AI-DRIVEN ELECTRONIC HEALTH RECORD (EHR) SUMMARIZATION

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Abstract- *AI-driven Electronic Health Record (EHR) summarization systems are a critical component of modern healthcare information management, as they directly influence clinical efficiency, decision accuracy, and patient safety. Their primary objective is to reduce information overload while ensuring rapid access to clinically relevant patient data throughout the care lifecycle. This paper discusses current technical approaches to EHR summarization, focusing on the application of artificial intelligence, natural language processing, and machine learning techniques to analyze large volumes of unstructured medical records. The relationship between automated summarization and intelligent clinical decision support is also examined, highlighting its growing importance in next-generation healthcare systems. Limitations in existing manual and rule-based summarization methods are identified based on observations from recent healthcare data management practices. These findings emphasize the need for innovative AI-based solutions that enhance accuracy, efficiency, and interpretability while complementing existing clinical workflows rather than replacing established healthcare processes*

Keywords -
EHR, Natural language Processing, Clinical text summarization, Medical Decision support, Automated reporting.

I. INTRODUCTION

Electronic Health Record (EHR) systems serve as centralized repositories for information and play a supervisory role in supporting clinical decision-making, continuity of care, and healthcare quality management. These systems are designed to ensure that critical patient data is accurately recorded, readily accessible, and utilized effectively while minimizing risks associated with incomplete or overlooked information. With the rapid digitization of healthcare and the increasing volume of clinical documentation, the need for intelligent EHR summarization has become a key requirement in modern healthcare environments. AI-driven EHR summarization systems aim to reduce information overload by automatically extracting and condensing essential medical insights from extensive and often unstructured clinical records. Enhanced summarization capabilities support healthcare professionals by enabling quicker review of patient histories, reducing manual documentation effort, and improving response times in time-critical clinical scenarios. Fundamentally, EHR systems have the following features:

- Clinical Information Extraction, which involves identifying relevant patient data such as diagnoses.
- Clinical classification and organization, which focuses on category

manual and rule-based summarization toward intelligent, automated solutions. However, the complexity of medical language and the interdependence of clinical events across patient records continue to pose significant challenges, emphasizing the need for robust and adaptive EHR summarization systems. At a fundamental level, EHR summarization systems perform three primary functions: identifying clinically relevant information from diverse data sources such as physician notes, laboratory reports, and prescriptions; categorizing and organizing extracted data to reflect medical context, severity, and temporal relevance; and generating concise summaries that support informed clinical decisions while preserving data accuracy and interpretability

II EHR DEVELOPMENT FRAMEWORK

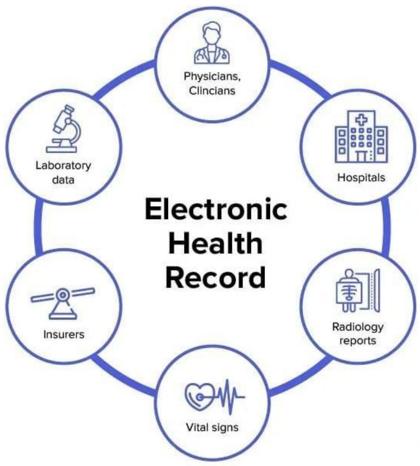

Fig.1 EHR Development vs project phrases

Physical and information processing elements of EHR are closely entwined and linked. Therefore, an EHR system's functions are determined by the physical components of the EHR and their attributes. The operational modes and mission phases of the EHR have a significant impact on its design as well. In order to weigh the necessary HW redundancy against the diagnosis and recovery procedures included into the On-Board Software (OBSW), EHR systems must be properly designed. Essentially, the idea of an EHR system can be formed between two extremes: having an easy-to-use onboard EHR(where only essential components are examined on-board and the associated recovery is handled entirely by the ground segment) or utilizing more advanced on-board EHR concepts (where failures are detected at the lowest feasible level and resolved automatically by the Record, minimizing the need for ground intervention).

Another crucial component is hardware redundancy, particularly for those operations where failure could result in mission loss. Testing EHR systems is difficult since it is impossible to replicate every potential error and its combinations during test campaigns. This document is structured as follows and is based on actual satellite projects completed at OHB System AG... An overview of spaceship onboard autonomy and health management principles is provided in this section. While Section IV discusses the problems of upcoming space missions, which call for ever-more-rich on-board autonomy and health management capabilities, Sections II and III review the existing industrial methodologies and practices used to design, develop, validate, and operate EHR systems.

