Towards a standardized enterprise architecture: enhancing decision-making in oncology multidisciplinary team meetings

Nassim Bout[1,2], Hicham Belhadaoui[2], Nadia Afifi[2], Mounia Abik[3], Mohamed El-Hfid[4], Ali Azougaghe[3,4,5]

[1]National Higher School of Electricity and Mechanics, Hassan II University, Casablanca, Morocco
[2]Higher School of Technology, Hassan II University, Casablanca, Morocco
[3]National Higher School of Computer Science and Systems Analysis, Mohammed V University, Rabat, Morocco
[4]Tangier-Tetouan-Al Hoceima University Hospital Centre, Abdelmalek Essaadi University, Tangier, Morocco
[5]National School of Applied Sciences, Cadi Ayyad University, Marrakech, Morocco

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ABSTRACT

This study proposes a novel enterprise architecture (EA) designed to enhance the efficiency and decision-making processes of multidisciplinary team meetings (MDTMs) in oncology by integrating advanced artificial intelligence (AI) technologies. The architecture addresses current inefficiencies in MDTMs, particularly the lack of real-time data integration and limited decision support, by providing a structured framework that improves interoperability and standardizes clinical workflows. Developed using the open group architecture framework (TOGAF) framework and the ArchiMate modelling language, this conceptual architecture lays the groundwork for future empirical research, offering a scalable solution that can be adapted to various healthcare settings. The AI component, centered on generative pretrained transformer (GPT) models, is designed to support oncologists by providing evidence-based treatment recommendations tailored to individual patient cases. Although the study focusses on the theoretical development of this architecture, it opens the door for subsequent empirical testing and validation, with the aim of ultimately improving patient outcomes and streamlined oncology care through enhanced decision support systems.

Corresponding Author:

Nassim Bout
National Higher School of Electricity and Mechanics, Hassan II University
Route d'El Jadida, BP 8118, Oasis, Casablanca, Morocco
Higher School of Technology, Hassan II University
Casablanca, Morocco
Email: nassim.bout.doc21@ensem.ac.ma

1. INTRODUCTION

Multidisciplinary teams (MDTs) have become a cornerstone in oncology for coordinating comprehensive patient care across diverse specialties. These meetings, known in various contexts as tumor boards or *réunions de concertation pluridisciplinaire* (RCP) in French [1], play a pivotal role in developing treatment plans tailored to individual patient needs. These meetings bring together diverse healthcare professionals to develop and refine comprehensive treatment plans. Despite the critical role of multidisciplinary team meetings (MDTMs), they face substantial challenges, including the complexity of integrating data from multiple specialties, inefficiencies in decision-making processes, and limitations in information management systems. These challenges are exacerbated by the lack of standardized approaches to MDTM coordination and data interoperability. MDTMs are mandated by law in many countries and are crucial in deciding treatment protocols based on similar cases, international repositories, or novel studies [2]–[4].

Recent studies have highlighted the transformative impact of the coronavirus disease (COVID-19) pandemic on telehealth integration, highlighting the urgent need for improved infrastructure and regulatory frameworks to support multidisciplinary care [5]. However, the literature reveals persistent inefficiencies in MDTMs that require more advanced technological solutions, particularly in the realms of real-time data integration and decision support systems. Rapid deployment of inpatient telemedicine using consumer-grade technology has shown effectiveness and potential permanence in various healthcare settings [6]. These findings advocate for enhanced telehealth integration to ensure efficient and accurate patient care planning.

Although global implementations of telemedicine, such as India's satellite-based approach [7], underscore the potential of remote healthcare delivery, the integration of internet of things (IoT) technologies further enhances this capability by enabling real-time data collection and advanced analytics [8], highlighting advances in network communications, artificial intelligence, and wearable sensors. This review emphasizes significant focus on IoT-based healthcare applications and identifies key opportunities for future research to resolve existing ambiguities in telemedicine. Improving the structure and technology behind MDTMs is crucial for enhancing patient outcomes and optimizing clinical workflows. An artificial intelligence (AI) based enterprise architecture that consolidates information and facilitates better decision-making processes is essential.

Other researchers, such as Tummers *et al.* [9] highlight the importance of robust reference architectures in addressing various stakeholder concerns. This study aims to design an enterprise architecture for MDTMs in oncology to improve collaboration and decision-making within this healthcare context. The methodology will detail the research approach, including the collection of data from the existing literature, the analysis of current MDT systems, and the design of the proposed AI-based enterprise architecture framework.

To address these challenges, this study advances existing models by introducing a holistic AI-based enterprise architecture that not only integrates real-time data access and decision support but also addresses interoperability challenges, creating a unified framework for MDTMs, this architecture aims to streamline the collaborative process and improve patient outcomes. The remainder of this paper is structured as follows: This Introduction reviews the relevant literature, focusing on the challenges and technological solutions in MDTMs. Section 2 outlines the research methodology, including data collection and analysis techniques. Section 3 presents the proposed AI-based enterprise architecture and discusses its potential impact on MDTM processes. Finally, section 4 concludes with a discussion of the study's contributions, limitations, and suggestions for future research.

A review of the literature reveals that MDTMs are pivotal in oncology, facilitating collaborative decision-making among specialists. According to [10], MDTMs have shown significant positive impacts, with 40% of participants confirming that these meetings facilitate optimal patient care solutions through rigorous debate. Additionally, 81% of physicians in training report enhanced decision-making capabilities and alignment with educational objectives. However, the study also identified significant shortcomings, including inadequate IT support, which affects 26% of participants, and insufficient real-time data entry, affecting 20%. These challenges highlight the need for improved technological infrastructure to support the full potential of MDTMs in enhancing patient care. Inadequate IT support can lead to delays in information retrieval and sharing during MDTMs, potentially compromising the timeliness and accuracy of treatment decisions. Similarly, the lack of real-time data entry can result in outdated information being used in critical discussions, thereby increasing the risk of suboptimal patient outcomes. MDTMs influence oncology by providing multiple therapeutic options for cancer treatment, leveraging the expertise of specialists, improving care quality and diagnostic accuracy, and enabling earlier case discussions.

