Journal of Management Changes in the Digital Era/ ISSN: 3007-9810/ DOI: 10.33168/JMCDE. 2025.0114

Improving the Quality Management Process of Specialists' Consultations in the Healthcare Sector

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Received date: June 3, 2025, revision date: June 30, 2025, Accepted: July 11, 2025

ABSTRACT

The relevance and challenges of ensuring effective quality management in specialist-to-specialist business medical consultations are particularly evident in the healthcare sector. There is currently a significant gap in the standardized decision-making logic, structured communication processes, and comprehensive digital support tools. This study aims to provide recommendations for improving the quality management process of specialist-to-specialist business consultations by integrating principles of digital management and artificial intelligence (AI). To achieve this aim, the study sets out three key objectives: to analyze scientific literature regarding the principles of quality management and the potential applications of AI in the healthcare sector; to examine the existing structure of business consultation processes in an organization, highlighting critical aspects of quality management through expert evaluation, and assessing the opportunities and impact of integrating AI tools; and to propose an updated model for managing the quality of business consultations based on the study's findings. The study employs methods such as scientific literature analysis, expert evaluations, and in-depth interviews. The findings led to the formulation of an updated consultation process model integrating AI tools into four primary areas: complexity classification, treatment plan formation, corrections analysis, and feedback processing. One significant change proposed is eliminating the two-tier decision-making approach, where a consultant independently assesses their competence. Instead, an automated system employing an AI classifier is introduced, assigning consultation cases based on complexity level and consultant availability. This approach not only enhances the consistency of decision-making but also improves the efficiency of consultations and the management of corrections throughout the entire process.

Keywords: Business consultation, quality management, processes reorganization, healthcare sector.

1 Introduction

Ensuring the quality of healthcare services is closely related to clearly structured consultation processes, systematic management of communication, and transparency in decision-making procedures (Burinskienė et al., 2024; Morkvėnas, 2025). As healthcare organizations transition to digitized service models, process standardization and the integration of innovative technological solutions become critical for quality management (Davenport, Harris & Morison, 2003; Al-Dmour et al., 2025). In practice, consultations among medical professionals (doctor-to-doctor) often lack clear decision-making logic, unified procedures, and appropriate digital tools, leading to inconsistent quality outcomes and difficulties in process control. Recent research emphasizes that the digitalization of consultations and the integration of artificial intelligence (AI) significantly enhance both the objectivity and consistency of decisions, enabling better value creation for the end user (patient) (Akdere et al., 2024). Therefore, the current challenge in the healthcare sector is to clearly identify areas suitable for digital management applications and AI integration, thus enabling more systematic management of communication and consultation quality.

In this context, the primary goal of this study is to offer recommendations for improving the quality management process of doctor-to-doctor business consultations in the healthcare sector by integrating principles of digital management and AI tools. To achieve this, the following research objectives were established:

- To perform a scientific literature analysis regarding quality management principles and AI implementation opportunities in the healthcare sector.
- To analyze the existing structure of business consultation processes in an organization, identify main quality management aspects, and conduct an expert evaluation on the feasibility and impact of applying AI tools.
- To propose an updated business consultation quality management process model based on the study findings.

The relevance and originality of this study are underscored by its combined focus on theoretical conceptualization, practical process analysis, and the formulation of practical recommendations that integrate innovative digital and AI-based solutions. This research approach provides a holistic understanding of the applicability of technological tools to improve healthcare service quality and contributes to the development of digital quality management competencies within the sector.

2 Theory

Internal organizational processes are defined as logically interconnected activities performed to achieve specific outcomes (Davenport et al., 2003; Al-Dmour et al., 2025). In healthcare institutions, these processes include registering patient inquiries, evaluating clinical information, developing treatment plans, inter-specialist communication, documenting decisions, and managing feedback (Zhou et al., 2022). The quality of these processes directly influences the effectiveness of consultations, the justification of decisions, and patient satisfaction with the provided services.