III. THE CURRENT PROCESS OF EHR DEVELOPMENT AND INDUSTRIAL PRACTICES

The procedures now employed in industry to design, develop, validate, and run FDIR systems are outlined in this section. It is necessary to see EHR system development as a comprehensive system- level endeavor requiring in-depth understanding of space system engineering. The development methods supporting efficient clinical decision-making and improved healthcare workflow outcomes.

established by the European Cooperation for Standardization constitute the basis for EHR development practices. The many stages of the EHR system development and how they relate to the various stages of the spacecraft project are depicted

A. EHR's INITIAL LIFE CYCLE STAGE

The requirements and core functionalities of an AI-driven Electronic Health Record (EHR) summarization system are determined during the initial life cycle stage based on high-level clinical objectives, system constraints, regulatory requirements, and outcomes of early data and risk analysis processes. Techniques analogous to Failure Modes and Effects Analysis (FMEA) and dependency analysis are used to identify potential data quality issues, information loss risks, and failure points within clinical documentation workflows. Deductive analysis approaches focus on high-impact clinical failures, such as missing critical diagnoses or medication errors, and trace their root causes within data sources and processing pipelines. In contrast, inductive analysis evaluates how specific data inconsistencies, incomplete records, or model errors may affect overall summary accuracy and clinical decision-making. Once the functional requirements of the EHR summarization system are defined, the corresponding software modules—including data preprocessing pipelines, natural language processing models, and summarization engines—are developed and integrated into the healthcare information system. These implementations are then validated against clinical accuracy, reliability, and compliance requirements. However, current EHR development practices often suffer from delayed consolidation of data quality assessments and clinical risk evaluating.

B. ARCHITECTURE OF THE EHR SYSTEM

The EHR system architecture is typically organized into multiple hierarchical layers, each characterized by distinct interfaces, levels of data abstraction, processing responsibilities, and output granularity. Lower layers, which are primarily data-driven and software-based, operate at the data source and preprocessing level and are responsible for tasks such as data ingestion, normalization, and validation to ensure data integrity. When lower layers are unable to adequately resolve issues such as ambiguity, missing information, or noise in clinical data, higher-level layers are activated to perform contextual interpretation and decision-oriented analysis. During the system definition and early development phases, EHR summarization concepts are refined and translated into a comprehensive EHR system architecture, along with the identification and allocation of functional responsibilities across system components. The architecture is designed to support efficient data processing, reliable information extraction, and scalable summarization while ensuring interoperability and data security. In such cases, higher architectural layers utilize processed outputs, metadata, and alerts generated by lower layers to execute advanced natural language processing, clinical reasoning, and summarization functions. These layers integrate information across multiple clinical domains to generate coherent and clinically meaningful summaries.

The following levels make up the hierarchical structure of the EHR system:

- ***Level 0:*** data noise, data issues, data bus failures, and other faults and failures that are local to a unit and can be fixed locally (such as EDAC, error detection and failures have no effect on system performance.

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| Data Sources |
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   |
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| Data Preprocessing |
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- ***Level 1***: This level manages data inconsistencies and errors detectable beyond a single data source and operates at the departmental or subsystem level (e.g., conflicting lab values, incomplete medication records, or missing clinical notes). Monitoring modules analyze extracted data to identify anomalies that may degrade summary accuracy. Redundant data sources or alternative records are used to recover missing information..

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+-------------------+
|    Data sources|
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|  Data processing  |
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| Information extraction|
|   Module                  |
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- ***Level 2:*** This level handles system-level summarization failures managed by AI and NLP models, such as incorrect context interpretation, temporal inconsistencies, or failure to capture critical clinical events. Cross-document analysis, semantic validation, and contextual reasoning are used to detect and isolate such issues. Failures at this level may result in partial loss of summary quality or clinical relevance.

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| Contextual Validation |          |
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- ***Level 3:*** This level is associated with failures in the central AI processing modules, including NLP engines, summarization models, or inference pipelines. Fault management includes model health monitoring, confidence scoring, fallback to rule-based summarization, system reinitialization, or controlled degradation of functionality. Recovery mechanisms ensure continuity of service with reduced intelligence if required.

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| Summarization Engine |
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| Recovery & Control |
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- ***Level 4:*** refers to all critical failures that can result in a mission loss. As a result, the driving requirement is typically the complete mutual understanding of the spacecraft to handle reconfiguration procedures (based on certain patterns typically stored in a non-volatile memory) and then enter Safe Mode for ground intervention.The driving requirement is typically complete mutual independence and hot redundancy between the nominal system functions and the ones devoted to the detection and recovery from such critical events, since level 4 handles all the critical failures that can result in a loss of mission.

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| Subsystem 1 EHR  |
|    Module          |
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         |
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| Subsystem 2 EHR  |
|    Module          |
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| Subsystem 3 EHR  |
|    Module          |
+---------+----------- +
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+---------v----------- +
|  Central EHR       |
|  Coordination      |
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In order to provide a more economical implementation, a common tendency in spaceship manufacturing is to turn numerous hardware implemented functions into software modules. The EHR function is being implemented with an increasing amount of relevance from the OBSW, as this method is becoming regular practice in the field .

