modal and cross-modal perspectives, performing DIKWP transformation calculations and constructing processing scenarios. By integrating intent for the deduction, the resource transformation yields DIKWP resources that meet the intent requirements, enhancing the medical process's transparency, interpretability, and computational efficiency, avoiding doctor–patient disputes, and resolving diagnostic differences. To some extent, this approach surpasses the doctors' diagnostic and treatment capabilities. Regarding the treatment plan differences between D_A and D_C, for the intra-modal transformation of five modalities, we provide formal representations, transformation calculations, and processing illustrations, as shown in Table 4.

We give the formal representation for the twenty cross-modal transformations, as shown in Tables 5 and 6.

Table 4. Homo-modal DIKWP conversion computing and processing.

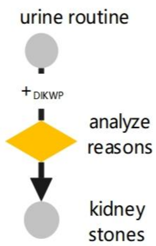
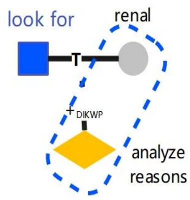
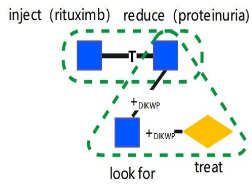
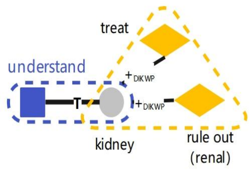
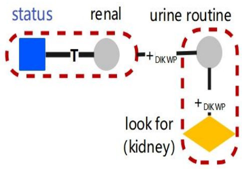
Type	Formalized	Graphic
DAT → DAT	$< urine\ routine >_{DAT} +_{DIKWP} < analyze\ reasons >_{PUP} \rightarrow < kidney\ stones >_{DAT}$	
INF → INF	$< look\ for >_{INF} +_{DIKWP} < analyze\ reasons >_{PUP} \rightarrow < look\ for(renal) >_{INF}$	
KNG → KNG	$< inject(rituximb) \rightarrow reduce(proteinuria) >_{KNG} +_{DIKWP} < look\ for >_{INF} +_{DIKWP} < analyze\ reasons >_{PUP} \rightarrow < reduce(proteinuria) \rightarrow treat(kidney) >_{KNG}$	
WIS → WIS	$< renal(status) >_{WIS} +_{DIKWP} < routine >_{DAT} +_{DIKWP} < look\ for(kidney) >_{PUP} \rightarrow < urine\ routine \rightarrow look\ for(kidney) >_{WIS}$	
PUP → PUP	$< rule\ out(renal) >_{PUP} +_{DIKWP} < understand(kidney) >_{WIS} +_{DIKWP} < treat >_{PUP} \rightarrow < treat(kidney) >_{PUP}$	

Table 5. Cross- modal DIKWP conversion computing and processing (DAT,INF).

Type	Formalized
DAT → INF	$< urine\ rountine >_{DAT} +_{DIKWP} < understand(renal)) >_{INF} +_{DIKWP} < understand(renal) \to start(urine\ rountine) >_{KNG} +_{DIKWP} < cstar >_{PUP} \to < has(renal\ problems) >_{INF}$
DAT → KNG	$< two\ weeks >_{DAT} +_{DIKWP} < test \to cause >_{KNG} +_{DIKWP} < pain\ time >_{DAT} +_{DIKWP} < cause >_{PUP} \to < pain\ time \to !cause \wedge test >_{KNG}$
DAT → WIS	$< test\ results >_{DAT} +_{DIKWP} < test \to treatment\ plan >_{KNG} +_{DIKWP} < treatment\ plan \to treat(ache) >_{KNG} +_{DIKWP} < relieve >_{PUP} \to < relieve(ache) >_{WIS}$
DAT → PUP	$< uarthritis >_{DAT} +_{DIKWP} < treatment\ plan >_{DAT} +_{DIKWP} < find >_{PUP} \to < find(treatment\ plan) >_{PUP}$
INF → DAT	$< pain(lower\ back) >_{INF} +_{DIKWP} < pain(lower\ back) \wedge fatigue \to stones >_{KNG} +_{DIKWP} < test >_{PUP} \to < CT >_{DAT}$
INF → KNG	$< pain(knuckle) >_{INF} +_{DIKWP} < test\ results \to diagnose >_{KNG} +_{DIKWP} < cause >_{PUP} \to < cause \to testresults >_{KNG}$
INF → WIS	$< pain(knuckle) >_{INF} +_{DIKWP} < pain(knuckle) \to ache >_{KNG} +_{DIKWP} < relieve >_{PUP} \to < relieve(ache) >_{WIS}$
INF → PUP	$< eat(medicine) \wedge no(recover) >_{INF} +_{DIKWP} < best(treatment\ plan) \to recover >_{KNG} +_{DIKWP} < adjust >_{PUP} \to < adjust(treatment\ plan) >_{PUP}$

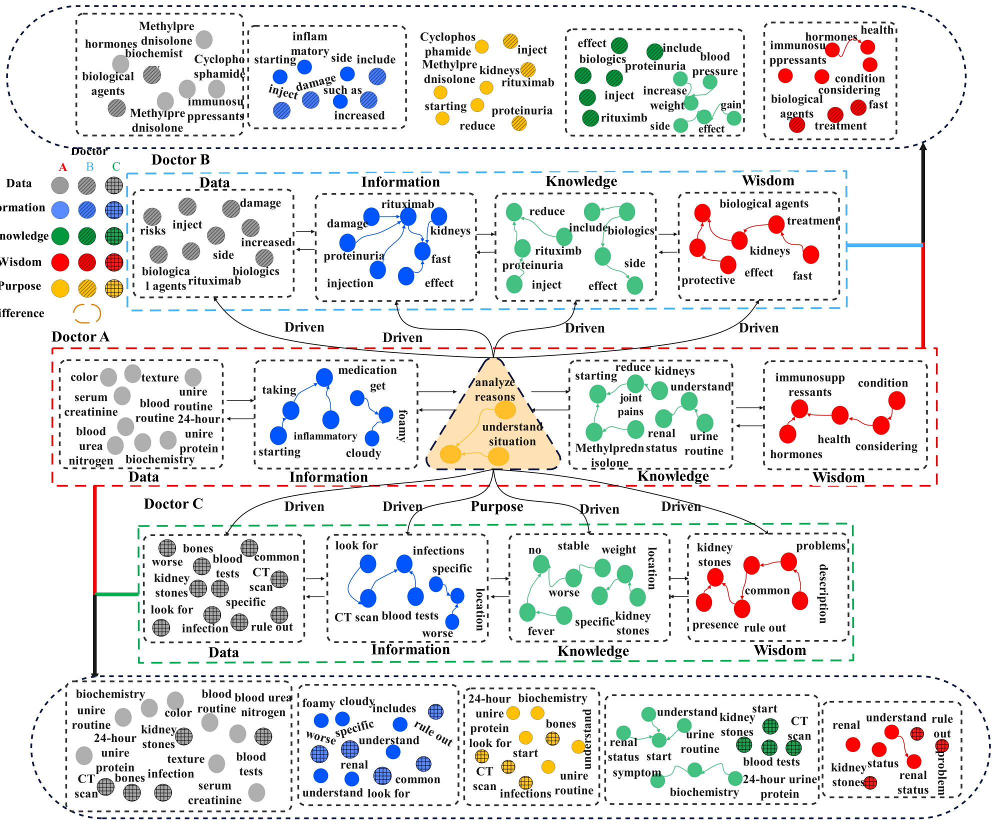


Figure 11. Schematic of spatial marking and treatment of different doctor differences.