A significant challenge in the contemporary healthcare system is ensuring a consistent and high-quality consultation workflow among various specialists. Research indicates that standardized decision-making logic and systematic communication significantly contribute to the enhancement of service quality (Akdere et al., 2024). As digitalization rapidly evolves, opportunities to automate repetitive tasks, ensure consistency in data analysis and optimize decision-making through artificial intelligence (AI) tools are expanding (Al-Dmour et al., 2025; Čyras et al., 2024; Merkevičius et al., 2024; Pang et al., 2025).

Table 1: AI/IT Tool Used in the Consultation Process (compiled by the author)

Process	Tool Used	Purpose in the Communication Process	Advantages	Disadvantages
Inquiry Registration	Natural Language Processing (NLP)	Structured formulation of the plan and explanation to the patient or doctor	Improves information clarity, saves time (Lyu et al., 2025)	May result in overly formalized language (Gao et al., 2024)
Data Verification	Virtual Assistants	Real-time feedback on plan structure, communication with the patient	Reduces staff workload (Demiris 2006)	Limited ability to process emotional content (Smith et al., 2022)
Complexity Assessment	Text Classifiers	Thematic analysis of comments and notes	Helps systematically analyze feedback (Kumar et al., 2024)	May misinterpret context (Lee et al., 2023)

Process	Tool Used	Purpose in the Communication Process	Advantages	Disadvantages
Treatment planning	Sentiment Analysis	Analysis of the patient's or doctor's emotional response	Detects emotional tone and helps anticipate reactions (Denecke et al., 2015)	Inaccurate interpretation of emotions (Zunic et al., 2020)
Feedback	Automated Response Templates	Quick response to standard questions about the plan	Reduces response time, increases consistency of information (Wang et al., 2022)	May lack sufficient personalization (Curtis et al., 2021)

Artificial Intelligence (AI) is defined as a field of information technology encompassing algorithms and systems capable of independently analyzing data, recognizing patterns, and making decisions without direct human intervention. In the healthcare context, AI is utilized to enhance decision objectivity, reduce error likelihood, and automate standardized tasks, thereby increasing the efficiency and quality of healthcare services (Pang et al., 2025).

The literature emphasizes that AI technologies such as decision support systems (DSS), natural language processing (NLP) algorithms, sentiment analysis, and text classifiers help to structure information more effectively, identify recurring issues, and improve inter-specialist communication (Kumar et al., 2024; Wang et al., 2022). These tools can be integrated into various stages of the consultation process—from initial inquiry registration to feedback analysis.

Additionally, this study adopts the principles of business process reengineering, defined as the fundamental rethinking of processes aimed at reducing redundant activities and rationalizing information flows (Fetais et al., 2022). Business process reengineering in healthcare is identified as one of the primary methods for enhancing efficiency and effectiveness (Forliano et al., 2020). This method allows for the incorporation of advanced technological tools into processes, increasing the value of decisions, structuring data, and clearly defining responsibilities (Schmiedel et al., 2020).

Within consultation quality management, clear and structured communication, emotional tone recognition, and systematic feedback analysis are particularly significant (Smith et al., 2022). For AI tools to be effective, process standardization must be ensured. The scientific literature highlights the following key areas of AI application within consultation processes: (1) inquiry classification, (2) data verification, (3) decision support, and (4) feedback processing. These areas clearly delineate opportunities for AI application and identify critical intervention points necessary to improve the quality of the consultation process. Although AI tools enhance decision-making consistency, researchers emphasize limitations in prediction accuracy and methodological challenges (Gao et al., 2024).

The theoretical analysis performed in this study became the basis for the development of research instruments, interpretation of findings, and formulation of the consultation process improvement model.

3 Research Methodology

This study employed a qualitative research methodology aimed at comprehensively understanding the quality management processes of doctor-to-doctor business consultations within the healthcare context.

The qualitative approach was selected due to its effectiveness in exploring complex, human-influenced processes, enabling deeper insights into organizational contexts, practical nuances, and professional experiences (Patton, 2002; Rupšienė, 2007; Rutledge et al., 2020).