MDTMs encompass various professionals, including attending physicians, oncologists, radiologists, and radiotherapists, who deliberate on patient cases using the MDTM sheet. This document integrates patient data from the electronic health record (EHR) along with personal notes and proposed treatment plans [3], [11]. However, EHR systems often suffer from interoperability issues, making it challenging to integrate information from different specialties, which can hinder collaborative decision-making. Accessibility to the MDTM sheet for all members is crucial, whether meetings are conducted in-person or virtually [3], [12]. Virtual MDTMs have gained importance due to technological advancements and the COVID-19 pandemic [13], but these platforms often lack robust decision support mechanisms, limiting their effectiveness in complex case discussions.

Cancer care requires collaboration across multiple specialties due to its complexity. For example, breast cancer cases can be discussed on Mondays, while Thursdays could be dedicated to thyroid cancer [3]. Table 1 categorizes the types of MDTM meetings, each tailored to specific cancer types.

Table 1. Types of the MDTM

Cancer Type	MDT Meeting	Involved specialties
Gastrointestinal (liver, stomach, colon, rectal, and pancreas)	Digestive	Gastroenterology, oncology
Head and neck, breast, cervix, prostate, eye, thyroid, and prostate	Radiotherapy	Different specialties
Bladder, kidney, penile, prostate, testicular, and urethral	Urology ROC/NOI	Urology, oncology
Leukemia, brain and spinal cord tumors, lymphoma, neuroblastoma, Wilms tumor, retinoblastoma, and cancers of the bone and soft tissue	Pediatric	Different specialties
Chest cavity, lung, thymic, tracheal	Thoracic	Pulmonology, oncology
All types	Medical oncology	Chemotherapy, hormonal therapy, biological therapy, targeted therapy, oncology
Ear, nose, throat	Otorhinolaryngology (ORL)	Head and neck surgery, oncology
Woman's reproductive organs, cervical, ovarian, uterine, vaginal, vulvar	Gynecology	Gynecology, radiology, oncology
Bone, cartilage, fat, vascular, hematopoietic tissues	Sarcoma	Different specialties
Brain, spinal cord, spinal column, peripheral nerves	Neurosurgery	Radiology, neurosurgery, oncology
Neurological system	Neuro-oncology	Different specialties
All types	Onco-radiotherapy	Different specialties
All types	Onco-cardiology	Different specialties

Standardizing MDTM interoperability is crucial. Krauss *et al.* [3] developed an automated business process model and notation (BPMN) model. The preparatory phase involves patient registration, data collection, and information review. During MDTMs, cases are reviewed sequentially, custom and predefined treatments are considered, and final decisions are verified and documented. However, the lack of real-time data update capabilities in current models remains a significant barrier to optimal decision-making.

A framework of [14] enhances the efficiency of MDTM by structuring patient summaries, selecting cases for discussion, and improving decision-making processes. While this framework improves organization, it does not fully address the technological limitations, such as inadequate IT support and data interoperability issues, which continue to hinder the effectiveness of MDTMs. Comprehensive documentation of decisions, including case characteristics and influencing factors, is crucial to establishing knowledge and ensuring the accuracy of decisions over time.

MDTMs follow international guidelines from organizations such as the French high health authority (HAS) and the UK national health service (NHS) [4], [11], [15], [16]. These guidelines emphasize structured MDTM processes, from reviewing MDTM sheets to recording therapeutic proposals in the EHR and informing patients about decisions. However, despite these guidelines, the practical implementation of MDTMs often varies significantly, leading to inconsistencies in care quality.

The use of medical applications (apps) improves clinical workflows and decision-making, and younger physicians show a strong preference for these tools [17]. However, the integration of these apps into the broader MDTM workflow remains challenging, particularly in ensuring seamless data exchange between different systems. In local healthcare settings, such apps can improve access to necessary tools and information, streamline processes, and improve diagnostic precision and treatment quality.

The integration of artificial intelligence (AI) in healthcare enterprise architecture has shown significant promise in enhancing decision-making processes. Lysaght *et al.* [18] discuss the ethical considerations and benefits of AI-assisted decision making, focusing on improvements in efficiency in healthcare systems. However, many AI-driven analytics tools are implemented in isolation, without full integration into the broader MDTM workflow, leading to disjointed decision-making processes. Sodhro and Zahid [19] propose an AI-enabled framework utilizing fog computing to manage data efficiently and ensure reliable patient monitoring, yet the adoption of such technologies remains limited due to practical implementation challenges. Similarly, Kaur and Mann [20] highlight the importance of real-time predictive and prescriptive analytics through an AI-based platform, but these tools often lack user-friendly interfaces, hindering their adoption by clinicians. Burri *et al.* [21] explore sustainable AI architectures in healthcare, focusing on activities that improve healthcare outcomes, but the integration of these architectures into existing MDTMs is not yet fully realized. Furthermore, Masuda *et al.* [22] investigate the application of adaptive enterprise architecture in digital healthcare, particularly in drug development, enhancing process efficiency and knowledge sharing, but also highlight the significant gaps that need to be addressed.

In Morocco, the lack of a legislative framework for MDTMs forces institutions to develop their own procedures [23]. Aligning these procedures with international best practices can improve therapeutic decision making and clinical workflows, improving patient outcomes across oncology centers. However, the absence of standardized protocols and technological infrastructure presents ongoing challenges.

