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Research Article

Medical Telediagnoses in Countries with Limited Resources: Comparison of A General Generative AI System with A Clinical Decision Support System

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Abstract:

Background/Aim: Achieving correct clinical or morphological diagnoses in countries with limited resources is a major challenge due to the lack of methods such as immunohistochemistry, molecular biology, or imaging, as well as the lack of specialists. Artificial intelligence (AI), whether in the form of generative intelligence or clinical decision support systems, is a promising method for bridging the gap in diagnosis between developed countries and countries with limited resources. For this purpose, we used the general generative AI system ChatGPT and the specialized semantic net-based AI system Memem7 as medical diagnostic support systems to improve telemedicine diagnosis in a resource-limited country. Materials and methods: 102 randomly selected cases from 3 hospitals in northern Afghanistan were classified by up to 7 telemedicine experts. In 61 cases (59.8%), the experts provided a disease classification (target diagnosis). In the remaining 41 cases, the experts only provided a list of differential diagnoses. We investigated how often ChatGPT and Memem7 could predict the target diagnosis or provide a list of essential differential diagnoses. Results: In 36/61 (59.0%) and 47/61 (77.1%) cases, respectively, ChatGPT and Memem7 recognized the target diagnosis. In 88/102 (86.3%) (ChatGPT) and 93/102 (91.2%) (Memem7) cases, a helpful list of differential diagnoses was provided.

Conclusion: Both artificial intelligence (AI-)-based systems show promising results, either in confirming the target diagnosis or in providing a helpful list of differential diagnoses.

Key words: telemedicine; telepathology; telecytology; artificial intelligence; ChatGPT; clinical decision support system

Introduction

The use of artificial intelligence (AI) in medicine, especially in disease classification (diagnosis), is constantly increasing [1-2]. Before assessing or testing its usefulness, two situations had to be distinguished [3-6]: [1] AI is used to classify a disease entity by selecting one of a few possibilities (narrow task-specific AI). Its usefulness is well documented and proven by very good test performance. [2] AI has to choose between all possible disease entities for a given patient, as coded in SNOMED, ICD-10, ICD-11, and ICD-O [7-10]. This approach is covered by clinical decision support systems (CDSSs) [11] or, more recently, generative AI such as ChatGPT [3,12-15]. Both approaches can be applied to telemedicine.

Telemedicine is a rapidly growing field of medicine [16-20] with 2 interesting features that are not primarily related to telemedicine consultations: [1] images and string variables of telemedicine consultations can be used for further research, provided that ethical aspects are considered and fulfilled, and [2] telemedicine consultations solve one of the most outstanding problems in countries with limited resources: the lack of experts. Considering both areas of interest (AI and telemedicine practice in a country with limited resources), 2 methods can be used to improve the quality of medical diagnosis: [1] generative intelligence approaches using natural language models [12-14] and [2] clinical decision support systems [11].

ChatGPT is a virtual assistant based on large natural language models. This system's potential to improve the quality of medical diagnosis needs to be evaluated, especially when used in resource-constrained countries, where the risk of uncontrolled use of ChatGPT is particularly high [12-15].

In contrast, CDSSs [11] have a longer history of clinical use. CDSSs provide the clinician with a ranked list of possible differential diagnoses (DDs), accompanied by information about the proposed DDs. Examples of CDSSs include Isabel, ADA, Google Bard, and Memem7 [21-24].

While both systems are well studied in developed countries, studies of their use in resource-limited countries are rare, especially when combined with telemedicine and AI methods.

Our feasibility study aimed to investigate how often a target diagnosis (suggested by human experts in a telemedicine consultation) could be predicted by both systems (ChatGPT and a CDSS).

We tested the hypothesis that both a CDSS and ChatGPT could recognize the target diagnoses generated by the experts and provide a list of additional possible DDs in medical cases in a resource-limited country. These analyses were conducted on 102 pseudonymized real-world cases.

Materials and Methods

Patients: Data from 102 patients treated for various symptoms and diseases (see Table 1 and Part IV of the Supplement for details) were uploaded to a telemedicine platform (iPath-Network; see Afghanistan Forum below) for disease classification. Cases were randomly selected from 3865 telemedicine consultations conducted from October 1, 2021, to May 31, 2023, in northern Afghanistan. No cases were excluded from the random selection. These telemedicine consultations and classifications were performed by 4 pathologists (GS, PF, CF, PD), one dermatologist (KA), one emergency physician (CF), and one surgeon (RR). Not all experts were present at each case. Cases were uploaded by 3 local Afghan physicians (RR, SA, HF). A brief description of the patient's age (in years, not birthday) and sex was available, as well as a brief description of the symptoms. In all cases, one or more static images (IPEG format, 1-20 images/case) were available. Histological, cytological, macroscopic, dermatological, and radiological images were uploaded. Computed tomography (CT) and magnetic resonance imaging (MRI) images were uploaded as written reports or as a sequence of images (rare). All cases were documented on iPath-Network. The uploading institutions were 2 private laboratories (Firooz Medical Laboratory, Herat; Balk Hospital, Mazar-e-Sharif) and 1 district hospital (Ibn Sina Hospital, Mazar-e-Sharif). All telemedicine consultations were free of charge. Expert diagnoses were made just in time (less than 3 days), explaining why, in some cases, only 2 experts gave their classification. Each day, all cases were discussed between the attending physician (SA, HF, RR) and the first-line experts (GS, PD, PF, CF, RR, HF). If there was no consensus among the first-line experts, we consulted experts with particular experience in a medical subspecialty, e.g., in bone tumor diseases, hematology, neuropathology, skin pathology, or radiology. Therefore, 3 levels of medical classification of a case were used (see Examples 1 and 2 in the Appendix): [1] the diagnosis of the local doctor in charge of the patient, [2] human experts and their disease classification (level 2 or first line of telemedicine diagnosis), and [3] the opinion of experts in a medical subspecialty if the case required specialist knowledge (level 3 or second line of telemedicine diagnosis). Finally, each case was discussed and concluded with an expert diagnosis or a list of DDs provided by the experts. The exact procedure is described in a flowchart (Figure 1). We presented ChatGPT or Memem7 with the parameters (descriptors) given by the physicians (symptoms, descriptions of images related to microscopy, macroscopy, radiographs, CT, or MRI). All descriptors (parameters) mentioned in the case description were transformed into a Memem7 code (alphanumeric code). The transformation was done by one of the authors (PF; see also Example 1 or 2 in the Appendix). ChatGPT and Memem7 were given the semantic meaning of the Memem7 code. To start ChatGPT and Memem7, we used the same parameters defined for each case (symptoms, image description in the form of macroscopy, microscopy, or descriptions of X-rays, CT, or MRI). The images were transformed into descriptors (string variables) by one of the authors (PF). These descriptors were considered as objects with or without attributes and uploaded to ChatGPT or Memem7 (for examples, see Supplement Cases 1 and 2). For all participants (GP, consultants, Memem7, and ChatGPT), we used exactly the same information (as a string variable or as the sentence "patient has a" for ChatGPT) (see examples in Supplement Cases 1 and 2). The data output was given in string variables (also termed phemes in Memem7) with an unique alphanumeric code.