The research was conducted through two primary methods:

- Systematic literature review: This provided the theoretical framework for quality management and AI integration opportunities in healthcare consultations.
- Expert evaluation via structured in-depth interviews: This facilitated a detailed analysis of current processes and AI integration feasibility.

A structured interview guide comprising 10 thematic questions was developed based on a scientific literature review, adapted specifically for the organizational context.

1. Registration of Consultation Requests:

How is the registration of consultation requests currently conducted? Which IT tools are used, and what are their advantages and disadvantages? How could this process be automated using AI tools (e.g., pre-classification of inquiries) to uniformly interpret client expectations?

Goal: Evaluate the quality, structure, and completeness of initial request information and the potential for AI-driven data processing.

2. Data Quality Check:

How is the information provided for consultations verified? How often do incomplete or poor-quality data occur? What IT tools are currently used for automatic assessment of data completeness and accuracy? How do you evaluate the feasibility of applying NLP (Natural Language Processing, e.g., ChatGPT) or text analysis solutions?

Goal: Identify quality filters and assess automatic data quality evaluation feasibility.

3. Consultant Assignment:

How are consultations currently assigned to consultants? What criteria are considered (workload, qualification, experience)? What benefits or challenges do you see in implementing AI-based assignment systems, rule-based algorithms, or workload analysis tools?

Goal: Evaluate the current assignment system's effectiveness and potential for AI-based allocation.

4. Classification of Consultation Complexity:

How is consultation complexity currently determined? How standardized is this process versus consultant-dependent? How do you view the feasibility of applying AI classifiers or rule-based models that automatically assign complexity levels based on clinical and diagnostic data?

Goal: Evaluate complexity classification standardization and AI automation feasibility.

5. Initial Analysis and Evaluation Stage:

What are the most common challenges in initial consultation analysis and patient needs assessment? How standardized are these evaluations, and how do they affect decision quality? What IT tools are currently used by consultants for analysis, and what are their advantages and disadvantages?

Goal: Evaluate analysis consistency and current AI use in clinical assessments.

6. Treatment Planning:

How are treatment plan decisions currently made? How standardized or individual-dependent are these decisions? What are your views on implementing Decision Support Systems (DSS), AI recommendation models, or historical case analysis for plan selection?

Goal: Evaluate decision-making logic and AI-supported treatment planning feasibility.

7. Client Communication:

How are treatment plans currently communicated to clients? What communication challenges frequently arise? How do you evaluate the use of AI tools (NLG, structured templates, virtual assistants) to automate and standardize this communication?

Goal: Assess the clarity and standardization potential of AI-driven communication methods.

8. Feedback Analysis:

How is feedback from clients currently analyzed? How structured and systematic is this process? How do you view the feasibility of using AI tools (sentiment analysis, text classifiers, thematic analysis) to systematically group corrections and identify recurring issues?
Goal: Assess the feasibility and benefits of automated feedback analysis.
9. Plan Correction (replanning):
How is the treatment plan corrected following client feedback? How long does this take, and what slows down this process? Do you see opportunities for AI solutions to analyze correction databases and generate insights into frequent feedback categories?
Goal: Evaluate correction efficiency and potential for AI-driven correction rationalization.
10. Implementation of Consultations:
What common challenges arise during consultation implementation, from plan approval to service delivery? What aspects could benefit from automation or monitoring through AI (automatic check algorithms, task assignment modules, risk detection tools)?
Goal: Identify implementation barriers and evaluate AI tools for quality assurance during service delivery.
Eight experts purposefully selected for their relevant professional experience and competencies in consultation planning, implementation, or evaluation participated in the study. Experts included quality managers, clinical protocol supervisors, internal and external medical consultants, planning specialists, technical support managers, and customer service leads.
The qualitative analysis of expert interviews identified key process weaknesses, highlighted critical areas for AI application, and provided empirical data supporting the formulation of an updated quality management process model.