In conclusion, the identified gaps highlight the urgent need for an integrated solution that not only enhances interoperability, real-time data integration, and decision support, but also directly aids MDTM attendees in selecting the best treatment plan for patients. Although this study proposes an architecture to facilitate seamless data exchange and uniform decision-making processes between multidisciplinary teams, it is important to emphasize that this work is primarily theoretical. The proposed architecture introduces AI-driven analytics designed to generate treatment recommendations by analyzing the most current patient data in real-time. This system ensures that MDTM attendees are equipped with the most accurate and up-to-date information to make informed decisions about patient care. In addition, the architecture includes robust IT support features to improve data integration and user interaction, addressing key limitations in current MDTM practices. However, the practical effectiveness of these improvements will require empirical validation in future studies. By addressing these foundational challenges in a conceptual framework, this study seeks to lay the groundwork for future advancements in MDTM efficiency and effectiveness, ultimately aiming to enhance clinical decision-making and improve patient outcomes across diverse healthcare settings.

2. METHOD

This section outlines the development of an AI-based enterprise architecture specifically designed to improve the efficiency and effectiveness of MDTMs in oncology. The study focuses on addressing existing challenges in MDTMs by proposing an architecture that integrates advanced AI technologies to streamline decision-making processes. By leveraging AI-driven tools, the proposed framework aims to provide physicians with evidence-based recommendations that are personalized to each patient case, ensuring more accurate and informed treatment plans. This integration seeks to not only optimize clinical workflows but also enhance the overall quality of patient care in oncology settings.

2.1. Study of the existing situation

Our study commenced with an in-depth analysis of the existing multidisciplinary team meeting (MDTM) procedures at the regional oncology center (ROC) in Tangier and the Tangier-Tetouan-Al Hoceima University Hospital Centre (UHC TTA), both of which rely on the ENOVAR&T hospital information system. This analysis involved conducting field research that included interviews with cancer specialists to gain insights into their experiences and challenges with the current system. Additionally, we participated in the acceptance testing of the MDTM module, which allowed us to evaluate its functionality firsthand. This comprehensive assessment revealed several areas for improvement, particularly in data interoperability, user interaction, and system adaptability, highlighting the need for a more advanced and integrated solution to support decision-making processes.

The current MDTM process at ROC Tangier is structured as follows: The attending physician first registers the patient’s information on an MDTM sheet, which is then electronically transmitted for discussion during the MDTM session. The session involves several critical steps, including reviewing new cases, filtering incomplete ones, sequentially passing MDTM sheets, and assessing each case’s situation. However, functional discrepancies were identified, such as inadequate data interoperability, limited fields for specialist notes, and insufficient support for external MDTM sheets. These shortcomings highlighted the need for a more comprehensive and AI-integrated solution to streamline decision making and improve the overall MDTM process.

This initial analysis using BPMN [24] to map out the existing MDTM workflows, highlighting inefficiencies and gaps in the system's design. This systematic approach provided a clear foundation for conceptualizing a new enterprise architecture aimed at addressing these limitations, particularly by integrating AI technologies to improve decision-making processes. Drawing from previous studies, insights into the transformative potential of AI in healthcare became evident, showcasing the advantages of incorporating AI into MDTMs. The works of Watson for oncology and the oncology expert advisor [25]–[27] further validated these findings, demonstrating how AI-driven systems can enhance clinical decision-making, streamline workflows, and provide evidence-based recommendations tailored to patient needs. These insights underscored the critical need for a modernized architecture that leverages AI for improved efficiency and outcomes in multidisciplinary oncology care.

2.2. Conceptualization of the enterprise architecture

To formulate our vision for an interoperable MDTM module, we grounded our design in the principles of TOGAF enterprise architecture [28]. Using the ArchiMate enterprise architecture modelling language [29], we systematically captured and modelled the architecture, ensuring alignment with the architecture development cycle. This approach integrates key concepts such as motivation elements and core layers to encompass the entire architecture lifecycle and achieve a comprehensive framework. The goals of the stakeholders are addressed using motivation elements, answering the “what?” Question. The business, application, and technology layers represent the "how?" question. Implementation and migration elements address changes and impacts, answering the "when?" and "by what?" Questions.

For reference, as shown in Figure 1 is a visual overview of the elements used in this study. For further details on ArchiMate symbols and their meanings, the official documentation and sources provide comprehensive explanations [30], [31].

