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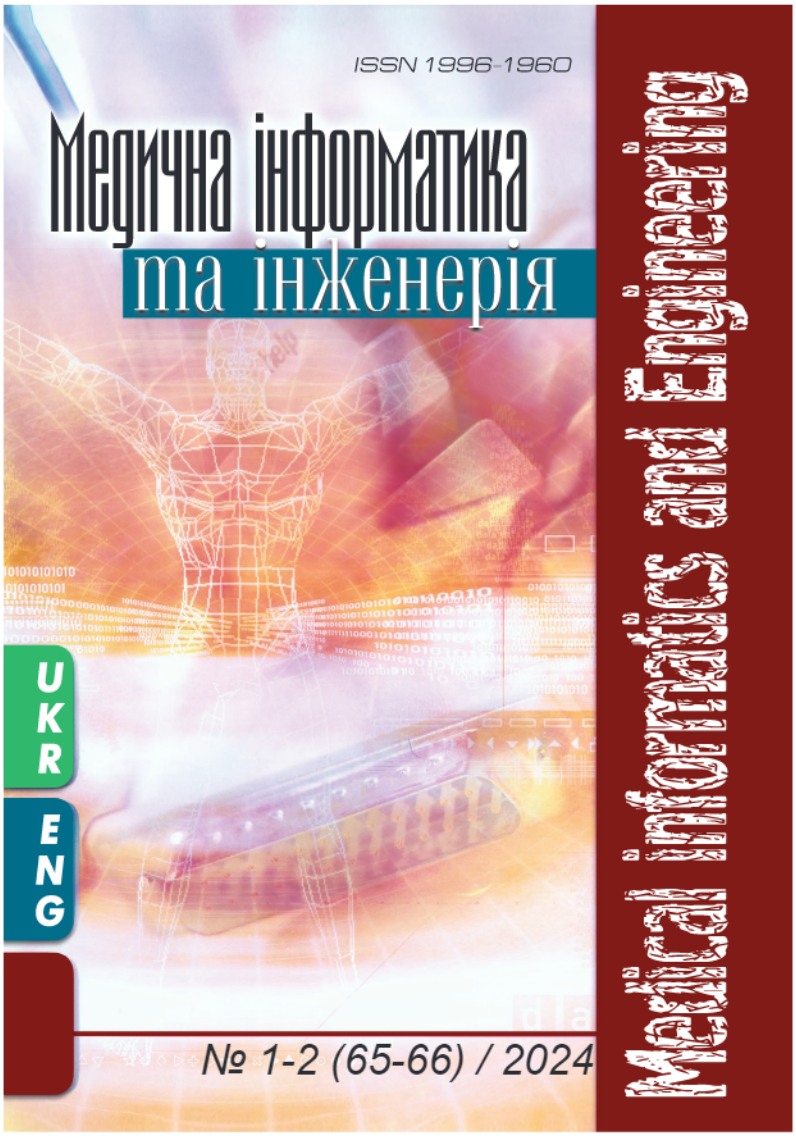

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CONTENT

Vector Diagnosis of Patient Conditions in Telemedicine. Conceptualization.

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ABSTRACT

Telemedicine is a rapidly growing field in healthcare, offering wide-ranging opportunities to address various challenges faced by healthcare workers and patients. Despite its many benefits for both patients and healthcare providers, there are still a number of unresolved issues. This study aims to explore the potential of telemedicine by conceptualizing it as the interplay of two vectors: the patient's condition and technological readiness for consultation.

Research Objectives. The patient's condition vector includes physiological, biochemical, and clinical indicators. The technological readiness vector is defined by the treating physician's competence, the consultant's expertise, modern information processing capabilities, and the availability of necessary time, among other factors. Conclusions. 1. Telemedicine consultations require a robust real-time medical data management system that allows consultants and attending physicians to efficiently process data, retain validated data for patient-specific recommendations, and enhance the global telemedicine framework with decision-making expertise. 2. Integrating big data analytics can improve the prediction and identification of disease diagnoses and prognoses, aiding in the development of effective strategies for complication prevention and disease treatment. Real-time communication with each patient and complex data processing can only be achieved through artificial intelligence. Manual intervention is insufficient for serving thousands of users simultaneously. 3. It's crucial during telemedicine consultations to consider not only the static indicators of the patient's condition but also their baseline data, stable condition indicators from previous studies, and personalized correlation galaxies. Recommendations based solely on the analysis of the patient's status during the telemedicine session risk incorrect conclusions. 4. Biosemiotics, which focuses on the language and rules of signals and codes in biological systems, combines ideas from systems theory, information theory, and linguistics. This integration may offer a new perspective on the classification and interpretation of biological and medical signaling. A coherent theory of biosemiotics needs to be developed.