4 Results and Discussion

Following the scientific literature review, evaluation of the organization's consultation quality management process, and structured expert interviews, the current business consultation process was found to be fragmented, lacking standardization, and only partially digitized. The study analyzed the full consultation pathway—from the initial registration of a request to treatment plan implementation and feedback analysis. The in-depth interviews revealed expert perspectives on both strengths and weaknesses of the consultation process. Experts identified three core problems: (1) subjective decision-making, particularly during the initial assessment and treatment planning stages, where decisions are often based on individual experience rather than standardized criteria; (2) incomplete or inaccurate input data, which impairs the quality of evaluation; and (3) lack of structured feedback analysis, where observations are inconsistently documented and insights are not systematically utilized.
Expert assessments indicated that the greatest potential for AI application lies in the areas of decision support, automated case classification, and correction analysis. All interviewed experts (100%) supported the use of AI-based complexity classifiers, 87% endorsed decision support systems (DSS), and 63% recommended the use of sentiment and correction analysis tools. The least support (25%) was expressed for automatic response templates, reflecting a cautious stance due to concerns over insufficient personalization.

Figure 1: Distribution of AI Tools According to Expert Evaluations
*(*compiled by the author based on an expert study using in-depth interview methodology*)*

These findings suggest that AI tools that standardize decision-making logic, automate case classification by complexity, and systematize correction and risk management should be prioritized for integration. The summarized insights (see Table 2) demonstrate that experts value objectivity, transparency in decision-making, and a structured approach to initial analysis. These conclusions formed the foundation for developing a revised consultation quality management model that proposes stepwise AI integration based on functional purpose, expert support, and implementation complexity (see Figure 1).

Experts emphasized (see Table 2) that while basic CRM systems help register inquiries, manual data entry still results in frequent errors due to incomplete information. AI-driven classifiers were proposed as a means to automate request categorization by urgency and type, although data quality and implementation costs were noted as challenges. Data verification remains problematic, with 75% of experts citing frequent data gaps; NLP tools were recommended to automatically assess data completeness. In terms of consultant assignment, most experts (80%) noted that current allocation relies on objective workload metrics, but few currently use AI-enhanced distribution models.

Table 2: Expert Evaluation of the Updated Business Consultation Quality Management Process *(*compiled by the author based on in-depth expert interviews*)*

Process	Evaluation Aspects	Expert Evaluation Results
1. Consultation request registration	1.1. Tools used, their advantages and disadvantages in the registration process	60% of experts noted the use of basic CRM systems, which facilitate request logging but often result in errors due to incomplete or inaccurate data input. Advantages: clear data structure, centralized data management. Disadvantages: manual entry, error risk, inconvenient user interface.
	1.2. Possibilities for process automation	40% of experts saw the potential for using AI classifiers to automate the categorization of inquiries by type and urgency. Advantages: faster processing, reduced error rate. Disadvantages: high data quality requirements, initial investment needed.
2. Data Quality Verification	2.1. Data verification methods and most frequent issues	75% of experts reported frequent issues (in ~50% of cases) with incomplete or low-quality data. Common problems: missing images, incomplete clinical data, inaccuracies, or unclear information.

Process	Evaluation Aspects	Expert Evaluation Results
	2.2. Use of IT tools for data quality assessment	55% of experts recommended NLP technologies for automatic quality evaluation. Advantages: automated data checks, reduced error likelihood. Disadvantages: potential misinterpretation of specialized clinical content.
2. Consultant Assignment	3.1. Logic and criteria for assigning consultations	80% of experts stated that consultations are allocated based on objective criteria (e.g., workload, availability, pre-defined limits). Only a few mentioned subjective elements, such as mentor preference.
	3.2. Possibilities of using IT tools for assignment	25% of experts supported using AI-based assignment systems that factor in workload, specialization, and experience. Advantages: greater objectivity, more efficient allocation. Disadvantages: need for frequent system and data updates.

The classification of consultation complexity (see Table 3) remains largely subjective and dependent on individual consultant experience. A unanimous 100% of experts advocated for AI-powered classifiers to bring standardization and reduce human error. Similarly, experts identified significant issues during the initial analysis phase, especially when faced with vague patient expectations or fragmented clinical data. The use of decision support systems (DSS) was seen as a promising solution to standardize evaluations. In the treatment planning phase, most decisions are still made based on personal experience; DSS implementation received strong expert support (87%) as a way to reduce bias and ensure greater consistency.