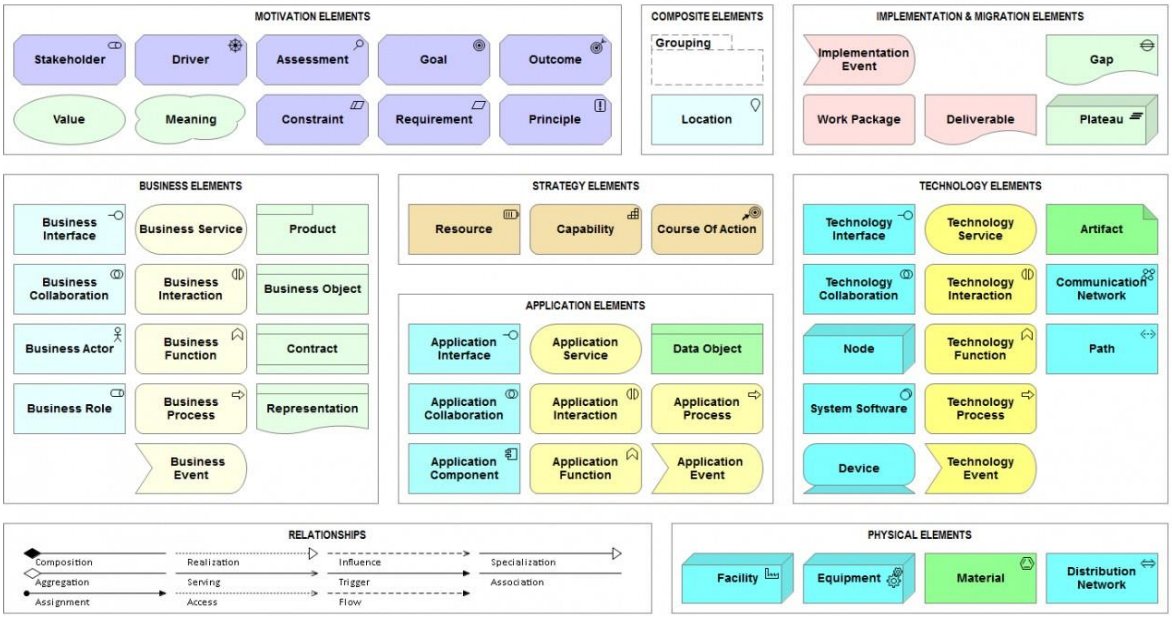

Figure 1. ArchiMate core elements and relationships

2.3. Communication methods and real-time data exchange

In designing the architecture, particular attention was paid to the communication methods used between the systems involved in MDTM. The architecture supports real-time data exchange through RESTful APIs, which facilitate communication between the electronic health record (EHR) systems and the AI decision support module. The RESTful APIs were chosen for their scalability, stateless nature, and ability to support a wide range of data formats (*e.g.*, JSON, XML), making them suitable for integrating various health-care applications.

Real-time data exchange is crucial to ensure that all MDTM participants have access to the most current patient data. To achieve this, the architecture incorporates WebSocket technology, which enables continuous two-way communication between client applications (such as those used by attending physicians) and the server hosting the AI decision support system. This setup allows instantaneous updates to patient records, ensuring that any new information entered by a team member is immediately available to all others. Data interoperability is further enhanced by implementing the fast healthcare interoperability resources (FHIR) standard, which provides a consistent framework for data exchange between different healthcare systems. The modular components of FHIR allow the architecture to adapt to various EHR systems, ensuring seamless integration between different hospital settings.

2.4. AI models in decision support systems

The AI component of the architecture is designed to support decision-making processes by analyzing patient data and providing treatment recommendations. The AI models utilized in this system include supervised learning algorithms trained on large datasets of historical patient outcomes. Specifically, the architecture employs gradient boosting algorithms (such as XGBoost) for predictive analytics, which have been shown to perform well in medical decision support scenarios due to their ability to handle large, complex datasets with multiple features.

In addition to predictive models, the architecture integrates natural language processing (NLP) techniques to analyze unstructured data, such as physician notes and research articles. This capability allows the AI system to provide recommendations that consider both structured EHR data and the latest medical literature, ensuring that treatment suggestions are both evidence-based and contextually relevant.

The AI decision support system is designed to be transparent and interpretable, providing explanations for its recommendations to ensure that physicians can trust and understand the basis for the suggested treatments. Techniques such as Shapley additive explanations (SHAP) are used to provide these interpretability features, which are crucial in clinical settings where trust in AI systems is essential.

2.5. Implementation and testing

Although the architecture provides a global perspective on AI integration into MDTMs, the implementation strategy emphasizes modularity and adaptability, allowing for incremental adoption of the system across different healthcare facilities. A pilot implementation at the ROC Tangier is planned as part of a subsequent phase of the project, which will involve further steps such as UML modeling, data schema development, and the coding process, all conducted under the SCRUM methodology. This phase will integrate a generative pre-trained transformer (GPT) model [32] as the core AI component, which will be incorporated into the existing ENOVAR&T system. Initial testing, as part of this future work, will compare GPT-generated recommendations with those made by the multidisciplinary team to assess both the concordance and effectiveness of the AI system.

Given the adaptable nature of the architecture, the system is designed to be scalable across various oncology centers, ensuring that it can meet the diverse needs of different healthcare environments. Although this study focusses on the creation of an architecture based on theoretical aspects, the future implementation of the GPT model within this architecture is expected to significantly enhance decision-making processes and provide a robust framework for advancements in digital healthcare. In conclusion, the integration of AI into the enterprise architecture of MDTMs represents a significant advancement in the management of oncology cases. By leveraging AI technologies, such as those used in Watson for oncology and the oncology expert advisor, and focusing on real-time data exchange and communication methods, our proposed architecture offers a comprehensive, adaptable solution that enhances decision-making processes and improves patient outcomes.

As the architecture was conceptualized based on the identified gaps in existing systems and the theoretical frameworks discussed, the following Results and Discussion section will explore the potential impact of this architecture on decision-making processes within MDTMs. It will outline how the proposed system addresses current limitations and provide a roadmap for future research opportunities. This includes the potential for testing and validation by other researchers or practitioners, offering an opportunity to evaluate the system's performance, scalability, and adaptability across different healthcare settings.

3. RESULTS AND DISCUSSION

In this section, we present the core findings of our research, detailing the conceptual foundations of the proposed architecture and the anticipated benefits of AI integration in MDTMs. The architecture is designed to enhance genericity and interoperability by organizing the system as a collection of loosely coupled services (microservices). Understanding the ArchiMate notation is crucial for managing the complexity of the proposed enterprise architecture; hence, an overview of the ArchiMate core layers' elements and their relationships is described in [31].

Although our findings do not include empirical measurements, the exploratory nature of this study is intended to lay the foundation for future research. The proposed architecture serves as a conceptual framework for integrating AI into MDTMs, offering a new avenue for improving decision-making processes in oncology. By focusing on the design and strategic elements, this study emphasizes the importance of further empirical validation to assess the effectiveness and scalability of the architecture in real-world settings.

Despite the robustness of ENOVAR&T's existing architectures, they fall short in addressing the specific needs of an AI service system tailored for the oncology service. The limitations identified, particularly the lack of dedicated AI components and the complexity of the oncological context, necessitated the development of a new MDTM model. The model in Figure 2, is explicitly designed to support the MDTM committee's tasks by integrating AI functionalities that operate independently of the existing ENOVAR&T information systems.