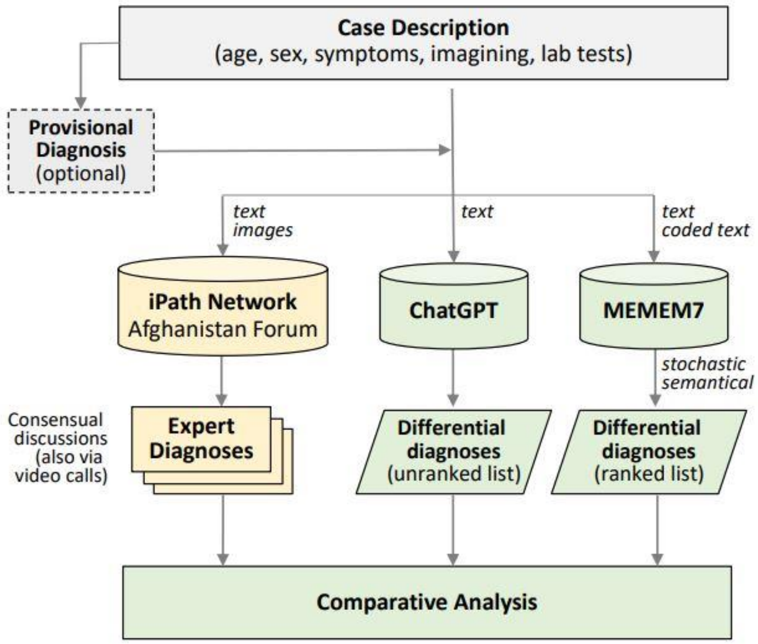

Figure 1: Flow chart of the study

Handling of images: Images (regardless of their structure) were transformed into a sequence of string variables. The macroscopic image of a skin tumor can be described as skin change: circumscribed; diameter: 2.5 cm; skin change: scaly.

Software system used:

iPath-Network: iPath-Network is a platform for telemedicine (originally telepathology) [25-29]. iPath-Network has been operational since 2010 and has processed more than 100,000 real-world cases [28], including the Afghanistan Forum, which has more than 20,000 consultations. The 102 study cases were randomly selected from the Afghanistan Forum, which is moderated by one of the authors (RR). Therefore, simple cases with a dermatological picture as well as extremely complex and difficult cases are part of the study. As all local examinations must be paid for by the patient and many special examinations required by international guidelines are not possible in northern Afghanistan, incomplete medical reports of our cases are common. All telemedicine diagnoses and consultations are free of charge. Immunohistochemistry or molecular biology tests were not available in northern Afghanistan.

Memem7: This is a non-commercial CDSS (computer-aided clinical decision support system) developed by 2 of the authors (KA, PF) [21]. It is based on a large semantic network (over 600,000 nodes) that is transparent to the user and contains all types of entities and relationships, such as objects, classes, parts, attributes, processes, states, properties, etc. The inference algorithms use the processing of the semantic network based on linguistic logic, which includes ambiguity, vagueness, and uncertainty. In any case, a search function can be used based on the terms entered. The input is mainly structured, but unstructured narrative input (e.g., medical reports) is also possible, which is processed by modified NLP (neuro-linguistic programming) algorithms. The result is an output with an ordered list of DDs of unlimited length. For each diagnosis, Memem7 provides a relevance value indicating the relevance of the search terms to the suggested diagnosis. Memem7 uses Bayesian methods to generate the list of diagnoses, i.e., the more terms that match leading symptoms, the higher the relevance score. Each natural language element (such as headache) is coded in Memem7 (headache = HC11|). This code is related to the ICD-10 and ICD-O codes and is part of a semantic up-and-down tree. In our example, there are 2 up-tree codes like head (A110) and pain (EP) and 38 down-tree codes like thunderclap headache (34673Z).

ChatGPT: ChatGPT is a recently developed generative AI system developed and maintained by OpenAI Inc. in Delaware. It is freely available [8-11,30]. We used ChatGPT version 3.5, which can be used via a natural-language text dialogue. We presented the list of symptoms to ChatGPT and asked for possible diseases. Images (either microscopic, macroscopic, ultrasound, or X-ray images) were transformed into string variables (see example in the Supplement).

Statistical methods: All data were part of the iPath-Network 2.0 documentation and are available to anyone registered with iPath-Network. Data were extracted from iPath-Network into an Excel spreadsheet (see Supplement). Statistical analysis was performed using R (version 4.3) [27]. p-values < 0.05 were considered significant. For the analysis of the 3 groups (experts vs. ChatGPT and Memem7), we used R's aov method and the pairwise listed t-test [31,32]. A target diagnosis was classified as recognized by either ChatGPT or Memem7 if it was mentioned in the list of DDs. In addition, the list of DDs was classified as helpful or not by 2 of the authors (PF, CF) if the proposed disease entities fit the patient's symptoms. The target diagnosis (correct or consensus diagnosis of the human experts) was defined as the disease entity used to guide further treatment decisions. The target diagnosis (consensus diagnosis of the human experts) was considered the gold standard, but not the ground truth. The ground truth remains unknown, especially when medical work is done in countries with limited resources. For data evaluation, we distinguished 2 situations: [1] the human experts provide a clear target diagnosis, and [2] the human experts provide only a list of DDs. In Situation 1, AI-proposed diagnoses were considered successful if the target diagnosis was mentioned in the proposed list of DDs. In

Situation 2, AI diagnoses were considered helpful if the AI's list of DDs contained clinical diagnoses of interest.