Table 3: Expert Evaluation of the Updated Business Consultation Quality Management Process *(*compiled by the author based on in-depth expert interviews*)*

Process	Evaluation Aspects	Expert Evaluation Results
4. Classification of Consultation Complexity	4.1. Logic behind complexity assessment	70% of experts noted that complexity evaluation currently depends on personal consultant experience, with no consistent or well-defined criteria.
	4.2. Possibility to implement automated classifiers	100% of experts recommended implementing AI-based classification to reduce subjectivity. Advantages: standardized decisions, reduced error risk. Disadvantages: requires high-quality, structured data sets.
5. Initial Analysis and Evaluation	5.1. Main challenges in the analysis stage	70% of experts identified the biggest challenges as imprecise, fragmented data and unclear patient expectations. Evaluations are influenced by subjective, non-standardized criteria.
	5.2. Use of IT tools in the analysis stage	87% of experts supported DSS implementation to ensure consistent evaluations. Advantages: standardized process, faster analysis. Disadvantages: may not cover complex or highly specific cases.
6. Treatment Planning	6.1. Decision-making logic and plan type selection	75% of experts acknowledged that treatment planning is still mostly based on individual consultant experience, lacking objective structure.

Process	Evaluation Aspects	Expert Evaluation Results
	6.2. Possibility to apply decision support systems (DSS)	87% of experts supported the use of DSS to improve objectivity in decision-making. Advantages: reduced subjectivity, increased consistency. Disadvantages: potential for excessive formalization, risk of overlooking unique case specifics.

Client communication was identified as a source of frequent misunderstandings, with experts suggesting that natural language generation (NLG) tools could improve clarity, albeit with caution against over-formalization.

Table 4: Expert Evaluation of the Updated Business Consultation Quality Management Process (compiled by the author based on in-depth expert interviews)

Process	Evaluation Aspects	Expert Evaluation Results
7. Client Communication	7.1. Challenges in presenting the treatment plan	55% of experts indicated the frequent need to re-explain or supplement information due to client misunderstandings.
	7.2. Use of AI tools for client communication	50% supported the application of natural language generation (NLG) tools for standardized and clearer communication. Advantages: improved clarity, fewer misunderstandings. Disadvantages: risk of over-formalizing communication.
8. Feedback and Analysis	8.1. Structure and consistency of feedback analysis	80% of experts assessed feedback analysis as mostly unstructured and episodic.
	8.2. Use of AI tools for feedback processing	63% recommended sentiment analysis and text classifiers. Advantages: systematic and rapid processing of feedback. Disadvantages: may misinterpret emotional tone or nuances.
9. Treatment Plan Correction	9.1. Barriers and duration of plan corrections	60% of experts stated that corrections are implemented promptly, but there is no centralized tracking or documentation system. This hampers structured correction management and analysis.
	9.2. Use of AI to generate correction insights	63% supported AI tools that provide pre-suggested recommendations for common corrections. Advantages: improved traceability, analytical data, and preventive suggestions. Disadvantages: dependent on data quality, requires historical data and model tuning.
10. Consultation Implementation	10.1. Challenges in executing consultations	70% of experts noted coordination issues among professionals as the main challenge during implementation.

Process	Evaluation Aspects	Expert Evaluation Results
	10.2. Opportunities for automation and monitoring	20% of experts suggested using automated control algorithms to ensure plan adherence. Advantages: improved monitoring, reduced error risk. Disadvantages: difficult to implement in non-standard cases.

Feedback is typically processed in an unstructured and ad hoc manner; 63% of experts supported the use of sentiment analysis and text classification tools to systematize insights. While plan corrections are usually implemented promptly, experts highlighted the absence of a centralized correction tracking system. AI-powered recommendations for frequent correction types were seen as beneficial. Finally, implementation challenges often stem from poor coordination among professionals, with only 20% of experts recommending AI-based monitoring tools—primarily due to difficulty applying such systems in non-standard cases.