3.1. Implementation and migration viewpoint

The implementation and migration viewpoint, as depicted in Figure 3, provides a structured framework for identifying and implementing enhancements to our enterprise architecture. This viewpoint is grounded in the conceptual underpinnings of the model elements and their interrelations, as outlined in [31], and plays an instrumental role in aligning programs and projects with the architectural components they are designed to transform. By offering a roadmap for the integration of AI elements, this viewpoint ensures that each addition aligns seamlessly with the operational goals of MDTMs, facilitating a coherent and systematic evolution of the system.

Furthermore, this perspective supports a seamless transition from the current state to an advanced AI-enabled system that is better equipped to meet the dynamic needs of oncology care. It highlights key steps in the transformation process, such as adapting workflows, enhancing interoperability, and incorporating decision-support mechanisms to improve care delivery. This structured approach not only promotes consistency across different implementation stages but also ensures that the architecture remains adaptable to evolving healthcare requirements, paving the way for more efficient and patient-centric multidisciplinary team meetings.

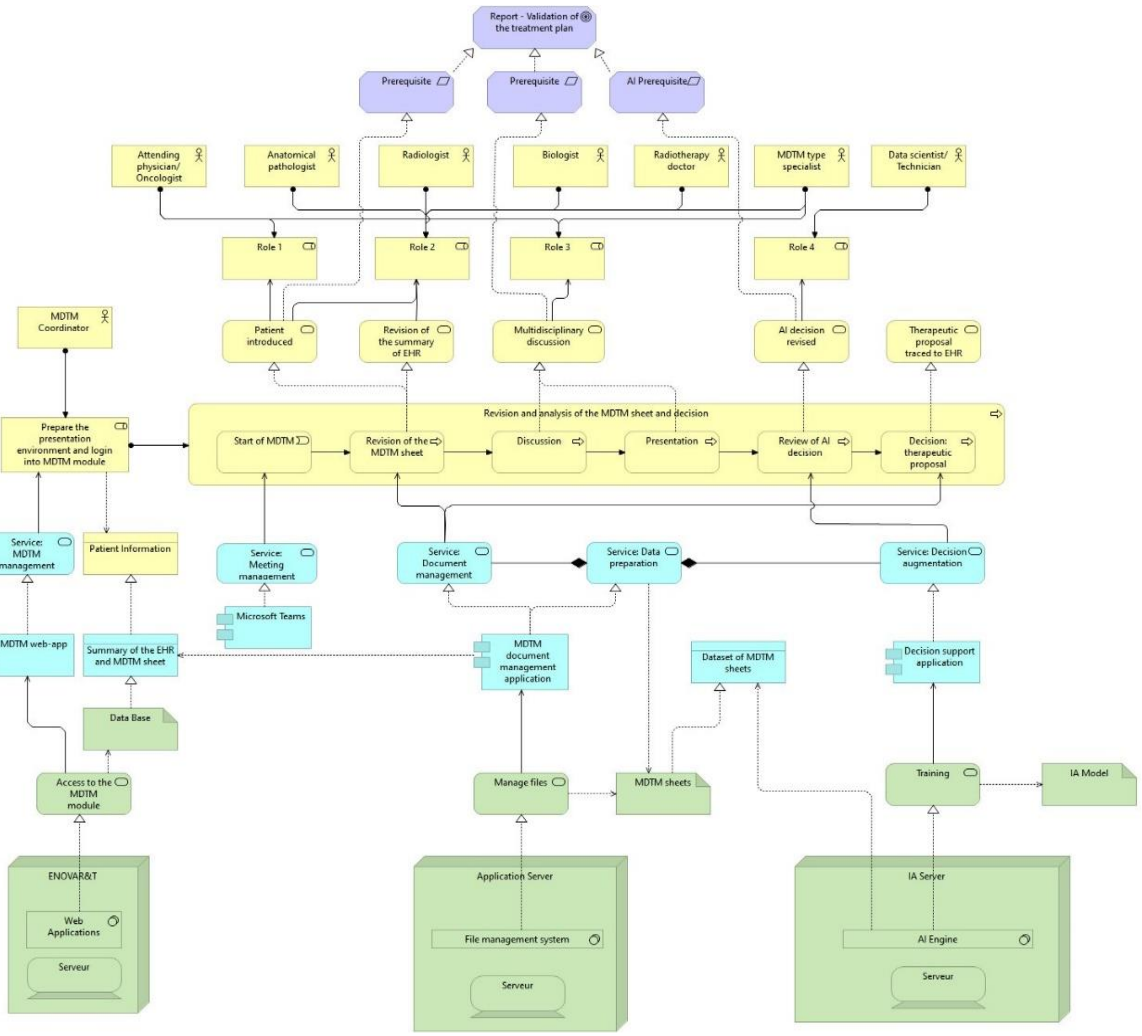

Figure 2. Current study's MDT meetings representation using ArchiMate

3.2. Motivation and business layer

In our proposed model in Figure 4, the architectural framework is structured to align with the strategic objectives of the stakeholders, primarily the MDTM committee. The core of this framework includes motivation elements that encapsulate the primary concerns of the MDTM committee, supported by a set of prerequisites fulfilled by designated business services.

The business layer of the architecture includes several key components:

a. Business actors: members of the MDTM committee and a data scientist, who collectively drive the decision-making processes.
b. Roles and services: each actor is associated with specific roles supported by business services. A critical service, for example, is the revision of the EHR summary.

c. Business processes: these are the operational activities that realize the business services, organized into a workflow activated by the MDTM's initiation.

At the foundation of the business layer are business processes, managed by the application layer, which ensures that all necessary data are accurately processed and available during MDT meetings.

