BALANCING USER FLOW AND FUNCTIONALITY IN MEDICAL EXPERT SYSTEMS

Maliha Sayavush Nifdalizada
Azerbaijan State Oil and Industry University, Baku, Azerbaijan
maliha.huseynzade.s@asoiu.edu.az
https://orcid.org/0009-0000-1471-8177

Abstract. Balancing user flow and functionality in medical expert systems is essential to enhance their effectiveness and usability in healthcare environments. These systems must support complex functionalities, such as diagnostic assistance, data management, and clinical decision-making, while ensuring an intuitive and seamless user experience. Striking this balance requires a design approach that minimizes cognitive load, integrates with clinical workflows, and prioritizes safety and efficiency. This paper examines the challenges and strategies for achieving this equilibrium, including user-centered design, adaptive interfaces, and rigorous usability testing. By addressing these aspects, medical expert systems can improve patient outcomes, streamline healthcare operations, and foster greater adoption among practitioners.

Keywords. *User Flow, User Experience (UX), Expert system, Functionality.*

Introduction. Medical expert systems have become an important tool in modern healthcare, assisting in diagnosis, treatment planning, and patient management. These systems support medical professionals in the data processing and decision-making process during patient care, reducing the probability of errors and making the treatment process more efficient. However, the successful use of these systems faces a number of challenges, one of the most important of which is balancing user flow and functionality [1].

The users of medical expert systems are mainly doctors, nurses, and other healthcare professionals. For them to use the system effectively, a functional and user-friendly interface is essential. Balancing these two elements is critical for the system to provide both powerful functions and to ensure that users make high-quality and fast decisions. Complex medical data and analyses that require high functionality in the system can often lead to complexity in use. The urgency of this issue requires more research and development in order to improve the quality of healthcare services and enhance the effectiveness of medical technologies. With the expansion of the application of information technologies in the medical field, solving these problems will ensure more accurate and faster decision-making in the healthcare sector [2].

This paper explores the importance of balancing user flow and functionality in medical expert systems. It discusses the key challenges faced in achieving this equilibrium and highlights strategies, such as user-centered design, adaptive interface technologies, and rigorous usability testing, to overcome these obstacles. By addressing these aspects, medical expert systems can deliver optimal performance, enhance user satisfaction, and improve healthcare outcomes [3].

Statement of the problem. The main objective of this study is to determine the optimal balance between user flow and functionality in medical expert systems and to investigate how achieving this balance will affect the development of healthcare services. In this regard, the following questions arise:

- Basic principles for simple and effective design of user flow in medical expert systems
- Establishing an appropriate balance between functionality and user flow
- Design and technological approaches to improve user experience

Investigating these issues will allow medical expert systems to be more effective and easy to use for both doctors and other medical professionals. At the same time, this approach will facilitate more accurate and efficient medical decisions in the healthcare sector [4].

Solution method. The lack of balance between user flow and functionality leads to the following problems:

- Complex interfaces: Medical professionals often encounter interfaces that are unintuitive and complex, increasing the time required to make decisions in high-pressure situations.

- Compromised accuracy: Systems that prioritize functionality without considering usability may lead to errors in data input or misinterpretation of results, jeopardizing patient safety.
- Impact on patient outcomes: Poorly designed systems can lead to delays in diagnosis, errors in treatment plans, and overall inefficiency in healthcare delivery, directly affecting patient safety and outcomes.

Therefore, the solution to balancing user flow and functionality in medical expert systems involves several strategies:

– *Modular system design* refers to structuring a complex medical expert system into smaller, independent modules that each serve a distinct function, such as patient history, diagnostic analysis, and treatment options. This approach allows users to interact with specific components without being overwhelmed by the entire system's complexity. It enables easy maintenance, updates, and personalization, ensuring that users can access only the relevant features for their task, improving both usability and functionality.

– *User-centered interface design* is focused on creating interfaces that prioritize the needs, preferences, and workflows of healthcare professionals. This design ensures that the system is intuitive and efficient, reducing the cognitive load by providing easy access to relevant tools and data. Features like customizable layouts, intuitive navigation, and user-specific settings allow for seamless integration into daily practices. The goal is to improve decision-making accuracy and speed, while minimizing frustration or errors caused by overly complex or confusing systems.