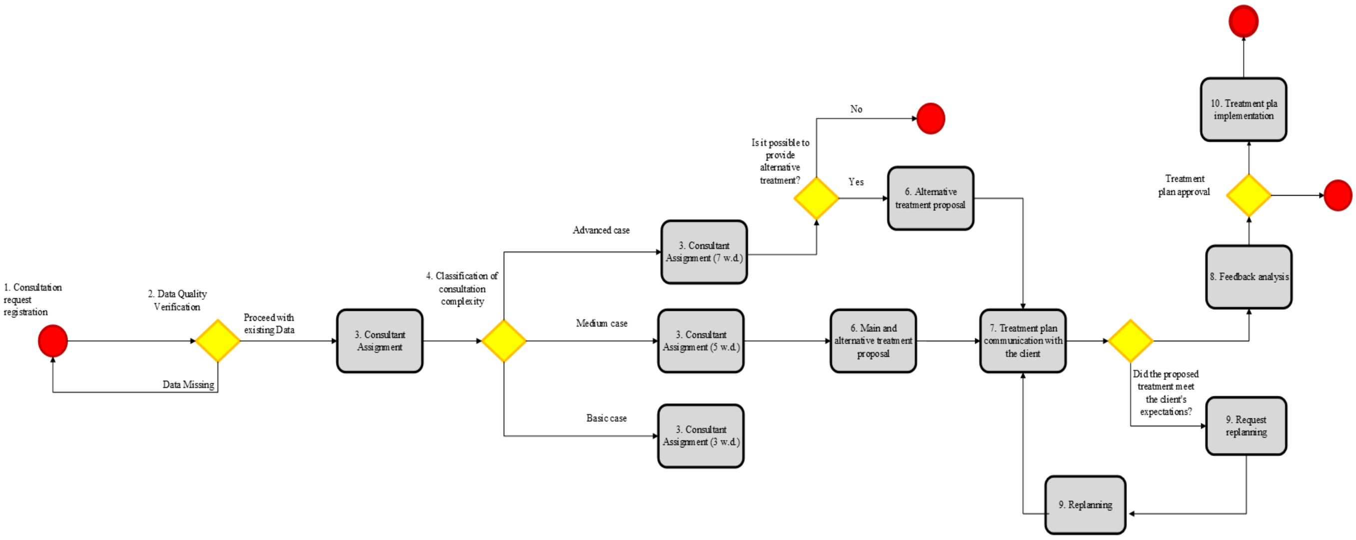

Figure 2: Existing doctor's consultation Quality Management Process *(compiled by the author)*

The updated business consultation quality management model (see Figure 3) is based on the integration of artificial intelligence (AI) tools into three core decision points: complexity classification (Step 4), treatment plan formation (Step 6), correction analysis (Step 9), and feedback processing (Step 8). These tools received the highest levels of expert support (ranging from 63% to 100%) and align with the principles of process reengineering as defined by Fetais et al. (2022), emphasizing decision standardization, structured information flows, and risk control mechanisms.