KEYWORDS

Telemedicine, transdisciplinary approach, vector diagnosis of patient conditions, data discrimination, information asymmetry, big data, error by omission, data envelopment analysis (DEA)

1. Introduction

The rapid advancement of diagnostic technologies presents a new challenge: the emergence of decision-making difficulties caused by inaccuracies in patient treatment procedures. These procedures become more complex with the introduction of telemedicine technologies. Common issues include data discrimination, information asymmetry, and missed opportunities for early diagnosis, which are widespread and resource-draining, but often receive little attention.

It is important to note that organizational culture transforms with the implementation of telemedicine. Motivating involved parties is a crucial component of the procedure. Patients often interact with various service providers within a healthcare organization, so telemedicine should promote a team-centric approach to coordinated care. Coordination is a key healthcare advantage as it eliminates geographical barriers that hinder communication between providers and patients.

2. Research Objectives

This study explores the potential of telemedicine as the interplay of two vectors: the patient's condition and technological readiness for consultation.

An additional objective is to identify the role of anamnestic data, the persistence of stable conditions amidst the dynamics of the pathological process in a specific patient, and the enduring symptom correlations manifesting as correlation galaxies.

The final objective is to establish a strategy for a secure and effective medical data management system within telemedicine technologies to ensure accurate diagnosis and prognosis.

3. Results Obtained

Telemedicine is defined as the provision of healthcare services by any healthcare specialist in situations where distance is a critical factor, using information and communication technologies (ICT). [1] It is used for the exchange of reliable information for diagnosis, treatment, prevention of diseases, research, assessment, and continuous education of healthcare professionals to strengthen individual and societal health.

The concept of information asymmetry (INAS) refers to an unequal distribution of information among participants in the treatment-diagnostic continuum. One entity may have more knowledge or understanding regarding diagnostic and treatment processes than the other. The concept was first defined within the healthcare domain by K. Arrow in 1963. [2]

Attention should be paid to six technologies where data discrimination threats are particularly significant. [3] These technologies, which will impact medicine over the next decade, include molecular diagnostics, image analysis, robotics, information management, and artificial intelligence.

The use of telemedicine has seen rapid growth and expansion. Although the feasibility of many applied programs has been tested for almost 50 years, discussions about regulatory support, clinical effectiveness, and cost optimality in telemedicine are still lively. [4] This is partly due to a long list of technological challenges, including interactive patient involvement (e.g., mental health-related requests), information asymmetry, examination data discrimination, missed diagnostic opportunities, and the safety and effectiveness of new telemedicine technologies (e.g., robotics, virtual reality). Unresolved issues also include the use of anamnestic information (due to semantic difficulties), the logic of operational image processing, and more.

The difficulties in telemedicine have led to the development of a new concept for remote patient consultation. This concept is based not on patient symptoms, but on identifying stable (or unstable) states (clusters) of the organism. The patient's trajectory is considered in three distinct phases:

1. Pre-transition, demonstrating high stability;

2. Critical, characterized by a certain instability and signaling impending adverse consequences (e.g., complications, exacerbation of a painful condition);

3. Post-transition, with increased stability after the transition.

Strategically, the telemedicine consultation procedure is viewed as the interaction of two vectors: the patient's condition vector and the technological readiness vector. The patient's condition vector covers physiological, biochemical, and clinical indicators, while the technological readiness vector is determined by organizational factors such as the attending physician and consultant's competence, modern information processing capabilities, and the availability of necessary time.

Note that the patient's state vector reflects the above steady state. Otherwise, a correction factor is introduced for the patient's state vector equal to the average Mahalanobis distance for all coordinates. The Mahalanobis distance is calculated as the distance of the real indicator (or a group of independent symptom complexes if a high correlation coefficient is determined between the symptoms included in the symptom complex) of the patient's condition from the mathematical expectation of its value in a multidimensional space determined by correlated (non-orthogonal) independent variables.

If the concern is the vector of technological readiness, its coordinates are determined by regulatory tables based on expert assessments. The extent to which various innovative technologies are used to enable evidence-based diagnostics to improve patient care is also determined. Expert assessments reflect the readiness of these technologies in terms of their effective integration and focus on patient care.

The experience of using telemedicine consultations clearly demonstrates significant problems associated with data processing. The integration of patient data (especially big data–indicators of instrumental studies), processing of various types of data (from batch to streaming), and their transformation for further use lack clear rules. The concepts of relevance, credibility, reliability, and persistence of information do not apply. This leads to many diagnostic errors, missed opportunities, and data discrimination.