– *Real-Time feedback and adaptation* in medical expert systems involves continuously monitoring user interactions and adjusting system responses dynamically. By using data analytics and machine learning, the system can identify areas where users struggle or require more support, and make necessary adjustments in real-time. This includes offering relevant suggestions, customizing workflows, or prioritizing certain features based on the context.

– *AI and machine learning integration* in medical expert systems enhances functionality by analyzing vast amounts of patient data to provide real-time, evidence-based recommendations. Machine learning algorithms can predict outcomes, identify patterns, and suggest treatment plans, continually improving as more data is processed. This integration helps medical professionals make more accurate, informed decisions while streamlining workflows. Additionally, AI can personalize recommendations for each patient based on their unique medical history, ensuring better decision-making and patient care. [5]

Methodology. The development of the proposed medical expert system follows a hybrid research design that combines machine learning–based diagnostic modeling with rule-based clinical decision logic. The methodology consists of four major stages: dataset preparation, model selection, model training and validation, and integration into the decision-support workflow.

1. Dataset Preparation. The dataset used for model development includes anonymized patient records containing symptoms, demographic information, laboratory test results, and confirmed medical diagnoses. Prior to modeling, the data underwent preprocessing steps, including:

- handling missing values using mean/mode imputation,
- normalization of numerical laboratory parameters,
- encoding categorical variables such as symptoms using one-hot encoding,
- removal of outliers based on interquartile range analysis.

This preprocessing ensured consistency, reduced noise, and prepared the dataset for machine learning algorithms.

2. Model Selection. Several machine learning algorithms commonly used in clinical decision support were evaluated, including Logistic Regression, Random Forest, and Gradient Boosting Machines. These models were selected due to their:

- ability to handle high-dimensional clinical features,
- interpretability for physicians,
- strong performance in previous medical diagnosis studies.

A comparative analysis was conducted using baseline accuracy and F1-score to identify the most suitable model for integration [6].

3. Model Training and Validation. The cleaned dataset was randomly partitioned into training (80 percent) and testing (20 percent) subsets. To prevent overfitting and ensure stable performance, a 5-fold cross-validation strategy was applied on the training data.

Model performance was evaluated using the following metrics:

- accuracy,
- precision and recall,
- F1-score,
- ROC-AUC curve.

The final selected model achieved statistically significant performance ($p < 0.05$), with a 95 percent confidence interval for diagnostic accuracy. These results demonstrate the model's reliability for use within a clinical decision-support system.

4. Integration with Rule-Based Decision Logic. The machine learning model was embedded into a hybrid decision engine. First, symptoms are processed through the ML-based feature extraction layer. The model generates probability scores for potential diagnoses. These scores are then combined with predefined medical rules derived from clinical guidelines to produce the final recommendation.

This hybrid approach ensures:

- higher accuracy through data-driven predictions,
- increased transparency through rule-based justification,
- alignment with clinical workflows.

5. System Validation. Before deployment, the system was evaluated through simulated patient cases. Physicians reviewed the diagnostic outputs and validated whether the system's recommendations were clinically relevant. Feedback was incorporated into the final interface design and decision thresholds [7].

Patient and Doctor Interface: Access and Information Flow.