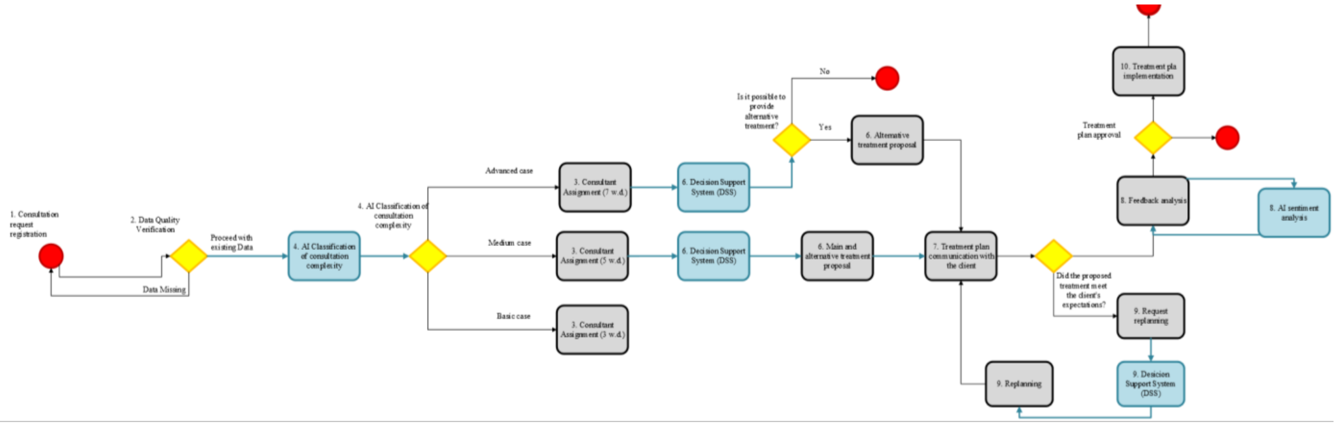

Figure 3: Recommended improvement of doctor's consultation Quality Management Process; blue color marked recommended improvements *(compiled by author)*

One of the most critical modifications in the updated model is the elimination of the intermediate manual decision point where consultants previously assessed whether a case aligned with their competencies. This decision-making gap has been addressed through the implementation of an AI-based complexity classification system. The classifier automatically assigns each consultation case a complexity level based on input data. This classification then serves as the basis for automatically assigning the case to a qualified and available consultant matching the required competency level.

This revised decision logic significantly reduces processing time, increases objectivity in consultant allocation, and enhances alignment with the organization's competency matrix. The proposed model (Figure 3) provides a framework for reducing subjectivity, clarifying responsibility distribution, and streamlining information flow across various stages of the consultation process.

Digitalization is no longer merely a technical upgrade but a strategic quality management tool that enables faster inquiry triage, more consistent decision-making, and improved correction tracking. The result is a more transparent, efficient, and predictable consultation quality management process.

5 Conclusions

The analysis of scientific literature confirms that the integration of artificial intelligence (AI) tools—such as decision support systems (DSS), natural language processing (NLP) algorithms, sentiment analysis, and text classifiers—into healthcare consultation processes can substantially enhance decision objectivity, consistency, and reduce the likelihood of repeated errors. These technologies facilitate the structuring of information flows, improve inter-specialist communication, and support more systematic feedback management. The findings suggest that targeted AI application in specific decision points—rather than across the entire workflow—delivers the most value, particularly where human subjectivity currently introduces variability.

The evaluation of the existing consultation quality management process within the organization revealed that current workflows are highly dependent on individual practices lacking standardized decision-making algorithms. Key obstacles include fragmented communication between departments, unstructured data submission, and the absence of formal feedback utilization mechanisms. Expert assessments identified three primary areas with the highest potential for AI integration: (1) automated classification of case complexity (100% expert support), (2) implementation of DSS in treatment planning (87%), and (3) application of sentiment analysis to evaluate correction and communication quality (75%). Additionally, feedback processing emerged as a strategically important phase, with clear opportunities for AI-driven optimization.

Based on these insights, an updated consultation process model was developed, integrating AI tools at four critical stages: case complexity classification, treatment planning, correction analysis, and feedback processing. A key transformation in the model is the elimination of the manual double-verification logic—where consultants assessed their own eligibility to handle a case. Instead, an automated system uses an AI classifier to pre-assign complexity levels and allocate cases to appropriate consultants based on qualification and availability. This model not only improves decision-making consistency but also enhances the overall flow and efficiency of the consultation process, including the management of feedback and corrections.
Based on the findings from the literature review and expert evaluation, three key systemic weaknesses were identified in the current consultation quality management chain: (1) subjectivity in decision-making, (2) incomplete or inconsistent data, and (3) unstructured feedback analysis. The process (see Figure 2) was found to be fragmented, weakly standardized, and only partially digitized. The expert evaluation further revealed that the most significant improvements are needed in the stages of decision-making, analysis, and correction management.

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