Thus, it becomes obvious that the challenge of data management during telemedicine consultations goes beyond simply organizing medical data. Directed personalized integration and analysis of the information received about the patient's condition are required.

4. Factors Complicating Telemedicine Consultations

First, let us focus on data discrimination (DD) in diagnostic procedures. The underlying factors for this issue include a lack of widespread problem awareness, numerous complex elements contributing to diagnostic errors, and the absence of well-defined, generalized measurement strategies for evaluating the diagnostic process and its outcomes, primarily data discrimination. Additionally, the diagnostic process is a core physician responsibility, making diagnostic errors a delicate discussion topic. This necessitates a conducive, non-hostile culture promoting patient safety. [5]

A contributing factor to data discrimination is information processing, which requires scientists to convert survey data into formal computer code. However, the choice of target variable and class labels is inherently subjective. Moreover, there is a tendency for data to be distorted within the model.

Bias in data collection can arise from the under- or over-representation of certain groups and/or protected

classes in a data set, potentially resulting in unfair or unequal treatment of the data. Often, certain groups of data receive undue attention. This increased attention can sometimes trigger intentional misconduct.

If the training data includes biased or discriminatory cases, the system will perceive them as valid and reproduce the bias in its output. In this scenario, the phenomenon of "overfitting" can occur, where models become over-specialized based on the training data. Therefore, a constant search for the optimal decision rule is necessary, which can only be done by monitoring patient observations. We emphasize that it is impossible to implement simple decision-making during telemedicine consultation.

A few words need to be said about the features of DD in big data technologies. From this perspective, the notion of norm and adherence to this norm are pivotal, necessitating a clear differentiation between prevalent and legitimate issues, and more abstract concerns like the alteration of the concept of personal identity through "profiling or analysis," "datafication," "information society," and so forth.

5. Information Asymmetry

Information asymmetry should be distinguished from incomplete information. While parties may lack all necessary information, they may still operate on equal (or unequal) terms. Potential patients, and sometimes potential expert groups, often hide the true goals of their behavior and use almost any method to obtain certain (own) results. In outpatient care, patients often do not provide the physician with all the information relevant to a specific diagnosis or treatment.

In general, doctors have an advantage over patients because of the preponderance of information about the latter's state of health and knowledge of the most beneficial treatments. In addition, the degree of information and knowledge asymmetry, along with the cost of obtaining relevant information, is likely to increase as the patient's health deteriorates.

Solving the problem of asymmetry of information and knowledge is one of the significant advantages of the introduction of information technologies in the field of healthcare. Currently, in many developed national health services, large eHealth infrastructures and systems are seen as central to the future provision of safe, effective, high-quality, and citizen-oriented health care. [6]

Asymmetric information between different parties at successive levels of the healthcare system makes it reasonable and even necessary to incentivize entities holding private information in the form of information rents. However, the most important finding of this analysis is that if there is a two-way information asymmetry between the parties to a transaction at different levels (i.e., low levels of trust between the parties to the transaction), then the incentive system between service providers and buyers (i.e., hospital or government institution) turns out to be perverted. In this case, [7] it is called a perverse incentive system because it punishes an effective doctor or medical institution and rewards an ineffective one.

Data processing and reasoning techniques frequently exhibit a bias towards "middle" or dominant groups. This is particularly noticeable during surveys. The entire testing concept reinforces this, as average results (like the frequency of a certain effect) are extrapolated to the broader audience.
Even with meticulous segmentation during testing, the ultimate "success" metric is derived from data decisions based on averages. However, relying on averages emphasizes a generalized "ideal" customer, which, at best, mirrors only a segment of the user's preferences.

The swift advancement of diagnostic technologies engenders a new issue – the onset of errors in decision-making due to inaccuracies in patient examination procedures. Among the global problems in organizing telemedicine consultations are diagnostic errors (DE) associated with the initial examination of patients, that is, before the actual telemedicine session. They are alarmingly common and harmful, but unfortunately receive insufficient attention in the field of patient safety. Diagnostic errors, including

inaccuracies, delays, or omissions in communication with patients, can lead to an escalation of morbidity, especially in children.

Even often, diagnostic errors are associated with the lost capabilities of different diagnostic methods, so named missed opportunity for diagnosis (MOD). "Error by omission" epitomizes a form of informational processing function misspecification, arising when discriminatory terms are overlooked or unaccounted for in the model. In essence, this implies the model neglects to consider the variances in algorithmic classification between protected and unprotected classes. These processes are recognized to be insufficiently studied in pediatrics, which gave rise to the European RedDE project. [8] National studies showed that DE or MOD rates in pediatric primary care became 54% for patients with advanced arterial pressure (n = 389), 11% for patients with pathological laboratory indicators (n = 381), and 62% for subjects building assessments presence of depression (n = 400).