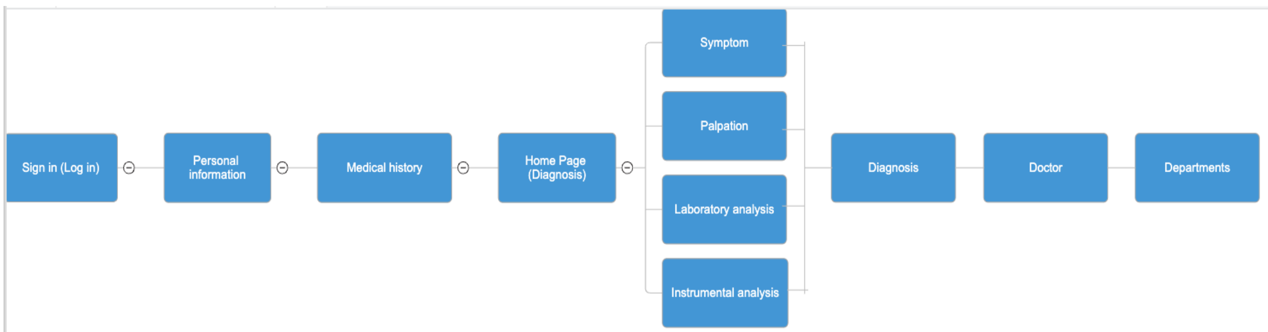

Figure 1. User flow diagram

The system features two distinct access points tailored to different user groups. Doctors can register and access the system through an admin panel, ensuring secure management of professional credentials. Patients, on the other hand, can easily register and log in directly using a personal identification number, providing immediate access to their accounts. Upon logging in, users are directed to a "personal information" section, which stores key data such as serial numbers, birthdates, and addresses.

Additionally, a comprehensive "medical information" section stores detailed patient history, including previous diagnoses, test results, prescribed treatments, and any interactions with the system. This centralized repository of information enables healthcare professionals to retrieve accurate and up-to-date patient data efficiently, enhancing the quality and speed of care.