Ethics votum: It was difficult to fulfill all ethical aspects [33-34] under the given conditions of the presented study, as the patient data originated from Afghanistan and the data analysis took place in Germany. All patients were asked to agree to a telemedicine consultation with their treating physicians (AS, HF, RR). Neither name nor date of birth was available (pseudonymized data). Ethical approval (Ärztekammer 27.022024, Aktenzeichen 1020/2024: see Supplement) for the retrospective use of pseudonymized data from Afghanistan is available. Patients were only included if they had given verbal consent to the treating physician (AS, HF, RR). Most patients were unable to provide written consent due to local conditions and, more importantly, the high prevalence of illiteracy. Therefore, some protection standards of developed countries [29-30] could not be applied in the daily working conditions of northern Afghanistan. All participants of the study gave informed (verbal) consent and were informed by the physicians locally in charge that their case would be classified in a telemedical platform (iPath-Network) and the anonymized data would be used for research. The declarations of the physicians in charge (Dr. Rokai Raoufi and Dr. Atiq Sediqi) are reported in the Supplement, like the ethics votum.

Results

The most common diagnoses in our study were dermatological, oncological, gynecological, gastroenterological, and head and neck diseases (see Table 1 and Supplement Part IV). The patients' mean age was 34 years (SD = 22.1), with a slight female preponderance. The human experts (PD, GS, PF, HF, RR, CF) were able to suggest a target diagnosis in 61 (59.8%) of the 102 study patients. In the remaining cases, DDs were provided, leaving the decision to the local physician in charge. In up to 34/102 cases (33.3%), a third opinion was sought from highly qualified and specialized experts in hematology, lymph node classification, or bone and neurological diseases (GO, GJ, Tzankov A, Feiden W). For each case, either a disease classification or a list of DDs was available. The characteristics of the study patients and the allocation of the study cases to the individual medical specialties are shown in Tables 1 and 2.

The expert diagnosis was made by up to 7 experts. On average, 6.3 medical terms (descriptors, string variables such as fever) were provided for disease classification (see Table 1). On average, 14 images per case were used for classification (Table 2).

The most common image types were microscopic, followed by macroscopic and radiological (radiographs, ultrasound, CT, or MRI). Laboratory data are rarely included, except in hematological cases. CT or MRI images were uploaded as written reports. All images were transformed into string variables as shown in Examples 1 and 2 (Supplement). These string variables were uploaded in Memem7 or as a verbal description ("patient has a") in ChatGPT. String variables were added, such as fever; headache; tumor cells: large; or lung mass: lower lung field: right side. This was considered as a vector of string variables [27], as defined in R.

Of the 61 cases with a clear human expert diagnosis (target diagnosis), 36 (59.0%) were recognized by ChatGPT and 47 (77.1%) by Memem7. Either ChatGPT or Memem7 or both recognized the target diagnosis in 51 cases (83.6%). The difference between human experts and Memem7 was not significant, nor was the difference between ChatGPT and Memem7 (p = 0.55).

The number of DDs identified by human experts was 1.4 (approximately only 1 DD per case), compared to 5.3 and 5.4 by ChatGPT and Memem7, respectively (see Figure 2). This difference was highly significant ($p < 0.00001$ in ANOVA). In 88/102 (ChatGPT) or 93/102 (Memem7) of the study cases, a helpful DD list was provided. The DDs suggested by ChatGPT or Memem7 were found to be helpful in (1) finding very rare diseases, (2) confirming one's own opinion, and (3) extending the list of DDs. Both AI systems performed equally well but generated significantly more DDs than human experts ($p < 0.00001$).

Patients	*N* = 102		Commentary
gender			Weak dominance of females
male	42	42.9%	Not significant, p:031
female	57.1	57.1%	
missing values	4		
Age (years)			
mean	34.0		Wide distribution of patients' age
SD	22.1		
median	35		
Number of primary descriptors			String variables/case Objects (symptoms) with or without attributes
mean	6.3		
SD	2.1		
median	6		
Number of experts involved			
mean	4.6		On average, 4 experts assisted with each videoconference
SD	2.2		
median	4		
Images presented/case			Most presented images are histology
mean	14.0		
SD	9.8		
median	10		
range	1-45		

Macroscopic images (mean)	1.4	1-2 macroscopic images
Cases with radiograms (mean)	0.4	In about every second case, an X-ray is available

Table 1: Features of the study patients

Medical disciplines *N* = 102 patients 140 assignments	***N* = 102**	**%**
Gastroenterology	9	18.6
Gynecology	17	12.1
Hematology	3	2.1
HNO (head, ear, neck, nose)	13	9.3
Infectiology	5	3.5
Oncology	29	20.7
Orthopedics	12	8.6
Pediatric disease	13	9.3
Pulmonology	2	1.4
Dermatology	25	17,6
Urology	6	4.2
Ophthalmology	4	2.8
Autoimmune disease	1	0.7
Neurology	1	0.7
Endocrinology	1	0.7

Table 2: Medical specialties. More than one assignment per case was possible.

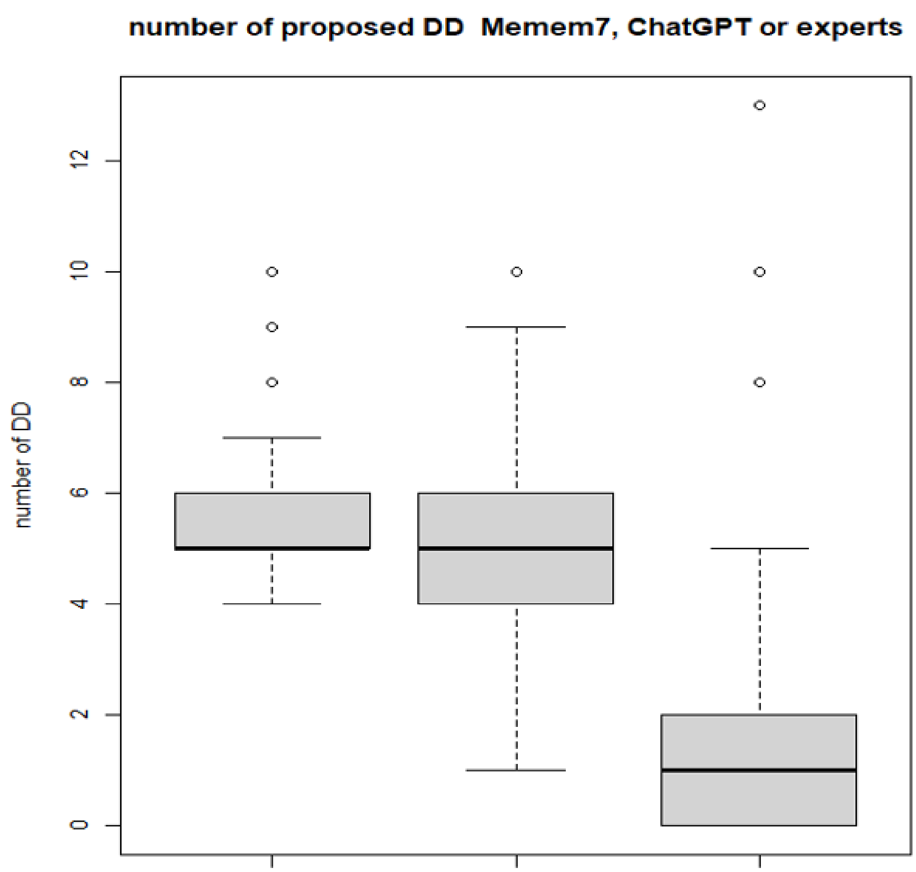

Figure 2: Comparison between the number of DDs provided by either ChatGPT, Memem7, or the human experts.