Table 6. Cross-modal DIKWP conversion computing and processing (KNG, WIS, and PUP).

Type	Formalized
KNG → DAT	$< gouty\ arthritis \rightarrow high(Uric\ Acid) >_{KNG} +_{DIKWP} < high(Uric\ Acid) >_{INF} +_{DIKWP} < diagnose >_{PUP} \rightarrow < gouty\ arthritis >_{DAT}$
KNG → INF	$< goutyarthritis \rightarrow high(Uric\ Acid) >_{KNG} +_{DIKWP} < high(Uric\ Acid) >_{INF} +_{DIKWP} < diagnose >_{PUP} \rightarrow < diagnose(gouty\ arthritis) >_{INF}$
KNG → WIS	$< gouty\ arthritis \rightarrow high(Uric\ Acid) >_{KNG} +_{DIKWP} < control >_{PUP} \rightarrow < control(Uric\ Acid) >_{WIS}$
KNG → PUP	$< gouty\ arthritis \rightarrow high(Uric\ Acid) >_{KNG} +_{DIKWP} < treat >_{PUP} \rightarrow < treat(gouty\ arthritis) >_{PUP}$
WIS → DAT	$< understand(disease) >_{WIS} +_{DIKWP} < allopurinol \rightarrow treat(Uric\ Acid) >_{KNG} +_{DIKWP} < understand >_{PUP} \rightarrow < gouty\ arthritis >_{DAT}$
WIS → INF	$< treat(gouty\ arthritis) >_{WIS} +_{DIKWP} >< allopurinol \rightarrow treat(gouty\ arthritis) >_{KNG} +_{DIKWP} < eat >_{DIKWP} \rightarrow < eat(allopurinol) >_{INF}$
WIS → KNG	$< treat(gouty\ arthritis) >_{WIS} +_{DIKWP} < gouty\ arthritis \rightarrow high(Uric\ Acid) >_{KNG} +_{DIKWP} < allopurinol \rightarrow control(Uric\ Acid) >_{KNG} +_{DIKWP} < treat >_{PUP} \rightarrow < allopurinol \rightarrow treat(gouty\ arthritis) >_{KNG}$
WIS → PUP	$< treat(gouty\ arthritis) >_{WIS} +_{DIKWP} < gouty\ arthritis \rightarrow high(Uric\ Acid) >_{KNG} +_{DIKWP} < allopurinol \rightarrow control(Uric\ Acid) >_{KNG} +_{DIKWP} < treat >_{PUP} \rightarrow < control(Uric\ Acid) >_{PUP}$
PUP → DAT	$< diagnose >_{PUP} +_{DIKWP} < diagnose(gouty\ arthritis) >_{INF} +_{DIKWP} < disease >_{PUP} \rightarrow < gouty\ arthritis >_{DAT}$
PUP → INF	$< treat >_{PUP} +_{DIKWP} < allopurinol \rightarrow treat(gouty\ arthritis) >_{KNG} +_{DIKWP} < eat >_{PUP} \rightarrow < eat(allopurinol) >_{INF}$
PUP → KNG	$< treat >_{PUP} +_{DIKWP} < gouty\ arthritis \rightarrow high(Uric\ Acid) >_{KNG} +_{DIKWP} < allopurinol \rightarrow treat(gouty\ arthritis) >_{KNG} +_{DIKWP} < eat >_{PUP} \rightarrow < eat(allopurinol) \rightarrow treat(gouty\ arthritis) >_{KNG}$
PUP → WIS	$< treat >_{PUP} +_{DIKWP} < adoptive(treatment\ plan) \rightarrow treat(disease) >_{KNG} +_{DIKWP} < find >_{PUP} \rightarrow < adoptive(treatment\ plan) >_{WIS}$

5. Model Verification and Comparative Analysis

In the medical consultation scenario, cognitive differences lead to diagnostic discrepancies, subdivided into differences from the cognitive input to the language output process of the interacting subjects, where a causal relationship exists between cognitive input and language output. Therefore, to better verify the advantages of the DIKWP model in addressing diagnostic differences, we selected three representative traditional methods for handling such problems for comparison with psychological analysis (PSY) and our constructed model. These three methods are the structural causal model (SCM) from the field of causal science, the global neuronal workspace (GNW) theory from consciousness science, and abduction reasoning (AR) from the field of logic. Taking the differences between D_A and D_C in Case 2 as an example, we provide the specific process.

5.1. Structural Causal Model

SCM is a commonly used model for causal inference oriented toward graphical models, falling under the methods for inferring causal relationships based on sample observational data. In Case 2, where the discrepancy arises, patients' chief complaints are "two weeks of back pain accompanied by a feeling of fatigue". D_A prescribes "routine urinalysis, 24-h urine protein, biochemistry, and complete blood count", whereas D_C orders a "CT scan and complete blood count". To address this issue, we need to assume a causal relationship exists between the doctors' cognitive input and their language output, and it is necessary to presuppose that doctors have textual parts of cognition. For instance, the cognition to perform a CT is derived from the patient's continuous back pain and symptoms of frequent but scanty urination, suggesting the possibility of stones, which require a CT scan for diagnosis. We can examine the relationship between the variables "back pain", "scanty urination", and "stones" to estimate the likelihood of stones in a person with scanty urination and back pain.