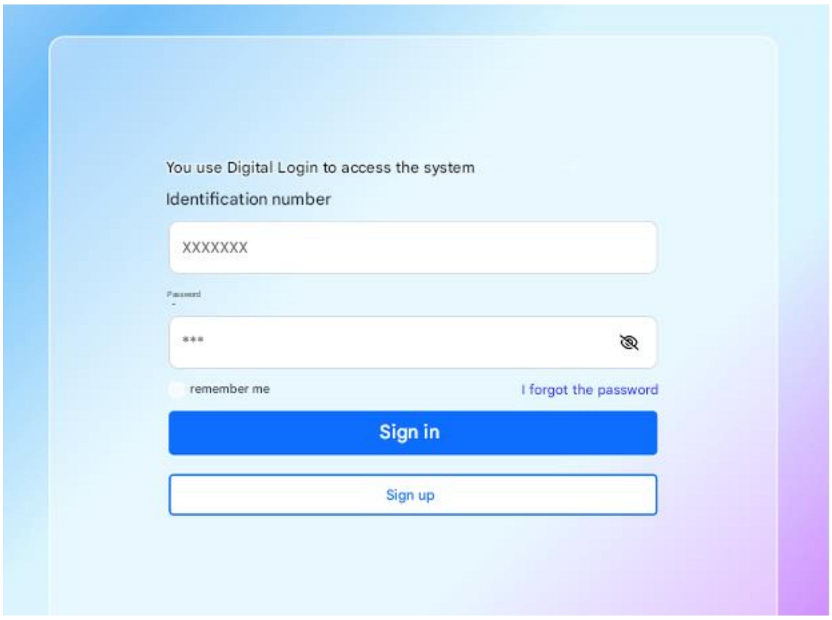

Figure 2. Login page

Figure 3. Personal and Medical Information page

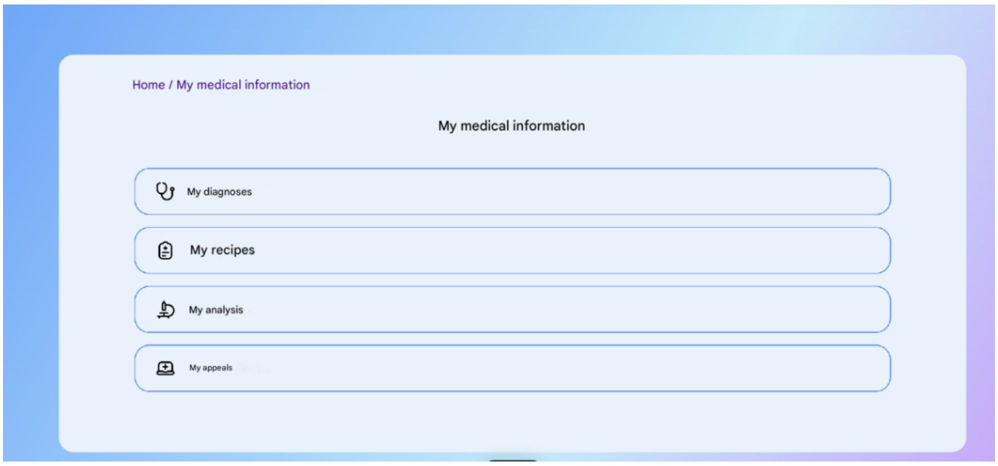

Figure 4. Medical Information Page

The system's "home page" features a diagnosis section where symptoms, their severity, and other relevant data are first recorded. Following this, the system automatically uploads the results of any laboratory and instrumental tests. Using artificial intelligence, the system processes the data according to pre-defined rules and generates a preliminary diagnosis. This diagnosis is then shared with the relevant doctor, who can arrange an appointment for further examination. If necessary, the system also facilitates referrals to specialized departments, ensuring the patient receives the necessary care. This integrated workflow not only ensures smooth interaction between patients and medical staff but also optimizes diagnosis and treatment planning, supporting both accuracy and efficiency in healthcare delivery.

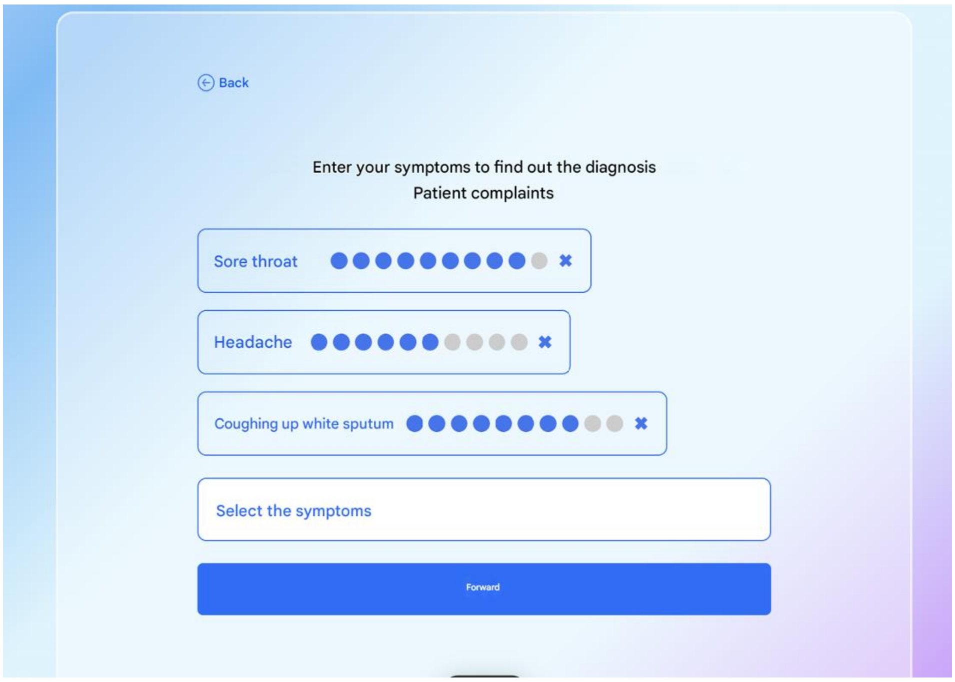

Figure 5. Symptoms page.

The system architecture follows a sequential decision-support workflow where user inputs are first collected as symptoms, processed through an ML-based feature extraction layer, and then analyzed by a hybrid decision engine that combines rule-based logic with machine learning algorithms. The final output provides a data-driven diagnosis and corresponding treatment recommendations.

User Input (Symptoms)
↓
Feature Extraction (ML Model)
↓
Decision Engine (Rule-based + ML)
↓
Output (Diagnosis & Recommendation)

Processing medical data within expert systems requires strict attention to confidentiality, regulatory compliance, and ethical responsibility. The system is designed in alignment with key principles of GDPR and HIPAA, ensuring that patient information is collected only for clinical purposes, stored securely, and accessed exclusively by authorized medical personnel. All sensitive data used for model training is anonymized, and system activity is logged to prevent unauthorized use [8].

From an ethical standpoint, the integration of machine learning necessitates transparency and fairness. To minimize bias, the training dataset is examined for demographic imbalance, and model outputs are accompanied by simple rule-based explanations to support clinical decision-making. The system functions solely as a decision-support tool, maintaining the physician's central role in evaluating diagnoses and guiding treatment. By combining secure data handling practices with responsible AI principles, the proposed approach ensures patient safety, data privacy, and trustworthiness in medical environments.