Discussion

We present data showing that both generative AI in the form of ChatGPT and a CDSS in the form of Memem7 significantly improved the diagnostic quality of human experts by expanding the list of DDs and confirming the experts' diagnosis in a high percentage of cases.

AI is expected to become increasingly important in medicine and telemedicine in the near future [35,36]. The bottleneck is how to prove the usefulness of AI in medical decision-making [37-40]. Two fundamentally different test situations need to be considered:

(1) Test Situation 1 (narrow task-specific AI). In this situation, the AI assistance has to choose between a small number of possible goals (arbitrarily n < 10). This situation exists, for example, when wearable AI is used to detect early heart failure [35]. When testing AI in this setting, high reliability, measured as sensitivity, accuracy, or area under the curve, can be expected (up to 97.1% sensitivity) [35, 36]. The number of possible decisions (disease entities to be found by the AI) below which the AI shows very high accuracy values (>90%) has not been investigated and is therefore arbitrary.

(2) Test Situation 2 (a holistic approach, i.e., including all possible diagnoses in the AI analysis). In this test situation, all possible diagnoses reported in medical ontologies, such as IC-10, ICD-11, or SNOMED, must be considered. ChatGPT and AI-based medical decision support systems generate a list of possible DDs based on probability from a pool of >10,000 possible diseases. In this situation, the test results' accuracy ranges between 58.2% and 82% (for a review, see Turcian et al. [35]). In Memem7 [21], for example, 17,422 diseases are reported. In ICD-10 [3], symptoms and diseases are mixed, but the number of coded disease entities is >20,000.

The holistic approach is difficult to test. The accuracy and test performance of the AI methods mentioned in Test Situation 1 (with few possible decisions) clearly cannot be expected in Test Situation 2 of medical decision support systems (with a holistic diagnostic approach). The classical CDSSs, such as Isabel, Ada, and Memem7 [21-25], have recently faced comparisons with generative AI systems such as ChatGPT [12-15]. In our 102 study patients, both Memem7 and ChatGPT show comparable results. However, Memem7 was also able to provide a ranked list of DDs (see the output of ChatGPT and Memem7 in Test Cases 1 and 2 in the Supplement), while ChatGPT only generated a list of unranked DDs. Although the number of DDs suggested by ChatGPT was significantly higher than that given by the human experts, no probability ranking was given to help decide in favor of a particular diagnosis.

In countries with limited resources, the situation is very complicated. Many diagnoses listed in ICD-10, ICD-11, or SNOMED [7-10] cannot be provided due to a lack of information or a lack of appropriate tests. Despite these limitations, a treatment decision must be made (if possible, in the local context as near as possible to the international standards). Working in countries with limited resources can be considered a modified Test Situation 2 with a high frequency of missing information.

One of the main advantages of generative AI, such as ChatGPT or Memem7, is its excellent human-like multilingual conversation, which does not require additional input/output support. Codes such as ICD-10, ICD-11, or ICD-O [7-10] are available in different languages, including Arabic [4].

An exciting and medically successful application of CDSSs and ChatGPT is the use of these systems in countries with limited resources. We have long experience using Memem7 and Isabel in northern Afghanistan [25-29]. In this publication, we present approximately 100 randomly selected real-world cases where expert diagnoses were compared with the results of using ChatGPT and Memem7. The results are as follows: (1) In 59.9% of cases with known target diagnoses, ChatGPT recognizes the target diagnosis, and Memem7 mentions the target diagnosis in 77.1% of cases; (2) in most cases, both systems provide a list of helpful DDs (about 86.3% for ChatGPT and 91.2% for Memem7); and (3) the number of DDs proposed by both systems was comparable and significantly exceeded the number of DDs provided by the human experts. We believe that both systems provide a meaningful and useful list of DDs when used to improve the quality of disease classification in low-income countries.

One problem with using AI in a holistic approach is that many different types of images are provided. Currently, verbal descriptors (string variables) have to be generated for all images, which must be transformed into string variables by doctors or paramedical staff (see Example Cases 1 and 2 in the Supplement). In Test Situation 1, image classification has been used very successfully in radiology [41,42] and increasingly in pathology [43]. We have developed an algorithm to classify breast fine-needle aspiration cytology images as benign or malignant (only 2 possible decisions) with an accuracy of 78.4% [44]. Image classification in Test Situation 2 (many target diagnoses to be recognized) is, to the best of the authors' knowledge, not yet possible.

The great promise of CDSSs and the use of ChatGPT as exemplified in our study are (1) its use in countries with limited resources; (2) the fact that the attention of non-specialists is drawn to rare diseases; (3) an educational impact, E.g. the local physician is confronted with the human experts (see point 3) and acquire substantial new knowledge available for him in Memem7; (4) its use in an n > 10 classification problem (holistic approach); and (5) the provision of a list of ranked DDs in unclear medical cases.

The disadvantages of the proposed approach to telemedicine diagnosis are as follows: (1) We are dealing with black box systems. We do not know the AI systems' arguments for proposing an unambiguous diagnosis. This is especially true for ChatGPT. (2) The doctors in charge are forced to do additional work with each proposed DD. They are often forced to rule out a DD that was not previously considered for the patient, but is now suggested by the CDSS. AI systems based on ChatGPT used in Test Situation 2 have additional disadvantages. Generative AI systems show a tendency to hallucinate in further dialogue [13]. Moreover, they still lack the ability to represent the details of information sources and the decision logic of their results [12,13], whereas semantic net-based AI systems can already do this. They provide access to the entire chain of reasoning and the information on which it is based. They also allow additional detailed analysis of symptoms and DDs based on their universal semantic logic and provide a list of ranked DDs. Human control is better in CDSSs than in ChatGPT, and all learning effects are easier to follow in CDSSs than in ChatGPT.