We define "back pain", "scanty urination", and "stones" as X, A, and Y respectively, where A acts as an intermediary variable between X → Y. Let M represent the SCM, and U=u denote the assignment of a certain exogenous variable. For example, U = u could represent a characteristic called u. Assuming X represents back pain, then X(u) denotes the condition of back pain in u. Thus, this SCM can be defined as follows:

$$
\begin{aligned}
X &= U_{pain} \\
A &= aX + U_{urine} \\
Y &= bA
\end{aligned} \tag{36}
$$

Given the condition of scanty urination (A = 1), the impact of back pain on the likelihood of stones represented as $E[Y_1 - Y_0|A = 1] = ab \neq 0$, is significant. However, to eliminate data inconsistency, such as changing the test item from a CT scan to a routine urinalysis, new data, information, and knowledge need to be introduced for processing. Therefore, in addressing uncertainty issues, when data and information are incomplete or imprecise, calculations can be performed using the SCM, as detailed in Table 7.

Table 7. DIKWP Treatment of SCM under Uncertainty.

	U_{CS}	U_{CP}	U_{PR}
DAT	×	$\{color, texture, kidneys\}_{DAT_A}$ AND $\{urine, stones\}_{DAT_C}$	$\{color, texture, kidneys\}_{DAT_A} \leftrightarrow \{urine, stones\}_{DAT_C}$
INF	×	$\{foamy, cloudy\}_{DAT_A}$ AND $\{pain, less\}_{DAT_C}$	$\{foamy, cloudy\}_{DAT_A} \leftrightarrow \{pain, less\}_{DAT_C}$
KNG	×	×	×
WIS	×	×	×
PUP	×	×	×

5.2. Global Neuronal Workspace

GNW proposes a cognitive architecture that divides the brain into modules with specific functions. When sensory inputs or task demands trigger responses in some modules, these responses compete. Through selective attention mechanisms, certain information enters the global workspace and is broadcast across different modules, facilitating the transfer of information between them. The entry and distribution of information to the global workspace and to other modules give rise to consciousness.

Taking the differential issue in Case 2 as an example, where the chief complaints are "two weeks of back pain accompanied by a feeling of fatigue", and D_C prescribes a "CT scan and complete blood count", from the patient's perspective, integrating the sensation of back pain "without a specific location, worsens after activity" into the global workspace, along with monitoring information about their physical condition "no fever, stable weight". After these integrated pieces of information are broadcast into the global workspace, consciousness about their health status is formed. In the role of D_C, the doctor integrates the information provided by the patient with their medical knowledge and experience. Considering the nature of the pain and accompanying symptoms, the doctor constructs a potential diagnostic model. Based on the diagnostic model, further examinations such as "CT and complete blood count" are prescribed. Therefore, in addressing uncertainty issues, assuming external resources cannot be accessed, and in situations where data, information, and knowledge are incomplete or imprecise, a brain space search can be conducted through GNW to supplement some data, information, and knowledge. For example, adding the knowledge "If the patient's urine is foamy and murky, it indicates a problem with the kidneys" into D_C's cognition, as detailed in Table 8.

Table 8. DIKWP treatment of GNW under uncertainty.

	u_{CS}	u_{CP}	u_{PR}
DAT	$\times$	$\{color, texture, kidneys\}_{DAT_A}$ AND $\{urine, stones\}_{DAT_C}$	$\{color, texture, kidneys\}_{DAT_A} \leftrightarrow \{urine, stones\}_{DAT_C}$
INF	$\times$	$\{foamy, cloudy\}_{DAT_A}$ AND $\{pain, less\}_{DAT_C}$	$\{foamy, cloudy\}_{DAT_A} \leftrightarrow \{pain, less\}_{DAT_C}$
KNG	$\times$	$\{foamy \wedge \ldots \rightarrow renal\}_{KNG_A}$ AND $\{fever \wedge \ldots \rightarrow stones\}_{KNG_C}$	$\{foamy \wedge \ldots \rightarrow renal\}_{KNG_A} \leftrightarrow \{fever \wedge \ldots \rightarrow stones\}_{KNG_C}$
WIS	$\times$	$\times$	$\times$
PUP	$\times$	$\times$	$\times$

5.3. Abduction Reasoning

AR can serve as a cognitive process that provides explanations for observed facts. In Case 2, where the patient's chief complaint is "two weeks of back pain accompanied by a feeling of fatigue", D_C prescribes a "CT scan and complete blood count". The reasoning process of D_C is as follows:

The letter E represents the effect, and the letter C represents the cause. To clearly distinguish between causal rules and non-causal rules, the lowercase letter c is used to represent causal rules, while the letter r is used for non-causal rules. If we have deduced the result, E1, from a certain cause, C1, using predictive reasoning, then inferring another cause 'C1' from E1 through explanatory reasoning is obviously unreasonable. Therefore, "E-C" is used to denote the defeasible rule from effect to cause, such as "C2: Pain intensifies after exercise⇒ E-C lumbar muscle strain", and "C-E" denotes the defeasible rule from cause to effect, such as "C3: Stones $\Rightarrow_{C-E}$ CT abnormalities". If there is no subscript, it indicates a non-causal rule, such as "R4: Young doctor ⇒¬reliable", implying there is no causal relationship nor a relationship of explanation.

As long as the observed facts match the premise of a certain rule, then that rule is triggered and activated. For example, if lumbar muscle strain is observed, the existing rule "C2: Pain intensifies after exercise $\Rightarrow_{E-C}$ lumbar muscle strain" is triggered, allowing for the construction of the argumentation framework A2=({Pain intensifies after exercise, (C2: Pain intensifies after exercise $\Rightarrow_{E-C}$ lumbar muscle strain)}, lumbar muscle strain). Next, by analyzing the attack and supporting relationships between arguments and based on the assessment system of AR, the best explanation for the subject's final purpose is provided. Therefore, in addressing uncertainty issues, assuming external resources cannot be accessed, when knowledge is inconsistent, incomplete, and imprecise, reasoning can be performed based on existing data and information, and new knowledge rules can be established. For example, the knowledge rule "If the urine is foamy and murky, the patient may have kidney disease" may not originally exist in D_C. However, AR allows for the artificial setting of this knowledge rule. Hence, in dealing with DIKWP uncertainty issues, under conditions of incomplete and imprecise knowledge, calculations can be conducted using the AR, as detailed in Table 9.