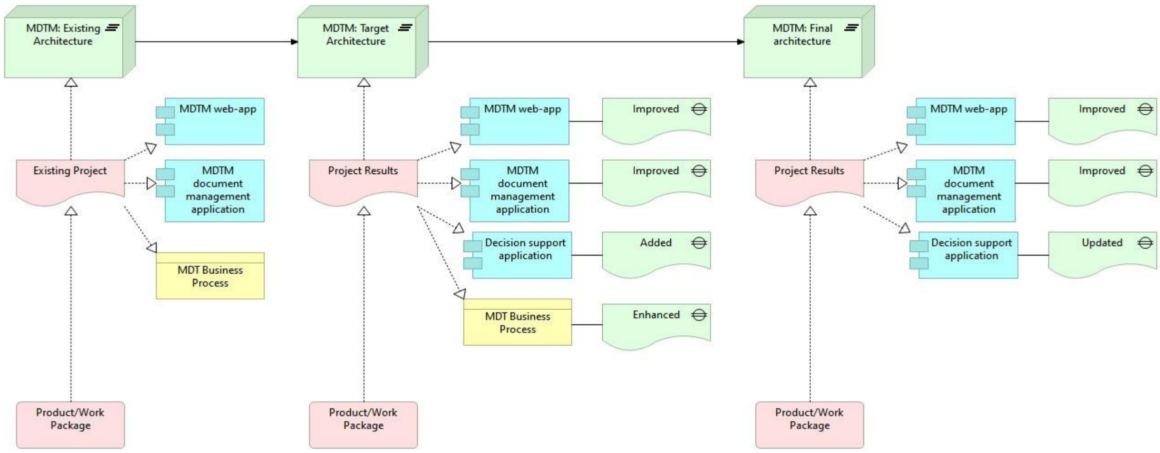

Figure 3. Current study's implementation and migration architecture

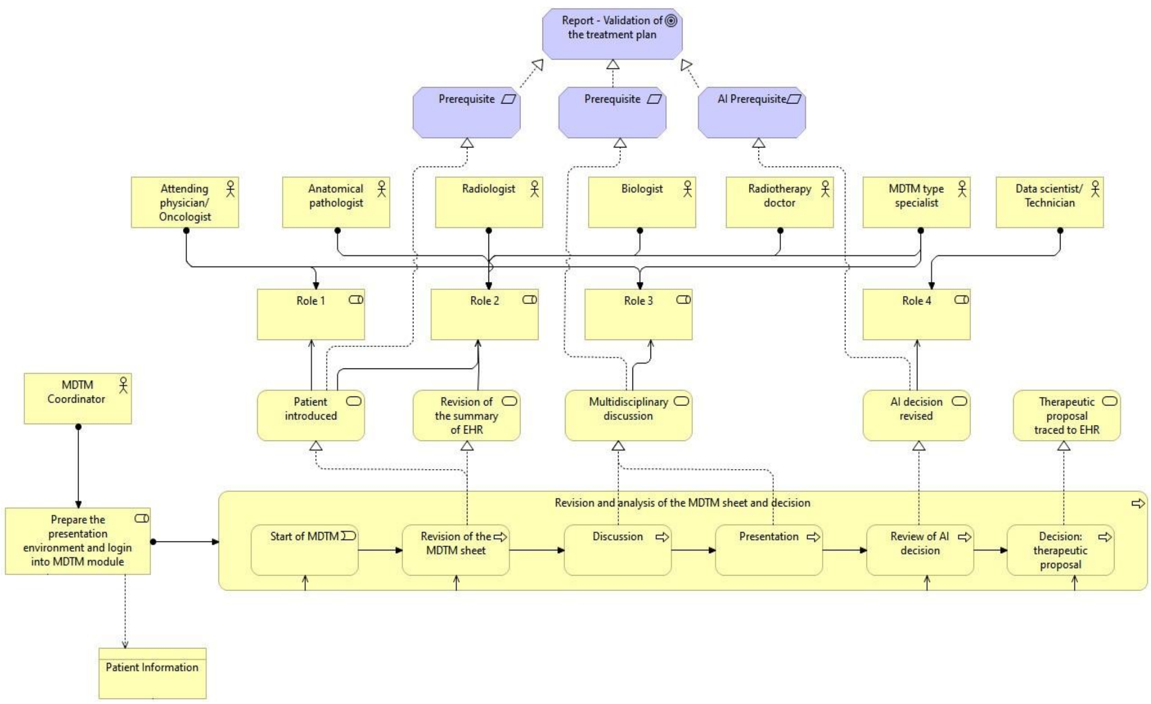

Figure 4. Motivation and business representation

3.3. Business and application layers

The application architecture delineates the structure, behavior, and interactions of integrated applications. In our refined architectural proposition as shown in Figure 5, two additional applications (decision support and MDTM document management) are integrated alongside the existing ENOVAR&T's Enova Sante´ application and Microsoft Teams. These applications are crucial for essential services like meeting management and decision augmentation, directly supporting underlying business processes.

a. Decision support application: enhances decision-making capabilities by providing comprehensive, data-driven insights to the MDTM committee.

b. MDTM document management application: manages the documents and records, ensuring that documentation is streamlined and accessible during MDT meetings.

These applications are interconnected through a series of APIs, ensuring seamless data flow and supporting scalability and future enhancements. The data architecture itself is manifested through critical data objects such as MDTM sheets and EHR summaries, essential for the operational integrity of the application layer.

The integration of these applications and their associated services into our enterprise architecture establishes a robust framework designed to enhance the efficiency and effectiveness of MDTM operations. By incorporating advanced technological capabilities, such as AI-driven decision support and seamless data interoperability, the architecture addresses critical gaps in current MDTM workflows. This alignment between technology and business processes ensures that the MDTM committee has access to real-time, accurate information and collaborative tools, enabling them to make well-informed and timely decisions. Ultimately, this approach not only streamlines operational workflows but also directly contributes to improved patient outcomes by supporting evidence-based treatment planning and fostering a more cohesive multidisciplinary approach to oncology care.