What future developments are needed for both approaches (ChatGPT and CDSSs) before we can use one or both methods in daily practice in countries with limited resources? (1) Improved opportunities for human-machine interaction, (2) an urgent need for better and stable Internet platforms such as iPath-Network that minimize the workload of local doctors or experts involved in telemedicine, (3) an urgent need for high-quality studies to measure quality improvement through the use of AI systems in telemedicine, (4) better control of the proposed output, and (5) the possibility of structured analysis in ChatGPT.

Conclusion

We report on the use of either ChatGPT or a CDSS to improve the quality of diagnosis in a country with limited resources, at the level of either predicting the expert diagnosis (with moderate sensitivity) or providing a helpful list of DDs (with high sensitivity). Considering the present study and its promise, a larger multicenter study should be planned to evaluate CDSSs in developing countries.

Ethical approval and consent to participate:

Approval by the Ethics Commission of the Bayerische Ärztekammer 27.022024, Aktenzeichen 1020/2024: All patients were asked to agree to a telemedicine consultation with their treating physicians (AS, HF, RR). Neither name nor date of birth was available (pseudonymized data). Patients were only included if they had given verbal consent to the treating physician (AS, HF, RR). Most patients were unable to provide written consent due to local conditions and, more importantly, the high prevalence of illiteracy. The abovementioned ethical approval confirmed that for our study, written consent was not necessary. Our study is in compliance with the Helsinki Declaration.

Consent for publication:

All coauthors are informed and agree to the publication.

Availability of data and material:

All data are available in iPath-Network for members of iPath-Network's Afghanistan Forum. Any physician or scientist may become a member of iPath by registering at iPath-Network.com.

Competing interests:

None of the authors declares a conflict of interest.

Funding:

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Authors' contributions:

Fritz P: manuscript preparation, expert diagnosis, statistics, algorithm for Memem7

Kleinhans A: manuscript preparation, algorithms for Memem7 and ChatGPT

Sediqi A: case upload, primary diagnosis

Raoufi R: case upload, primary diagnosis, expert diagnosis

Haroon F: case upload, primary diagnosis

Alaboud K: third opinion in all dermatological cases, study design

Fritz-Kuisle C: manuscript preparation, evaluation of Memem7 and ChatGPT diagnoses

Dalquen P: expert diagnosis, third opinion in all cytological cases, manuscript preparation

Jundt G: third opinion in all cases with bone diseases, manuscript preparation

Ott G: third opinion in all cases with lymphoproliferative diseases

Stauch G: expert diagnosis, study design, manuscript preparation

Alscher MD: manuscript preparation

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Authors' information:

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Supplement

Example case 1: (Afghanistan forum , iPath-network).

Ipath id: 1380272; Memem/ casuosom 6857

Input as string variables: 25 years, male, lung collapse right, lymphocytic serositis, pleural effusion.

Note that German and English language are interchangeable as one Memem7 code relates to the German and English meaning

Expert classification: Pleuritis tuberculosa

Memem 7 output: (semantic, stochastic search and similar case search)

A16.5 Pleuritis tuberculosa 1353X| 06-73 C42.1

Multiples Myelom M0801| 04-91

N00.8 Akute interstitielle Nephritis M5707|

04-63 N71.1 Chronische Endometritis M3486|

03-82 J84.1 Interstitielle Lungenerkrankung M0933|

03-79 I88.9 Lymphadenitis colli M1031| 03-73 J44.99

Chronisch-obstruktive Lungenkrankheit M0061| 03-72

Chat-GPT output:

ChatGPT: J90 Pleuraerguß M2068|, J98.1 Lungenatelektase 39737X|, A15-A19 Tuberkulose M0770|, C34.9 Lungenkrebs M0314|, D86.- Sarkoidose M0816|, J18.9 Pneumonie M0784|, D89.9 Autoimmunerkrankung

M2695|

Memem7 and Chat -GPT output (proposals of DD) recognised the target diagnosis and provided some meaningful DD.

Some results as chronic endometritis or acute interstitial nephritis in Memem7 or Autoimmunerkrankung in ChatGPT

were considered as not helpful

Example case 2: (Afghanistan forum , iPath-network).

IpATH ID. : ipath id, 1459368h, memem7: casusom6858

Input as string variables: 55 year, female., ovar, tumor cells: middle seized, hemorrhagia, cell nuclei: cleaved.

Note that German and English language are interchangeable (see example 1

Expert classification: Granulosa cell tumor

Memem7 output:

D76.08	Langerhans Histiozytose des Knochens 77545X|	07-72
C96.0	Langerhans-Zell-Histiozytose M1193|	07-72
	Dysgerminom 90603N|	06-74
C41.9	Leiomyosarkom des Knochens M2946|	05-75
C49.9	Mesenchymales Chondrosarkom 92403N|	05-75
C84.4	extranodal NK/T-cell lymphoma M8991|	05-71

Chat-GPT output:

ChatGPT: C56 Eierstockkrebs 213500R|, C56 Ovarialkarzinom M1172|, C80 Metastasen UT62|, D39.1 Ovarialtumor M2038|, N80.- Endometriose M0487|, N70.9 Ovarialabszess 52834X|

Both results (Memem7 and Chat_GPT) were considered as not very helpful. The Memem7 results failed to recognize granulosa cell tumor and provided only very rare DD. In addition two diagnosis with false localization were given. The Chat-GPT answer provided only very general list of DD and did not recognize the target diagnosis as well.

List of diagnosis used in the presented study

CG_1:102

ID-identificator	Target diagosis	diagnosis	ICD-10	ICD-0	C-classification	CG_Nummer
1292247	yes	dermatofibroma	D23.9	8832/0	C44	CG_001
1292661	yes	granuloma pyogenicum	L98.8	Not def	C44	CG_002
1293371	yes	Squamous cell carcinoma ear	C44.9	8070/3	C44.2	CG_003
1312268	no	DD	list of DD	List of DD	C41	CG_004
1312889	yes	cutaneous leishmaniosis	B55.1	Not def	C44	CG_005
1321185	no	DD	list of DD	list of DD	C44.3	CG_005
1323877	yes	cutaneous leishmaniosis	B55.1	Not def	C44	CG_006
1329270	no	DD	list of DD	list of DD	C07	CG_007
1329670	no	DD	list of DD	list of DD	C11.9	CG_008
1333142	yes	inverted follicular keratosis	L11.0	Not def	C44	CG_009
1337651	no	DD	list of DD	list of DD	C44	CG_010
1341844	no	DD	list of DD	list of DD	C44	CG_011
1341960	yes	psoriasis	L40.0	Not def	C44	CG_012
1347696	yes	nummular excema	L30.3	Not def	C44	CG_013
1352051	no	DD	list of DD	list of DD	C44	CG_014
1360374	no	DD	list of DD	list of DD	C44	CG_015
1372153	yes	serous carcinoma of ovar, high grade	C56	8461/3	C56	CG_016
1380477	no	DD	list of DD	list of DD	C40	CG_017
1382272	no	DD	list of DD	list of DD	C38.4	CG_018
1382565	no	DD	list of DD	list of DD	C44	CG_019
1386174	no	DD-	list of DD	list of DD	C44.6	CG_020
1386796	no	DD	list of DD	list of DD	C10	CG_021
1387420	no	DD	list of DD	list of DD	C44.6	CG_022
1388771	no	DD	list of DD	list of DD	C69.6	CG_023
1389210	no	DD	list of DD	list of DD	C69.9	CG_024
1389592	no	DD	list of DD	list of DD	C54.9	CG_025
1389701	no	DD	list of DD	list of DD	C44.5	CG_026
1390824	yes	mastitis	N61	not def	C50	CG_027
1390967	no	DD	list of DD	list of DD	C69.8	CG_028
1391528	yes	chronic osteomyelitis	M86.69	not def	C41	CG_029
1392057	yes	fibroma-like lipoma	D17.9	8850/0	C49	CG_030