Table 9. DIKWP treatment of AR under uncertainty.

	u_{CS}	u_{CP}	u_{PR}
DAT	$\times$	$\times$	$\times$
INF	$\times$	$\times$	$\times$
KNG	$\{renal \rightarrow start(test)\}_{KNG_A} \neq \{stones \rightarrow start(CT)\}_{KNG_C}$	$\{foamy \wedge \ldots \rightarrow renal\}_{KNG_A}$ AND $\{fever \wedge \ldots \rightarrow stones\}_{KNG_C}$	$\{foamy \wedge \ldots \rightarrow renal\}_{KNG_A} \leftrightarrow \{fever \wedge \ldots \rightarrow stones\}_{KNG_C}$
WIS	$\times$	$\times$	$\times$
PUP	$\times$	$\times$	$\times$

5.4. Psychological Analysis

In PSY, addressing diagnostic test discrepancies among doctors in Case 2 requires an analysis that involves a deep exploration of the individual's inner motives, subconscious impulses, and psychological defense mechanisms. With the patient's chief complaint being "two weeks of back pain accompanied by a feeling of fatigue", the transformation from fatigue and back pain to seeking medical care is analyzed. Utilizing PSY allows an in-depth investigation into the individual's psychological structure and inner world to find causal clues.

For instance, "fatigue" and back pain might reflect physiological states and represent the external manifestations of subconscious conflicts within an individual. For example, back pain could be viewed as a somatic response to specific life stresses or psychological conflicts. Seeking medical care becomes a subconscious plea for help, hoping to find a solution to their physical problems through a doctor. However, psychological analysis also carries the potential for over-analysis, meaning the patient's condition could simply be due to physical strain or injury caused by external factors, with no underlying psychological stress. Therefore, in the context of DIKWP under uncertainty, reasoning through PSY can be conducted, as detailed in Table 10.

Table 10. DIKWP treatment of PSY under uncertainty.

	u_{CS}	u_{CP}	u_{PR}
DAT	$\{urine\ routine, urineprotein\}_{DAT_A} \neq \{CT\ scan\}_{DAT_C}$	$\times$	$\times$
INF	$\{understand, renal\}_{INF_A} \neq \{look\ for\}_{INF_C}$	$\times$	$\times$
KNG	$\times$	$\{foamy \wedge \ldots \rightarrow renal\}_{KNG_A}$ AND $\{fever \wedge \ldots \rightarrow stones\}_{KNG_C}$	$\{foamy \wedge \ldots \rightarrow renal\}_{KNG_A} \leftrightarrow \{fever \wedge \ldots \rightarrow stones\}_{KNG_C}$
WIS	$\times$	$\times$	$\times$
PUP	$\times$	$\times$	$\times$

5.5. Qualitative and Quantitative Comparison

We have compared the capabilities of SCM, GNW, AR, PSY, and DIKWP in handling uncertainty issues from the perspectives of data, information, knowledge, wisdom, and purpose. The comparison table is as follows (Table 11):

Table 11. Comparison of five uncertainty-oriented DIKWP methods.

	u_{CS}	u_{CP}	u_{PR}
DAT	$PSY, DIKWP$	$SCM, GNW, DIKWP$	$SCM, GNW, DIKWP$
INF	$PSY, DIKWP$	$SCM, GNW, DIKWP$	$SCM, GNW, DIKWP$
KNG	$AR, DIKWP$	GNW, AR, PSY	$GNW, AR, DIKWP$
WIS	$DIKWP$	$DIKWP$	$PSY, DIKWP$
PUP	$DIKWP$	$DIKWP$	$PSY, DIKWP$

To evaluate the capabilities of the five methods, we take the diagnostic difference between D_A and D_C in Case 2 as an example and compare these methods from both qualitative and quantitative perspectives. For the qualitative comparison, we deconstruct the dialogue between D_C and the patient sentence by sentence, comparing them based on three qualitative indicators: interpretability, dependency, and depth of analysis. Three sub-dialogues were selected for comparison, as follows:

Tom's Question: Doctor, I have been feeling tired recently and often experience low back pain.

Doctor C's Question:Does your low back pain have a specific location? Is the pain associated with activity? Have you experienced any fever or weight loss?

Tom's Answer:The lower back pain is not localized. It worsens with activity. I have not experienced any fever, and my weight appears stable.

The detailed comparison is presented in Table 12.

Table 12. Uncertainty issues in multi-doctor cases with the same patient.

	No	PSY	SCM	GNW	AR	DIKWP
Interpretability	Tom	pain(lower back) → pressure	fatigue, pain(lower back), diagnosis	fatigue, pain(lower back) → GNW	6 Rules	Input($DIKWP_{CG}$) Output(expression)
	D_C	hold(lower back) → disease	exercise, fever, weight,...	information → GNW	11 Rules	Input($DIKWP_{CG}$) Output(question)
	Tom	ask(doctor) → disease	exercise, fever, weight,...	question → GNW	6 Rules	Input($DIKWP_{CG}$) Output(answer)
Dependence	Tom	depend(PSY)	depend(fatigue, pain(lower back), diagnosis)	Depend Workspaces	depend(6 Rules)	N/A
	D_C	depend(PSY)	depend(exercise, fever, weight,...)	Depend Workspaces	depend (11 Rules)	N/A
	Tom	depend(PSY)	depend(exercise, fever, weight,...)	Depend Workspaces	depend (6 Rules)	N/A
Depth of analysis	Tom	Subconscious Motivation	Three Terms	Global Search	6 Rules	Subjective and Objective
	D_C	Subconscious Motivation	Five Terms	Global Search	11 Rules	Subjective and Objective
	Tom	Subconscious Motivation	Five Terms	Global Search	6 Rules	Subjective and Objective

We summarize the detailed content and compare the methods using three levels: “High”, “Medium”, and “Low” (as in Table 13).

Table 13. Qualitative comparison of five methods under uncertainty.

	PSY	SCM	GNW	AR	DIKWP
Interpretability	Medium	Low	Medium	Medium	High
Dependence	Medium	High	Medium	High	Low
Depth of analysis	High	Low	High	Medium	High

Due to the inherent subjectivity in qualitative comparisons, we conduct a more detailed quantitative comparison to better illustrate the advantages of the DIKWP model in aspects such as interpretability. In Case 2, where D_A and D_C prescribe different tests, we map the text content into the DIKWP graph. We compare the coverage of text processing by the five methods sentence by sentence (as shown in Figure 12). To process DIKWP uncertainty issues, we compare—sentence by sentence—the capabilities of these five methods in addressing the issue (as shown in Figure 13), taking the following as an example:

$$\begin{aligned}
&CoverageDAT_{SCM} = \frac{NumDAT_{SCM}}{NumDAT} \\
&CoverageU_{SCM} = \frac{NumU_{SCM}}{NumU} \\
&NumU_{SCM} = \sum_i NumU_{i_SCM}, i = DAT, INF, KNG, WIS, PUP \\
&NumU_{PR_SCM} = \sum_j Numj_{PR}, j = DAT, INF, KNG, WIS, PUP \\
&NumU_{CS_SCM} = \sum_m Numn_{CS}, m = DAT, INF, KNG, WIS, PUP \\
&NumU_{CP_SCM} = \sum_n Numn_{CP}, n = DAT, INF, KNG, WIS, PUP
\end{aligned} \tag{37}$$

Here, $CoverageDAT_{SCM}$ represents the coverage rate of data in the text processed by the SCM method, and the same applies to other types. $CoverageU_{SCM}$ stands for the total coverage rate of uncertainty, $NumU_{SCM}$ represents the number of uncertainty issues, and

$NumU_{PR\_SCM}$, $NumU_{CS\_SCM}$, $NumU_{CP\_SCM}$ correspond to the number of issues related to U_{CS}, U_{CP}, and U_{PR}, respectively.