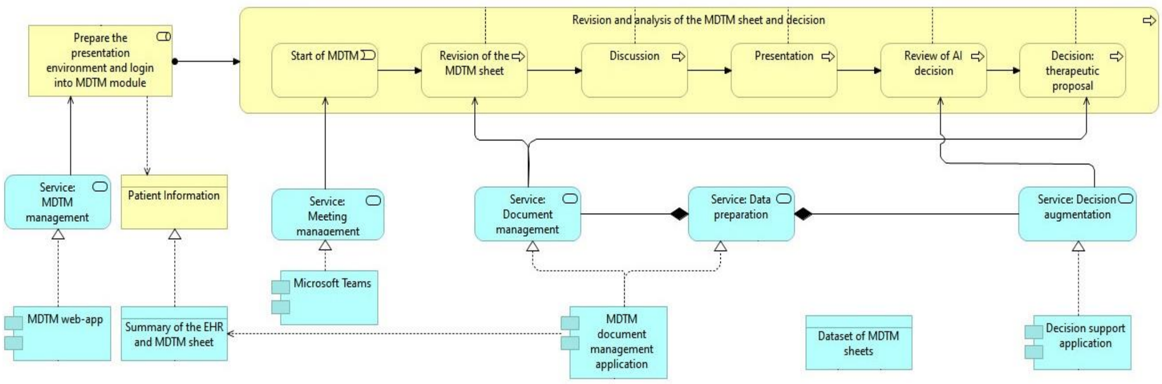

Figure 5. Business and application representation

3.4. Application and technology layers

The foundation of any enterprise solution lies in a robust technology infrastructure. ArchiMate models this technology layer effectively, employing elements like nodes, which embody platforms such as the AI service and the ENOVAR&T solution. These nodes deploy crucial technology elements and host system software, like file management systems and AI engines, integral for operational support. In our specific architectural framework, in Figure 6, the AI engine is hosted on a physical server, critical for the operations of our system, facilitating essential tasks such as training AI models.

This infrastructure is meticulously linked to the application layer, with technology services enhancing the functionality of application components. These services perform data management tasks essential for operational integrity, exemplified by the ENOVAR&T database managing MDTM sheets and EHR summaries. The seamless interaction between the application and technology layers underscores the system's efficiency in data handling and process facilitation.

Furthermore, our architecture shows that the ENOVAR&T solution, particularly its MDTM management module, is modular and replaceable. This modularity ensures that our enterprise architecture can interface with any health information system (HIS) provider, enhancing its versatility across various technological ecosystems. This modularity, along with the use of loosely coupled services, emphasizes the architecture's scalability and adaptability, making it universally applicable.

3.5. Comparison with existing studies

Our findings suggest that the proposed architecture addresses several key challenges identified in previous research on MDTM and AI integration. For example, while studies such as Watson for oncology and the oncology expert advisor have demonstrated the potential of AI in clinical decision support, they have also highlighted limitations related to system interoperability and adaptability to specific clinical contexts [25], [27]. Our architecture attempts to overcome these limitations by emphasizing modularity, scalability, and the integration of AI models tailored to the oncology domain.

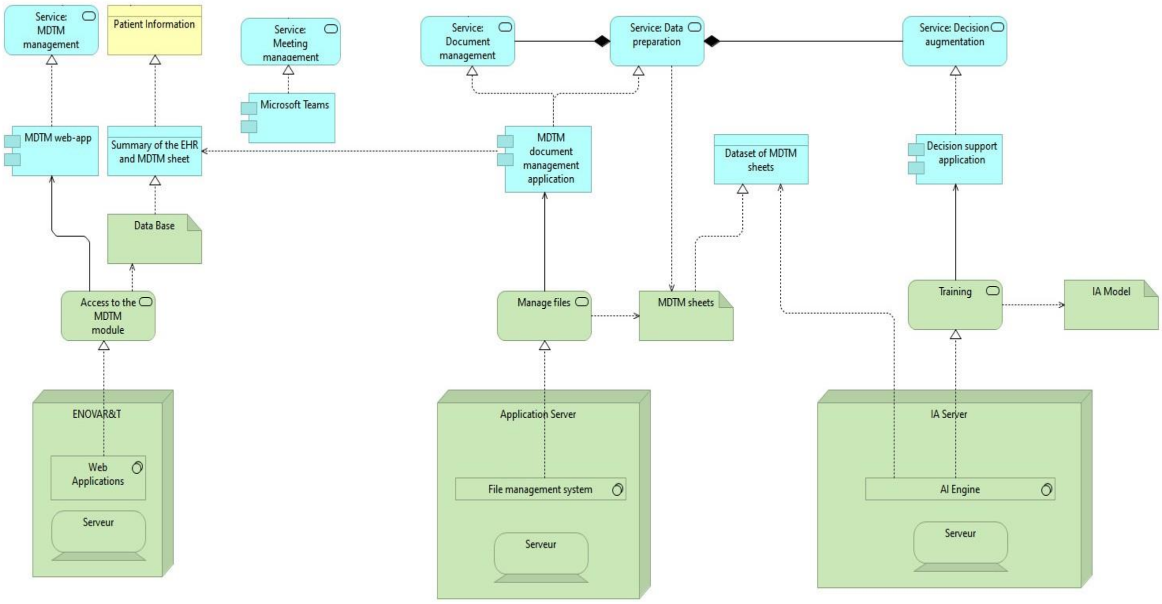

Figure 6. Application and technology representation

The use of ArchiMate and TOGAF frameworks in our approach ensures that the proposed architecture is both theoretically robust and practically applicable, addressing the unique challenges faced in diverse healthcare settings. Unlike earlier models, which often lacked adaptability or were narrowly focused, our architecture is designed to be versatile, providing a scalable solution that aligns with the dynamic and multidisciplinary nature of MDTMs. By leveraging these established frameworks, the architecture facilitates seamless integration with existing systems while maintaining the flexibility to accommodate advancements in healthcare technology.