1392064	yes	fibrocystic disease of breast	N60.1	not def	C51	CG_031
1392378	yes	Non-Hodgkin lymphoma	C83.-	9591/3	C77.9	CG_032
1392752	yes	lymph node metastasis	C77.9	8000/6	C77.9	CG_033
1393244	yes	squamous cell carcinoma of esophagus	C15.-	8070/3	C15.9	CG_034
1393520	yes	serous cystadenoma of testis	D36.9	8441/0	C62	CG_035
1393567	yes	Prostatic adenocarcinoma	C61	8140/3	C61	CG_036
1393867	yes	luteinized follicle cyst of ovary	N83.0	Not def	C56	CG_037
1394504	yes	squamous cell carcinoma oral cavity	C44.9	8070/3	C10	CG_038
1394516	yes	squamous cell carcinoma esophagus	C44.9	8070/3	C15.9	CG_039
1394527	no	DD	list of DD	list of DD	C44.5	CG_040
1394648	no	DD	list of DD	list of DD	C44.4	CG_041
1394665	yes	PUPPP*	O26.8	Not def	C44.9	CG_042
1394903	yes	Fibroadenoma of breast	D24.-	9010/0	C50.9	CG_043
1395149	no	DD	list of DD	list of DD	C49.9	CG_044
1395256	yes	Solitary fibrous tumour of pleura	D48.1	8815/0	C38.4	CG_045
1396364	yes	esophageal adenocarcinoma	C15.-	8140/3	C15.9	CG_046
1396387	yes	Malignant myoepithelioma forearm	ot def	8982/3	C54	CG_047
1396639	no	DD	list of DD	list of DD	C44.7	CG_048
1397019	yes	villous adenoma low grade bowel	D37.5	8263/0	C18.8	CG_050
1401487	yes	thyreoglossal cyst	K09.8	N81.4	C73	CG_051
1401545	yes	nodular lymphocytic dominant HL	C81.1	C81.4	C77.9	CG_052
1403160	yes	myoglandular hyperplasia prostata	N40	not def	C61.9	CG_053
1405929	yes	papillary thyroid carcinoma	C73	8260/3	C73	CG_054
1407827	no	DD	list of DD	list of DD	C41.9	CG_055
1408883	no	DD	list of DD	list of DD	C44.3	CG_056
1409518	yes	spindle cell lipoma	D17.9	8857/0	C49	CG_057
1409902	yes	reparative bone granuloma	K10.1	Not def	C41	CG_058
1410388	yes	Pneumonia	J18.9	Not def	C34	CG_059
1410408	yes	Pleomorphic adenoma salivary gland	D11.0	8940/0	C07	CG_060
1410840	yes	Esophageal squamous cell carcinoma	C44.9	8070/3	C15.9	CG_061
1411720	yes	Ewing sarcoma humerus	C41.9	9260/3	C40.0	CG_062

1412331	yes	neurinoma	D36.1	9560/0	C47.9	CG_063
1412885	yes	hyperkeratosis plantaris et palmaris	L85.1	Not def	C44	CG_064
1413600	yes	osteomyelitis	M86.-	Not def	C41	CG_065
1414127	no	DD	list of DD	list of DD	C49	CG_066
1418796	yes	neurinoma	D36.1	9560/0	C47.9	CG_067
1419100	yes	large cell lung carcinoma	C34.9	8012/3	C34	CG_068
1420265	yes	angiofibroma vagina	D21.9	9160/0	C52	CG_069
1420656	yes	low grade NHL	C85.9	9590/3	C77	CG_070
1421984	yes	granuloma pyogenicum	L98.8	Not def	C44	CG_071
1422784	no	DD	list of DD	list of DD	C42.1	CG_072
1426750	yes	breast cancer	C50.9	8500/3	C51	CG_073
1427771	no	DD	list of DD	list of DD	C70	CG_074
1428269	yes	simple bone cyst	M85.69	dot def	C41	CG_075
1428582	no	DD	list of DD	list of DD	C44.7	CG_076
1429732	yes	MALT lymphoma	C85.7	9699/3	C77.9	CG_077
1430194	yes	squamous cell carcinoma esophagus	C44.9	8070/3	C15.9	CG_078
1430478	yes	Wilms Tumor	C64	8960/3	C64	CG_079
1431229	yes	acute mastitis	N61	Not def	C50.9	CG_080
1431818	yes	squamous cell carcinoma lingula	C44.9	8070/3	C10	CG_081
1431889	no	DD	list of DD	list of DD	C42.1	CG_082
1434581	no	DD	list of DD	list of DD	C77.9	CG_083
1436380	yes	breast carcinoma	C50.9	8070/3	C51	CG_084
1437649	no	DD	list of DD	list of DD	C73	CG_085
1438752	no	DD	list of DD	list of DD	C54	CG_086
1440675	yes	osteochondroma	D16.9	9210/0	C41	CG_087
1440823	yes	PUPPP*	O26.8	Not def	C44	CG_088
1441292	yes	soor glossitis	B37.0	Not def	C10	CG_089
1442416	yes	atypical uterine leiomyoma	D21.9	8893/0	C54	CG_090
1442921	no	DD	list of DD	list of DD	C56	CG_091
1445614	yes	verruca vulgaris	B07	Not def	C44	CG_092
1445772	no	DD	list of DD	list of DD	C44	CG_093
1447409	no	DD	list of DD	list of DD	C62	CG_094
1448905	yes	torsion of testis	N44.0	Not def	C62	CG_095
1452894	no	DD	list of DD	list of DD	C77.0	CG_096
1460304	no	DD	list of DD	list of DD	C77.9	CG_097
1460095	no	DD	list of DD	list of DD	C77.9	CG_098
1459899	yes	verruca vulgaris	B07	Not def	C44	CG_099