In our proposed DIKWP doctor–patient interaction semantic prototype for addressing uncertainty issues, the purpose-driven inputs and outputs are set as follows:

$$\{OP(n,r)\}_{OUTPUT} = PUP(\{IN(m,i)\}_{INPUT}) \tag{38}$$

where OP(n, r) output function, n is the number of outputs, and r is the value of outputs. IN(m, i) is the input function, m is the number of inputs, and i is the value of inputs. The following is an illustration of the doctor's purpose of "ordering tests":

$$\begin{aligned}
&PUP : what(test)\\
&doctor(DAT), prescribes(INF), what(INF), tests(DAT), items(DAT)\\
&(\{IN(5, \{doctor, prescribe, what, tests, itemse\})\}_{INPUT})\\
&Pathway :< pain(lower\ back) >_{INF} +_{DIKWP} < fatigue >_{INF}\\
&+_{DIKWP} < pain(lower\ back) \wedge fatigue \rightarrow stones >_{KNG}\\
&+_{DIKWP} < pain(lowerbacl) \wedge fatigue \rightarrow infections >_{KNG}\\
&+_{DIKWP} < what(test) >_{PUP} \rightarrow\\
&< CT \wedge blood\ tests >_{DAT}\\
&OUTPUT : CT, blood\ tests\\
&(\{OP(2, \{CT, blood\ tests\})\}_{OUTPUT})
\end{aligned} \tag{39}$$

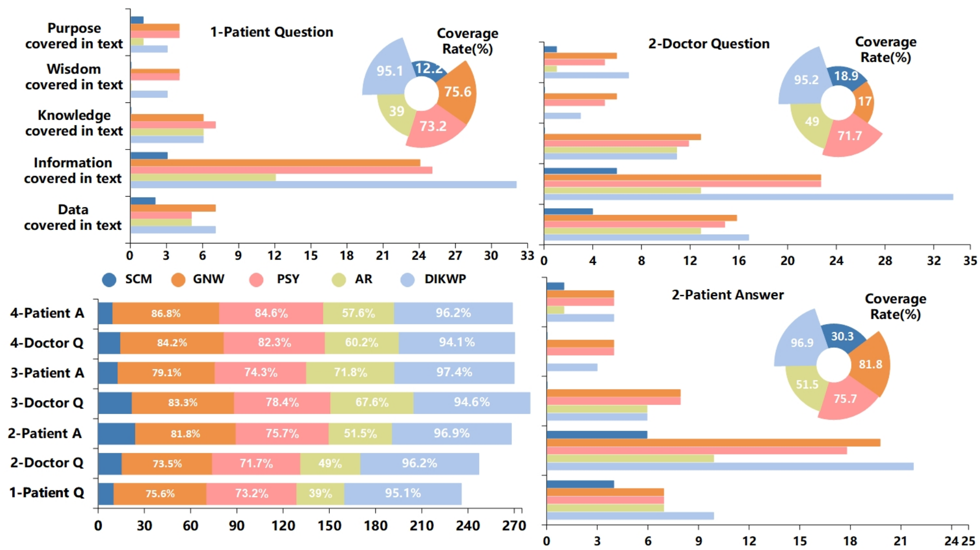


Figure 12. Comparison of text coverage rates by the five methods.

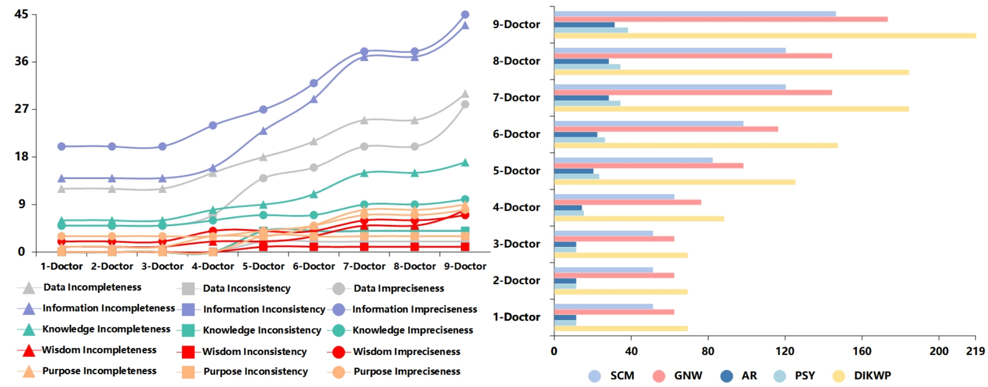


Figure 13. Comparison of the five methods' capabilities in processing DIKWP uncertainty issues.

5.6. Limitations

The case collection and the prototype platform implementation have a certain degree of limitation. In order to trace the causes of medical disputes and better demonstrate the problems arising from doctor–patient communication, we processed the audio of doctor–patient dialogues in local hospitals by collecting them and converting them into text utilizing manual translation. Although this can more intuitively show the problems in doctor–patient communication, the need to track the patient's entire consultation process makes the collection difficult and time-consuming, and ultimately, the number of collected cases is small. Secondly, we designed the DIKWP artificial awareness system based on the scheme of this paper. However, due to the insufficient number of collected samples, the system needs further validation.

6. Discussion

Doctor–patient disputes are contradictions in doctor–patient relationships, usually occurring in diagnosing and treating both sides of the rights and interests of the damage caused by the argument. Doctors and patients, during the diagnosis and treatment process, primarily communicate through intuitive contact. However, due to the interaction of subjective cognitive opacity on both sides, cognitive bias and interaction content bias occur; leading to the existence of DIKWP resource uncertainty. Ultimately, this affects the objectivity of the diagnosis and treatment results, making objective interpretation difficult. This can lead to doctor-patient disputes. The trust relationship between doctor and patient is primarily based on emotional empathy. However, existing AI technology that deals with such problems often faces inconsistencies, uncontrollability, poor self-interpretation, common sense, reasoning, and other defects, and it frequently lacks sufficient DIKWP elements.