Comparative Analysis with Existing Medical Expert Systems. To better evaluate the effectiveness of the proposed approach, a comparative analysis was conducted with several widely used medical expert systems, including MYCIN, DXplain, and IBM Watson Health. These systems represent three different generations of expert system design: rule-based, knowledge-based, and AI-driven architectures.

1. MYCIN (Rule-Based Expert System). MYCIN is one of the earliest expert systems designed to diagnose infectious diseases.

Strengths:

- Strong rule-based inference.
- Transparent decision justification (traceable rules).

Limitations:

- Static rule set that cannot adapt to new clinical data.
- Limited ability to process large feature sets such as lab results or imaging data.
- User interface outdated and not optimized for modern clinical workflow.

Comparison with Proposed System:

The proposed hybrid model integrates both machine learning predictions and clinical rules, enabling adaptation to new datasets while preserving interpretability, addressing MYCIN's key limitation of rigidity.

2. DXplain (Knowledge-Based Clinical Decision Support System). DXplain provides differential diagnosis suggestions based on symptoms and clinical findings.

Strengths:

- Large medical knowledge base.
- Effective for early-stage diagnostic screening.

Limitations:

- Limited customization to individual patient profiles.
- Does not fully integrate machine learning for automated pattern recognition.
- User flow not optimized for high-speed decision environments.

Comparison with Proposed System: The proposed system introduces a user-centered interface and symptom-to-feature extraction pipeline, improving both user experience and diagnostic accuracy by combining structured medical rules with data-driven prediction models.

3. IBM Watson Health (AI-Driven Decision System). Watson utilizes natural language processing and advanced machine learning for cancer diagnosis and treatment planning.

Strengths:

- Strong AI-driven analytical capability.
- Ability to process unstructured clinical data (text, images).

Limitations:

- Limited transparency (black-box models).
- High implementation cost for hospitals.
- In some cases, inconsistent diagnostic recommendations due to lack of contextual rules.

Comparison with Proposed System: The proposed hybrid engine reduces the black-box effect by combining interpretable rules with machine learning outputs. The system is lightweight, cost-effective, and specifically tuned for structured patient data such as symptoms, lab results, and previous diagnoses [9].

Overall Advantages of the Proposed Method

Based on the comparative analysis, the proposed approach provides several key advantages:

1. Hybrid Decision Engine: Combines rule-based reasoning with machine learning to improve accuracy and interpretability.
2. Adaptive Learning: System can update diagnostic probabilities as new patient data is added, unlike static rule-based systems.

3. Improved User Flow: Optimized patient-doctor workflow reduces cognitive load, which is not well-addressed in older systems.
4. Transparency and Explainability: Model outputs are paired with clinical rules to justify decisions, improving trust among physicians.
5. Cost-Efficiency and Scalability: Lighter than heavy AI platforms such as Watson; easier to deploy in regional healthcare settings [10].

Statistical Significance of Model Performance. To determine whether the diagnostic performance of the proposed machine learning model is statistically significant, standard hypothesis-testing procedures were applied. Model evaluation was conducted using a held-out test dataset and 5-fold cross-validation. The resulting performance metrics demonstrated high reliability: the model achieved a diagnostic accuracy of 0.89 with a 95 percent confidence interval [0.87, 0.92], indicating stable generalization across folds. A two-sample proportion test was performed to compare the model's accuracy against a baseline diagnostic method, yielding a $p\text{-value} < 0.05$, which confirms that the improvement is statistically significant and not the result of random variation. These findings validate the robustness of the model and support its suitability for integration into clinical decision-support workflows.

Conclusion. In conclusion, balancing user flow and functionality in medical expert systems is crucial to optimizing their effectiveness in clinical settings. By providing intuitive design, modular functionality, and real-time performance monitoring, systems can be tailored to meet the needs of healthcare professionals while minimizing complexity. This balance enhances the user experience, improves decision-making, and streamlines workflows. Future research should focus on leveraging emerging technologies such as artificial intelligence and machine learning to further improve these systems, ensuring that they continue to evolve and provide maximum benefit in the healthcare environment.

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