When contextualized within the broader scope of existing research, our findings highlight the significance of this architecture as a foundational model for future studies. Specifically, the architecture's AI-driven decision support capabilities offer an innovative approach to enhancing MDTM operations, paving the way for empirical testing to validate its practical benefits. Such future studies could evaluate the impact of AI-enhanced MDTMs on clinical workflows, decision-making efficiency, and patient outcomes, thereby contributing to the ongoing advancement of digital healthcare technologies and setting new standards for multidisciplinary collaboration in oncology care.

In summary, this study serves as a foundational exploration of the integration of AI within MDTM, offering a conceptual framework designed to improve decision-making processes in oncology. While empirical validation is necessary to fully assess the proposed architecture’s effectiveness, this work lays the groundwork for future research in this area. By proposing an adaptable, modular, and scalable enterprise architecture, our aim is to inspire subsequent studies that will empirically test and refine this framework in diverse healthcare settings. The following sections will explore potential challenges and opportunities for further development in this promising field.

4. CONCLUSION

This paper presents the conceptual development of a novel enterprise architecture for MDTMs in oncology, integrating advanced technologies and AI to enhance clinical workflows and decision-making processes. The theoretical foundations of the architecture provide a comprehensive framework that establishes a solid base for future empirical studies, aiming to revolutionize MDTM practices and significantly improve patient care outcomes. By addressing the complexities of oncology care, this architecture proposes a method to standardize and streamline decision-making processes while accommodating the specific needs of multidisciplinary collaboration.

The proposed architecture is specifically designed to assist MDTM attendees in selecting the most effective treatment plans for patients by leveraging AI-generated recommendations tailored to individual cases. Through the strategic integration of business, application, and technology layers, it enhances workflow efficiency, decision-making accuracy, and data interoperability. The detailed modeling underscores its significant potential benefits, although these remain theoretical at this stage. By incorporating adaptable and scalable design principles, the architecture ensures seamless integration into diverse technological environments, providing a sustainable approach to advancing oncology care.

While the theoretical contributions of this study are substantial, the true impact and effectiveness of the architecture can only be realized through rigorous empirical validation. Future research efforts must focus on pilot implementations and real-world testing to assess its practical utility and refine its design based on empirical outcomes. These steps are crucial to bridge the gap between theoretical modeling and practical application, ultimately paving the way for meaningful advancements in multidisciplinary oncology care.

Incorporating advanced AI technologies, such as the generative pre-trained transformer (GPT), the architecture analyses comprehensive patient data to generate evidence-based treatment recommendations tailored to individual patient needs. This AI-driven approach provides MDTM attendees with up-to-date and insightful information, facilitating more informed and timely clinical decisions. Nonetheless, it is important to acknowledge that the current work is exploratory, focusing on the creation of a theoretical model without empirical outcomes. The integration challenges and practical effectiveness of the AI components must be rigorously tested through real-world applications and extensive validation studies.

Future studies will involve the implementation and testing of this architecture in clinical settings, evaluating its performance in supporting MDTM processes and patient treatment outcomes. These studies will be critical in the transition from conceptual design to practical application, ensuring that the architecture meets the complex demands of cancer care effectively. Furthermore, subsequent research should explore the integration of emerging AI technologies, and addressing ethical considerations related to AI-driven clinical decision support systems.

In conclusion, the proposed enterprise architecture for MDTM in oncology represents a significant advancement in healthcare technology. By aligning sophisticated AI capabilities with the collaborative decision-making processes of MDTMs, this study opens new avenues for enhancing patient-centered care and optimizing treatment outcomes. Although currently conceptual, this architecture has the potential to transform oncology clinical practices and serve as a model for integrating AI-driven decision support systems in various medical specialties, thereby promoting greater improvements in healthcare delivery through technology and data analytics.

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BIOGRAPHIES OF AUTHORS

Nassim Bout received his master's degree in modeling complex systems applied to health-care at the Mohammed V University of Rabat. Currently, he is a Ph.D. candidate in computer engineering at Hassan II University of Casablanca, Morocco. His research interests include the integration of health information systems, improving patient care using information technologies, and computer engineering. He can be contacted at email: nassim.bout.doc21@ensem.ac.ma.

Hicham Belhadaoui received his Ph.D. degree at the National Polytechnic Institute of Lorraine, France. He is currently a professor at the Computer Engineering Department, Higher School of Technology, Hassan II University of Casablanca, Morocco. His research interests include the reliability, automatic signal processing and computer engineering. He can be contacted at email: belhadaoui_hicham@yahoo.fr.

Nadia Afifi is currently professor at Higher School of Technology (ESTC), Hassan II University of Casablanca - Morocco (UH2C). She is IEEE senior member; part of "Software engineering, business intelligence and security" (SEBIS) research team of "Networks, computer, telecom and multimedia" (RITM) Laboratory (ESTC). She can be contacted at email: afifinadia@yahoo.fr.

Mounia Abik professor of Higher Education, holding a Ph.D. in computer science from ENSIAS (2009), her research focuses on knowledge graphs and AI, e-Health, bioinformatics, AI and NLP, recommendation systems, and pervasive learning. She teaches courses in ontologies and semantic web, XML Technologies (XPATH, XSL, XQUERY), mobile application development, and geospatial semantic web. She can be contacted at email: m.abik@um5s.net.ma.

Mohamed El-Hfid associate professor at the Faculty of Medicine and Pharmacy of Tangier, he is an associate professor at the Faculty of Medicine and Pharmacy of Tangier and works in the Department of Radiotherapy at the Mohamed VI University Hospital of Tangier. He is affiliated with Abdelmalek Essaadi University in Morocco. He can be contacted at email: elhfid@gmail.com.

Ali Azougaghe professor of cybersecurity, holding a Ph.D. from the Ecole Nationale Supérieure d'Informatique et d'Analyse des Systèmes (ENSIAS), he is currently a professor of cybersecurity at the Écoles Nationales des Sciences Appliquées (ENSA) of Marrakech. He can be contacted at email: aliazougaghe@gmail.com.