We address these issues by taking the consultation process as the primary research object, tracking the whole process of outpatient consultation in local hospitals, and collecting the text of doctor–patient outpatient dialogues and records of test items. The cognitive bias between doctors and patients comes from the fact that the subjective external expression of the interacting subject (doctor–patient) is only a part of his/her internal cognition, and the interacting subject will draw a DIKWP cognitive picture for the other, which is different from the actual subject's cognitive picture. Therefore, we construct an intrinsic DIKWP cognitive model and an extrinsically expressed DIKWP content model for doctors and patients to make the doctor–patient interaction process transparent. The doctor–patient DIKWP cognitive model interacts with the patient/doctor DIKWP content model to form a DIKWP diagnostic content model, which is associated and mapped with DIKWP uncertainty to form a discrepancy space. Some elements of the difference space are processed using DIKWP inference computation and fusion transformation technology, and finally, a solution is given.

In order to better validate the advantages of the DIKWP model in dealing with cognitive and diagnostic differences, four types of representative traditional methods for dealing with such problems (SCM, GNW, AR, and PSY) were selected for comparative analyses with our constructed model. SCM can only handle the case of U_{CP} and U_{PR} on data and information, GNW can only handle the case of U_{CP} and U_{PR} on data, information, and knowledge, AR can only handle the case of U_{CS}, U_{CP} as well as U_{PR} on knowledge, and PSY can only handle the case of U_{CS} on data and information, U_{CP} and U_{PR} on knowledge. In addition, we try to use qualitative and quantitative comparisons for the five methods. On the qualitative comparison, the five methods are analyzed and compared from the three levels of interpretability, dependence, and depth of analysis, and the case part of the content of the specific analytical description, the results show that the DIKWP model shows better advantages in these three levels. However, the qualitative comparison has a certain degree of subjectivity. Therefore, we conducted further analysis from the perspective of quantitative comparison by comparing the five methods, sentence-by-sentence, on $CoverageDAT_{SCM}$ (Figure 12), $CovrageU_{SCM}$ (Figure 13), where the sentence-by-sentence coverage rate on $CoverageDAT_{SCM}$ is more than 95%. Compared with the other four methods, the DIKWP model also presents the best results on $CovrageU_{SCM}$ uncertainty processing. As the number of interactive dialogues increases, the DIKWP model gradually widens the number of uncertainty processing problems compared to the other methods.

7. Conclusions

Doctor–patient disputes are significant social problems worldwide, especially in countries with tight medical resources and imbalanced doctor–patient ratios. With the increasing demand for healthcare services, patients' requirements for healthcare services are becoming increasing, and the problems of asymmetric and non-transparent information, differences in cognitive levels, and expectations between doctors and patients have become more prominent, which are the leading causes of medical disputes. Existing solutions cannot fundamentally solve the crisis of trust and integrate the uncontrollable and unexplainable problems of AI technology applications in clinical practice. Therefore, we constructed a DIKWP semantic model of doctor–patient interactions to achieve transparency in the process of doctor–patient interactions, reduce misunderstandings and information errors, and identify potential dispute elements as early as possible. Based on the content and cognitive models of the DIKWP doctor–patient interaction semantic model, we identified elements of diagnostic differences, forming a DIKWP difference space. We semantically mapped the DIKWP difference spaces to DIKWP uncertainties and resolved them through purpose-driven DIKWP semantic fusion and transformation techniques. Compared with SCM, GNW, AR, and PSY, the DIKWP doctor–patient interaction semantic model effectively addresses diagnostic difference issues. In the future, we plan to continue refining the model and validating it across more scenarios.

This work has a specific effect in improving the transparency and interpretability of the doctor–patient interaction process, which can effectively alleviate the doctor–patient relationship and reduce the problem of medical disputes. However, there are still limitations, and in the future, the following problems need to be further processed and optimized. First, at this stage, case collection involves manually collecting audio and converting it into text content, which is labor-intensive and time-consuming, so a more convenient method is needed. Second, at this stage, we started the development of the DIKWP artificial consciousness prototype platform to research and collect the DIKWP uncertain cases generated during the diagnosis and treatment process and to validate the application. However, we still need a more significant number of cases. In addition, we will consider integrating the design of the integrated platform for healthcare and wellness and consider the influence of meteorological factors.