1459638	no	DD	list of DD	list of DD	C62	CG-100
1460230	yes	epidermoid cyst	L72.0	Not def	C15.9	CG_101
1462165	yes	Verruca-vulgaris	B07	8050/0	C44.6	CG_102

Pruritic urticarial papule and plaques of pregnancy. Note that the last two rows gave a clear code for each target diagnosis (in up to 40 languages) and a distinct discrimination of a given diagnosis. Not def= not defined in ICD-O. list of DD= means that a long list of ICD-10 classifications, ICD-O classifications and C-Code is present. The last row signifies the documented results in Memem7.

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Sediqi A[3,7]: case upload, primary diagnosis

Raoufi R[3,7]: case upload, primary diagnosis, expert diagnosis

Haroon F[5]: case upload, primary diagnosis

Alaboud K[3]: third opinion in all dermatological cases, study design

Fritz-Kuisle C[3] manuscript preparation evaluation of Memem7 and Chat-GPT diagnoses

Dalquen P[3,8]: expert diagnosis, third opinion in all cytological cases, manuscript preparation

Jundt[3,8]: third opinion in all cases with bone diseases, manuscript preparation

Ott G[1] : third opinion in all cases with lymphoproliferative diseases

Stauch G[3]: expert diagnosis, study design, manuscript preparation

Alscher MD[2]: manuscript preparation

Ethic votum:

Approval by the ethic Comittee of the Bayerische Ärztekammer 27.022024, Aktenzeichen 1020/2024

Ethik-Kommission
der Bayerischen Landesärztekammer

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Ihre Zeichen:
Ihr Schreiben vom: 27.11.2024

10.12.2024

Statement of the Ethics Committee

Studie zum Einsatz von CHAT-GPT und Medical Decision Support System (MDSS) zur Überprüfung und Verbesserung von Expertendiagnosen in Nordafghanistan (iPath-01/2024)

Our reference number: 2024-1020

Dear Dr. Fritz,

we confirm receipt of your letter of 27.11.2024.

Hereby we confirm that the Ethics Committee of the Bavarian State Chamber of Physicians advises doctors on the implementation of medical research projects on humans with usage of personal data. According to § 15 of the professional code of physicians of Bavaria retrospective reviews of anonymized patient data do not require ethical approval. Please note that for such studies a written Informed Consent from study participants is not required.

Sincere regards,

On behalf of

Sanja Fricke
Apothekerin
Abteilungsleitung der
Geschäftsstelle
Ethik-Kommission

In accordance with Art. 37 Abs. 3 BayVwVfG, this letter only contains a name and no signature.

Seite **1** von **1**

Die Ethik-Kommission ist bei der Bayerischen Landesärztekammer, Körperschaft des öffentlichen Rechts eingerichtet, § 13a der Satzung der BLÄK und Art. 18 GDG
Mühlbaurstraße 16
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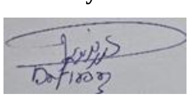
Hinweise zum Datenschutz erhalten Sie unter www.blaek.de

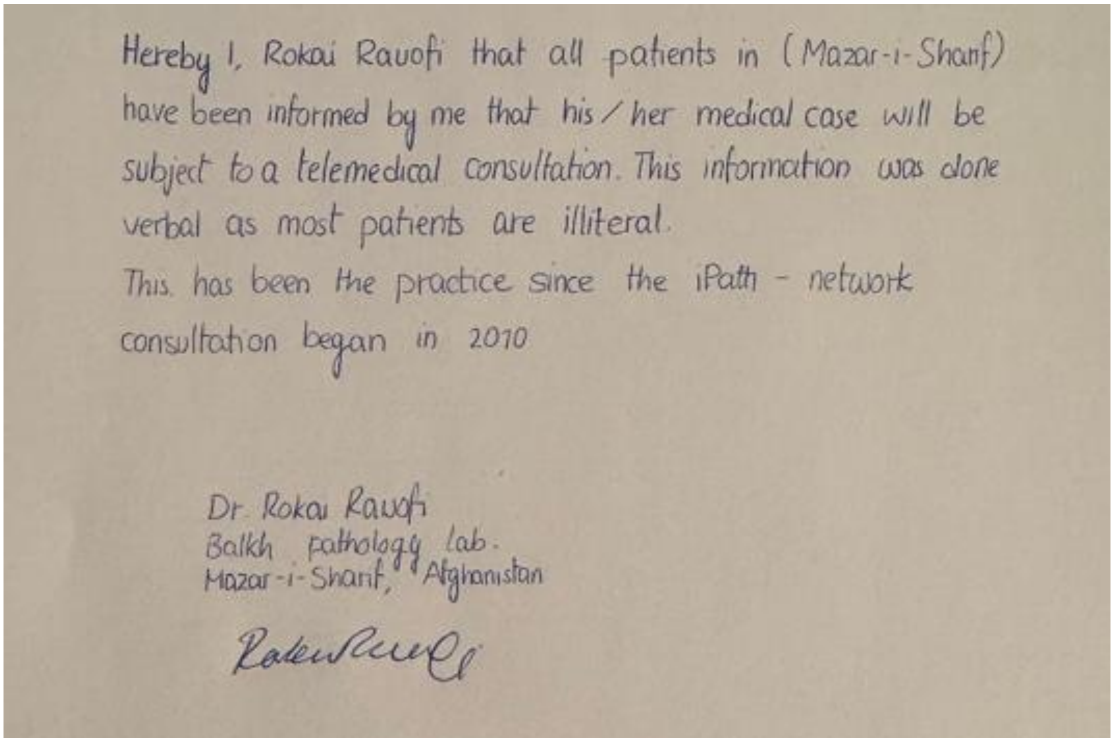
Hereby I Haroon Firooz **confirm that all patients in Herat have been informed by us that his/her medical case is subject to telemedicine consultation.** This information was done verbal as most patients are illiteral

This has been the practice since the ipath-Network consultation began in 2010.