According to a recent study published in the Journal of the American Academy of Pediatrics, pediatricians frequently report misdiagnoses and mistreatment of children that lead to chronic illness. Diagnostic errors are widespread in pediatric practice, and the error rate in these areas reaches 62%. More than 54% of licensed pediatricians know that diagnostic tests are performed once or twice a month. [8] The most common errors in pediatric patients were missed or inaccurate diagnoses for the following conditions: viral and bacterial diseases; appendicitis; mental disorders; increased blood pressure; side effects from drugs; and false or inaccurate results of laboratory tests. [9]

In particular, refusal of screening (68%) is the most common reason for missed adolescent depression. For missed hypertension, it was the inability to recognize (36%) and act on abnormal blood pressure values (28%). For "missing laboratory data," common scenarios included failure to notify families (23%) and document action (19%) regarding abnormal results. [10]

6. Routine Telemedicine Challenges

1. Image Quality and Resolution: Telemedicine consultations require substantial bandwidth to ensure the video image's resolution and quality, as a low-resolution video is inadequate for medical purposes.

2. Data Security and Interoperability: The second challenge arises from the need to secure and enable interoperable patient examination data, particularly when multiple healthcare organizations are simultaneously engaged in telemedicine consultations.

   Recently, assessing the effectiveness of telemedicine consultations has become an urgent problem. Various methods are used. A popular approach is based on the construction of the so-called efficiency frontier. [11] Associated with this concept are concepts such as the technological possibility frontier and the production function. The DEA method has a number of properties that are important for the practical application of telemedicine technologies: [12,13]

- allows you to calculate one aggregate indicator for each object in terms of the use of input factors (independent variables) to produce the desired output characteristics (dependent variables);

- can simultaneously process many inputs and many outputs, and each of them can be measured in different units of measurement;

- allows you to take into account variables external to the system under consideration – environmental factors. In other words, it is ideal for the two-factor approach proposed in this study;

- does not require a priori indication of weighting coefficients for variables corresponding to input and output parameters when solving the optimization problem;

- does not impose any restrictions on the functional form of the relationship between inputs and outputs;

- allows, if necessary, to take into account managers' preferences regarding the importance of certain input or output variables;

- forms a Pareto-optimal set of points corresponding to efficient objects. Note that the DEA method allows us to take into account the presence of environmental variables, i.e., variables that influence model calculations, but which cannot be influenced within the framework of the task being solved. Such variables cannot be classified as ordinary input variables since they cannot be controlled by the decision-maker (DM). Examples include climatic conditions in a given territory, the level of health of an individual (in the short term), concomitant diseases, etc.

7. Data Management in Digitalization Processes in Medicine

Modern data management methods are based on transdisciplinary foundations. A transdisciplinary approach in telemedicine underscores evolutions in data processing, grounded on novel elements of information theory. These elements spawn subsets of medical language, forming the foundation of telecommunications, biomedical data processing, and biomedical signaling. They further propose a metric for gauging the efficacy of health monitoring endeavors.
Biological and medical semiotics delve into the language and rules governing signals and codes within biological and medical systems. This field amalgamates insights from various domains including systems theory, information theory, and linguistics. Consequently, biomedical semiotics furnishes a fresh perspective on both the categorization and interpretation of biological and medical signaling, along with the errors tied to data discrimination.

8. Conclusions

1. Telemedicine consultations require a robust real-time medical data management system that allows consultants and attending physicians to efficiently process data, retain validated data for patient-specific recommendations, and enhance the global telemedicine framework with decision-making expertise.

2. Integrating big data analytics can improve the prediction and identification of disease diagnoses and prognoses, aiding in the development of effective strategies for complication prevention and disease treatment. Real-time communication with each patient and complex data processing can only be achieved through artificial intelligence. Manual intervention is insufficient for serving thousands of users simultaneously.

3. It is crucial during telemedicine consultations to consider not only the static indicators of the patient's condition but also their baseline data, stable condition indicators from previous studies, and personalized correlation galaxies. Recommendations based solely on the analysis of the patient's status during the telemedicine session risk incorrect conclusions.

4. Biosemiotics, which focuses on the language and rules of signals and codes in biological systems, combines ideas from systems theory, information theory, and linguistics. This integration may offer a new perspective on the classification and interpretation of biological and medical signaling. A coherent theory of biosemiotics needs to be developed.

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