Author Contributions: Conceptualization, Y.M. and Y.D.; methodology, Y.M. and Y.D.; formal analysis, Y.M.; writing—original draft, Y.M.; writing—review and editing, Y.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research project was supported in part by the Hainan Province Health Science and Technology Innovation Joint Program (WSJK2024QN025), in part by the Hainan Province Key R&D Program (ZDYF2022GXJS007, ZDYF2022GXJS010), and in part by the Hainan Province Key Laboratory of Meteorological Disaster Prevention and Mitigation in the South China Sea, Open Fund Project (SCSF202210).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Wang, M.; Zhao, H.; Tang, C.; Sun, Y.; Liu, G.G. A taxonomy of Chinese hospitals and application to medical dispute resolutions. *Sci. Rep.* **2022**, *12*, 18234. [Crossref] [CrossRef]
2. Jia, Z.; Gao, Y.; Zhao, L.; Han, S. Longitudinal relationship between cognitive function and health-related quality of life among middle-aged and older patients with diabetes in China: Digital usage behavior differences. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12400. [Crossref] [CrossRef]
3. Jensen, K.; Gollub, R.L.; Kong, J.; Lamm, C.; Kaptchuk, T.J.; Petrovic, P. Reward and empathy in the treating clinician: The neural correlates of successful doctor-patient interactions. *Transl. Psychiatry* **2020**, *10*, 17. [Crossref] [CrossRef]
4. Fremon, B.; Negrete, V.F.; Davis, M.; Korsch, B.M. Gaps in doctor-patient communication: Doctor-patient interaction analysiss. *Pediatr. Res.* **1971**, *5*, 298–311. [Crossref] [CrossRef]
5. Weng, H.; Chen, H.; Chen, H.; Lu, K.; Hung, S. Doctors' emotional intelligence and the patient–doctor relationship. *Med. Educ.* **2008**, *42*, 703–711. [Crossref] [CrossRef]
6. Masmoudi, R.; Feki, I.; Trigui, D.; Baati, I.; Sellami, R.; Masmoudi, J. Attitudes and practices of general practitioners towards elderly patients with cognitive deficits. *Eur. Psychiatry* **2017**, *41*, S658–S659. [Crossref] [CrossRef]
7. Fineschi, D.; Acciai, S.; Napolitani, M.; Scarafuggi, G.; Messina, G.; Guarducci, G.; Nante, N. Game of Mirrors: Health Profiles in Patient and Physician Perceptions. *Int. J. Environ. Res. Public Health* **2022**, *19*, 1201. [Crossref] [CrossRef] [PubMed]
8. Élaina, G.M. Reframing patient-doctor relationships: Relational autonomy and treating autonomy as a virtue. *J. Glob. Ethics* **2022**, *18*, 32–47. [Crossref]
9. Schillinger, D.; Duran, N.D.; McNamara, D.S.; Crossley, S.A.; Balyan, R.; Karter, A.J. Precision communication: Physicians' linguistic adaptation to patients' health literacy. *Sci. Adv.* **2021**, *7*, eabj2836. [Crossref] [CrossRef]
10. Sarwar, F.; Ring, D.; Donovan, E. Clinician communication strategies to navigate differences of opinion with patients. *Patient Educ. Couns.* **2024**, *123*, 108185. [Crossref] [CrossRef] [PubMed]
11. Stewart, M.A. Effective physician-patient communication and health outcomes: A review. *Patient Educ. Couns.* **1995**, *152*, 1423. [Crossref]
12. Brown, W., III; Balyan, R.; Karter, A.J.; Crossley, S.; Semere, W.; Duran, N.D.; Lyles, C.; Liu, J.; Moffet, H.H; Daniels, R.; McNamara, D.S.; Schillinger, D. Challenges and solutions to employing natural language processing and machine learning to measure patients' health literacy and physician writing complexity: The ECLIPPSE study. *J. Biomed. Inform.* **2021**, *113*, 103658. [Crossref] [CrossRef] [PubMed]
13. Roscoe, R.D.; Balyan, R.; McNamara, D.S.; Banawan, M.; Schillinger, D. Automated strategy feedback can improve the readability of physicians' electronic communications to simulated patients. *Int. J. Hum.-Comput. Stud.* **2023**, *176*, 103059. [Crossref] [CrossRef] [PubMed]
14. Cardon, A. Artificial consciousness, artificial emotions, and autonomous robots. *Cogn. Process.* **2006**, *7*, 245–267. [Crossref] [CrossRef] [PubMed]
15. Nassani, A.A.; Javed, A.; Rosak-Szyrocka, J.; Pilar, L.; Yousaf, Z.; Haffar, M. Major Determinants of Innovation Performance in the Context of Healthcare Sector. *Int. J. Environ. Res. Public Health* **2023**, *20*, 5007. [Crossref] [CrossRef] [PubMed]
16. Alexiuk, M.; Elgubtan, H.; Tangri, N. Clinical Decision Support Tools in the EMR. *Kidney Int. Rep.* **2024**, *9*, 29–38. [Crossref] [CrossRef] [PubMed]
17. Garg, D.; Verma, G.K.; Singh, A.K. A review of Deep Learning based methods for Affect Analysis using Physiological Signals. *Multimed. Tools Appl.* **2023**, *82*, 26089–26134. [Crossref] [CrossRef]
18. Moor, M.; Banerjee, O.; Abad, Z.S.H.; Krumholz, H.M.; Leskovec, J.; Topol, E.J.; Rajpurkar, P. Foundation models for generalist medical artificial intelligence. *Nature* **2023**, *616*, 259–265. [Crossref] [CrossRef] [PubMed]
19. Budler, L.C.; Gosak, L.; Stiglic, G. Review of artificial intelligence-based question-answering systems in healthcare. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2023**, *13*, e1487. [Crossref] [CrossRef]
20. Wang, H.; Fu, T.; Du, Y.; Gao, W.; Huang, K.; Liu, Z.; Chandak, P.; Liu, S.; Van Katwyk, P.; Deac, A.; et al. Scientific discovery in the age of artificial intelligence. *Nature* **2023**, *621*, 47–60. [Crossref] [CrossRef]