Sincerely

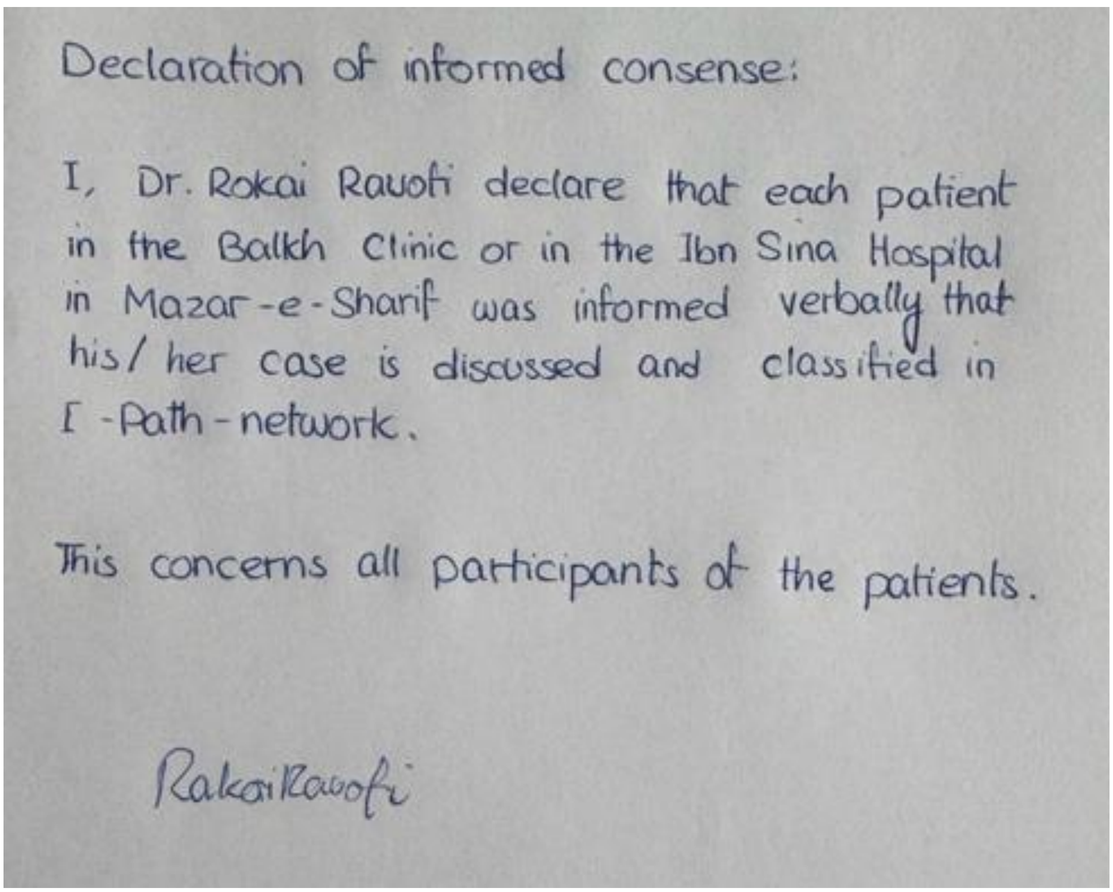


Dr. Haroon Firooz



Hereby I, Rokai Rauofi that all patients in (Mazar-i-Sharif) have been informed by me that his / her medical case will be subject to a telemedical consultation. This information was done verbal as most patients are illiteral.
This has been the practice since the iPath - network consultation began in 2010

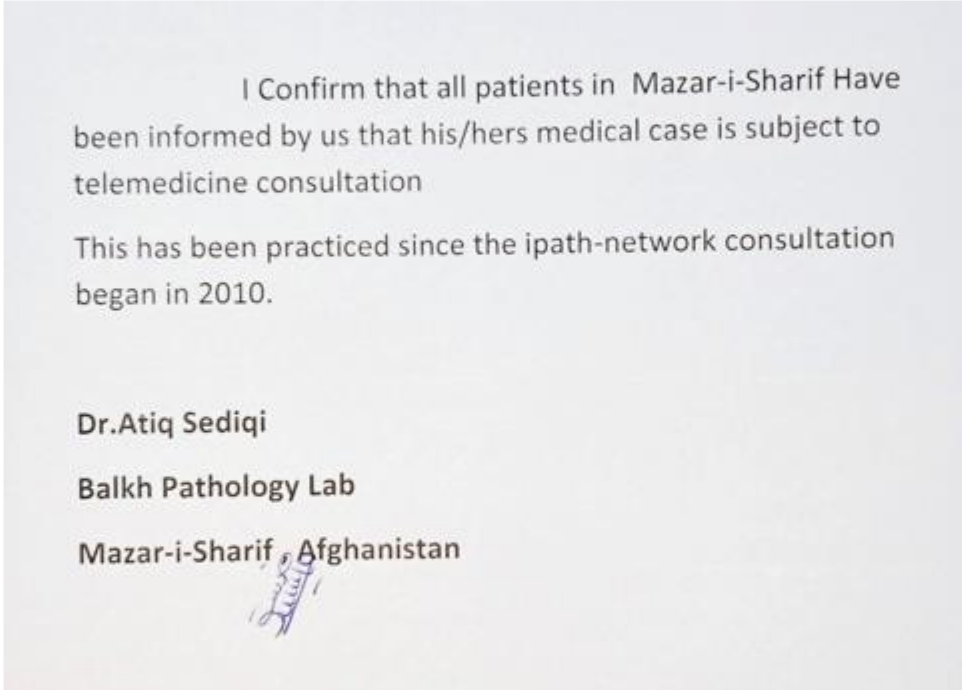
Dr. Rokai Rauofi
Balkh pathology lab.
Mazar-i-Sharif, Afghanistan



Declaration of informed consense:

I, Dr. Rokai Rauofi declare that each patient in the Balkh Clinic or in the Ibn Sina Hospital in Mazar-e-Sharif was informed verbally that his/ her case is discussed and classified in I-Path-network.

This concerns all participants of the patients.



I Confirm that all patients in Mazar-i-Sharif Have been informed by us that his/hers medical case is subject to telemedicine consultation

This has been practiced since the ipath-network consultation began in 2010.

Dr.Atiq Sediqi

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Authors declaration of no conflict of interest:

None of the authors declares a conflict of interest

Access to iPath.network.com: Every data scientist or scientist may have access to iPath-network. She/he needs a registration and should refer to the title of publication.

Internet: www.ipath.network.com

Data availability statement: Each reader (data scientist, physician or researcher) can have access to the data by registration to www.ipath.network.de , when pointing to the present publication. Then he can identify each research case by the iPath-network ID (first row table **List of diagnosis used in the presented study in Supplement).** Registration in iPath-network and Memem7 is free of charge.

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