21. Mainz, J.T. Medical AI: Is trust really the issue? *J. Med. Ethics* **2023**. [Crossref] Available online: https://jme.bmj.com/content/early/2023/07/26/jme-2023-109414 (accessed on 26 July 2023). [CrossRef] [PubMed]
22. Hatherley, J.J. Limits of trust in medical AI. *J. Med. Ethics* **2020**, *46*, 478–481. [Crossref] [CrossRef]
23. Siena, M.J.; Simons, J.S. Metacognitive Awareness and the Subjective Experience of Remembering in Aphantasia. *J. Cogn. Neurosci.* **2024**, 1–21.
24. Howard, S. Beefed up security or blocking patients: How to respond to patient violence. *BMJ* **2023**, *381*, 995.
25. Messeri, L.; Crockett, M.J. Artificial intelligence and illusions of understanding in scientific research. *Nature* **2024**, *627*, 49–58. [Crossref] [CrossRef]
26. Lenharo, M. The consciousness wars: Can scientists ever agree on how the mind works? *Nature* **2024**, *625*, 438–440. [Crossref] [CrossRef]
27. Acitelli, L.K. Relationship awareness: Crossing the bridge between cognition and communication. *Commun. Theory* **2002**, *12*, 92–112. [Crossref] [CrossRef]
28. Schurr, R.; Reznik, D.; Hillman, H.; Gershman, S.J. Dynamic computational phenotyping of human cognition. *Nat. Hum. Behav.* **2024**, 1–15. [Crossref] Available online: https://www.nature.com/articles/s41562-024-01814-x (accessed on 8 February 2024). [CrossRef]
29. Marchetti, G. The self and conscious experience. *Front. Psychol.* **2024**, *15*, 1340943. [Crossref] [CrossRef]
30. Chan, E.Y.; Septianto, F. Self-construals and health communications: The persuasive roles of guilt and shame. *J. Bus. Res.* **2024**, *170*, 114357. [Crossref] [CrossRef]
31. Rosenbaum, D.; Glickman, M.; Fleming, S.M.; Usher, M. The cognition/metacognition trade-off. *Psychol. Sci.* **2022**, *33*, 613–628. [Crossref] [CrossRef]
32. Warren, A. Preserved Consciousness in Alzheimer's Disease and Other Dementias: Caregiver Awareness and Communication Strategies. *Front. Psychol.* **2021**, *12*, 790025. [Crossref] [CrossRef] [PubMed]
33. Schnakers, C. Assessing consciousness and cognition in disorders of consciousness. *NeuroRehabilitation* **2024**, *54*, 11–21. [Crossref] [CrossRef] [PubMed]
34. Malhi, S.K. Welch-West, P.; Koo, A.M.; Fogarty, J.; Lazosky, A. Thinking without speaking: Neuropsychological testing with individuals who have communication impairments. *Neuropsychol. Rehabil.* **2022**, *32*, 1605–1619. [Crossref] [CrossRef] [PubMed]
35. Mudrik, L. Consciousness: What it is, where it comes from—And whether machines can have it. *Nature* **2023**, *623*, 25–26. [Crossref] [CrossRef] [PubMed]
36. Lenharo, M. AI consciousness: Scientists say we urgently need answers. *Nature* **2024**, *625*, 226. [Crossref] [CrossRef] [PubMed]
37. Boltuc, P. The philosophical issue in machine consciousness. *Int. J. Mach. Conscious.* **2009**, *1*, 155–176. [Crossref] [CrossRef]
38. Dehaene, S.; Naccache, L. Towards a cognitive neuroscience of consciousness: Basic evidence and a workspace framework. *Cognition* **2001**, *79*, 1–37. [Crossref] [CrossRef] [PubMed]
39. Dehaene, S.; Lau, H.; Kouider, S. What is consciousness, and could machines have it? *Science* **2017**, *358*, 486–492. [Crossref] [CrossRef]
40. Starzyk, J.; Prasad, D. A computational model of machine consciousness. *Int. J. Mach. Conscious.* **2011**, *3*, 255–281. [Crossref] [CrossRef]
41. Shevlin, H. General intelligence: An ecumenical heuristic for artificial consciousness research? *J. Artif. Intell. Conscious.* **2020**, *7*, 245–256. [Crossref] [CrossRef]
42. Gamez, D. The Relationships Between Intelligence and Consciousness in Natural and Artificial Systems. *J. Artif. Intell. Conscious.* **2020**, *7*, 51–62. [Crossref] [CrossRef]
43. Baars, B.; Edelman, D. Consciousness, biology and quantum hypotheses. *Phys. Life Rev.* **2020**, *9*, 285–294. [Crossref] [CrossRef]
44. Xu, G.; Xue, M.; Zhao, J. The Association between Artificial Intelligence Awareness and Employee Depression: The Mediating Role of Emotional Exhaustion and the Moderating Role of Perceived Organizational Support. *Int. J. Environ. Res. Public Health* **2023**, *20*, 5147. [Crossref] [CrossRef]
45. Paliga, M. The Relationships of Human-Cobot Interaction Fluency with Job Performance and Job Satisfaction among Cobot Operators—The Moderating Role of Workload.*Int. J. Environ. Res. Public Health* **2023**, *20*, 5111. [Crossref] [CrossRef]
46. Peer, M.; Brunec, I.; Newcombe, N.; Epstein, R.A. Structuring Knowledge with Cognitive Maps and Cognitive Graphs. *Trends Cogn. Sci.* **2021**, *25*, 37–54. [Crossref] [PubMed]
47. Yang, G.; Wu, H.; Li, Q.; Liu, X.; Fu, Z.; Jiang, J. Dorsolateral prefrontal activity supports a cognitive space organization of cognitive control. *eLife* **2024**, *12*, RP87126. [Crossref] [CrossRef]
48. VanRullen, R.; Kanai, R. Deep learning and the global workspace theory. *Trends Neurosci.* **2021**, *44*, 692–704. [Crossref] [PubMed]
49. Aceves, P.; Evans, J.A. Human languages with greater information density have higher communication speed but lower conversation breadth. *Nat. Hum. Behav.* **2024**, *8*, 644–656. [Crossref] [CrossRef]
50. Duan, Y.; Lu, Z.; Zhou, Z.; Sun, X.; Wu, J. Data privacy protection for edge computing of smart city in a DIKW architecture. *Eng. Appl. Artif. Intell.* **2019**, *81*, 323–335. [Crossref] [CrossRef]
51. Millikan, R. *Varieties of Meaning: The 2002 Jean Nicod Lectures*; MIT Press: Cambridge, MA, USA, 2004; pp 287–326; ISBN: 0262134446. [Crossref]
52. Bone, J.K.; Bu, F.; Sonke, J.K.; Fancourt, D. Leisure engagement in older age is related to objective and subjective experiences of aging. *Nat. Commun.* **2024**, *15*, 1499. [Crossref] [CrossRef] [PubMed]

53. Novak, P.; Systrom, D.; Marciano, S.P.; Knief, A.; Felsenstein, D.; Giannetti, M.P.; Hamilton, M.J.; Nicoloro-SantaBarbara, J.; Saco, T.V.; Castells, M.; et al. Mismatch between subjective and objective dysautonomia. *Sci. Rep.* **2024**, *14*, 2513. [Crossref] [CrossRef] [PubMed]
54. Cadario, R.; Longoni, C.; Morewedge, C.K. Understanding, explaining, and utilizing medical artificial intelligence. *Nat. Hum. Behav.* **2021**, *5*, 1636–1642. [Crossref] [CrossRef] [PubMed]
55. Gao, H.; Huang, W.; Duan, Y. The Cloud-edge-based Dynamic Reconfiguration to Service Workflow for Mobile Ecommerce Environments: A QoS Prediction Perspective. *ACM Trans. Internet Technol.* **2021**, *21*, 1–23. [Crossref] [CrossRef]
56. Li, Y.; Li, Z.; Duan, Y.; Spulber, A.B. Physical artificial intelligence (PAI): The next-generation artificial intelligence. *Front. Inf. Technol. Electron. Eng.* **2023**, *24*, 1231–1238. [Crossref] [CrossRef]
57. Song, M.; Xing, X.; Duan, Y.; Cohen, J.; Mou, J. Will artificial intelligence replace human customer service? The impact of communication quality and privacy risks on adoption intention. *J. Retail. Consum. Serv.* **2022**, *66*, 102900. [Crossref]
58. Huang, Y. *Trusted, Reliable and Responsible Based on DIKWP Research on Modeling and Validation of Smart Form Filling*; Hainan University: Haikou, China, 2023.
59. Hu, T. *Modeling, Analysis and System Implementation of Integrated Healthcare and Wellness for DIKWP*; Hainan University: Haikou, China, 2023.
60. Mei, Y.; Duan, Y.; Yu, L.; Che, H. Purpose Driven Biological Lawsuit Modeling and Analysis Based on DIKWP. In Proceedings of the 18th EAI International Conference on Collaborative Computing: Networking, Applications and Worksharing, Hangzhou, China, 15 December 2022; pp. 250–267. [Crossref]
61. Liu, Y.; Wang, W.; Wang, W.; Yu, C.; Mao, B.; Shang, D.; Duan, Y. Purpose-Driven Evaluation of Operation and Maintenance Efficiency and Safety Based on DIKWP. *Sustainability* **2023**, *15*, 13083. [Crossref] [CrossRef]