A typical spacecraft's operating concept defines one or more safe mode configurations, which stand for the system level FDIR's final response to serious abnormalities in the spacecraft. Both ground and urgent events occurring on board can put the aircraft in safe mode.For a predetermined amount of time, the spacecraft can operate in this mode without assistance from the ground segment.

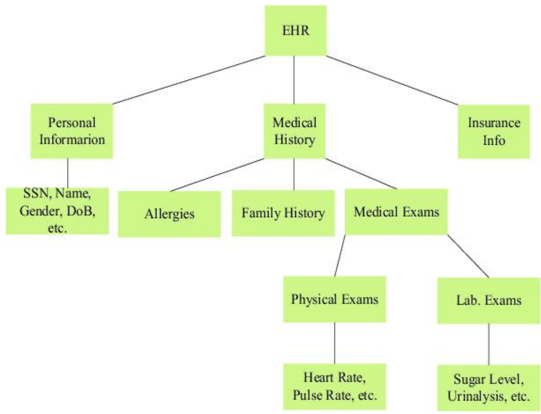

Fig.2 EHR Hierarchical structure

In critical operational conditions, the EHR summarization system transitions into a controlled safe mode in which automated summarization functions are restricted, non-essential processing modules are suspended, and secure access to core patient records is maintained. During this mode, data integrity, audit logging, and privacy safeguards remain active to ensure compliance and patient safety. Human oversight by clinicians or system administrators is required to restore the system from safe mode to full operational status after validation of data consistency and model reliability. During the development of software requirements, EHR summarization requirements and associated software artifacts undergo a comprehensive Verification and Validation (V&V) process aligned with standard healthcare software engineering practices From Level A (software whose anomalous behavior would cause or contribute to a failure resulting in a catastrophic event) to Level E (software whose anomalous behavior would cause or contribute to a failure resulting in a negligible event), SW V&V activities are defined in accordance with the corresponding SW criticality levels. EHR requirements are globally confirmed at the system/spacecraft level once all the hardware and software components that are in agreement with the system-level implementation of EHR requirements have been verified and integrated. In this regard, the Hardware/Software Interaction Analysis (HSIA) is crucial for identifying defects right from the start of a project. The V&V methods now employed in projects don't scale at all.the adage "if it works at all, it will always work" is generally severely invalidated when applied to autonomy-rich systems, where high environmental sensitivity is common. As a result, fewer tests are required to obtain the same level of confidence. However, a significant amount of environment and system state trajectory variation is required for the experiments, rendering the existing methods unrealistic. This comment opens the door to alternatives

IV. EHR COMPONENTS IN THE OPERATION OF HEALTHCARE

Clinical workflows, care protocols, and automated decision-support procedures are the primary tools used in traditional healthcare information systems. In conventional EHR operations, clinicians interact with patient records step by step by entering clinical data, reviewing reports, and interpreting diagnostic results through manual interfaces. These interactions involve continuous monitoring of patient information stored in structured and unstructured formats within the EHR. For healthcare settings with limited clinician availability or high patient load, predefined clinical workflows and scheduled data-processing routines are used to automate routine tasks such as report generation, alerts, and follow-up reminders, Advanced EHR systems employ automated processing pipelines and intelligent workflow engines that can analyze and execute rule-based or AI-driven procedures authored using high-level clinical logic and data models. These procedures are compiled into efficient internal representations that enable real-time processing and decision support.

Recent healthcare information systems increasingly adopt AI-driven EHR summarization mechanisms to overcome these limitations. The selection of summarization and automation strategies is influenced by system availability and reliability requirements. In high-availability healthcare settings, such as emergency departments or critical care units, intelligent summarization and fault-tolerant data processing techniques are employed to minimize clinical workflow disruptions and ensure timely access to essential patient information. In contrast, for healthcare environments with moderate availability requirements, semi-automated summarization combined with clinician oversight is often preferred to balance efficiency and safety. The operational behavior of modern EHR systems is governed by standardized healthcare data exchange and interoperability frameworks. These frameworks define extensible services that can be invoked through structured clinical requests, generating corresponding reports, alerts, or summaries as system responses. Such standards support the consistent handling of clinical events, data monitoring, and automated responses across healthcare platforms. Event reporting services enable the identification and classification of abnormal clinical patterns, monitoring services detect deviations in patient data or system performance, and action-oriented services manage automated responses such as alerts, summary regeneration, or escalation to clinician review. In critical situations, these recovery actions may involve disabling automated summarization and initiating comprehensive manual evaluation to ensure patient safety and system reliability. Accordingly, EHR systems operate under two primary modes: an **Automated Safe Mode**, where the system restricts advanced AI-driven summarization and alerts clinicians for manual review to prevent clinical risk, and an **Automated Fail-Operation Mode**, where alternative data sources, redundant models, or fallback summarization techniques are activated to maintain operational continuity. The degree of automation and autonomy in EHR summarization depends on the clinical context, system criticality, and phase of care.

It offers greater flexibility during both ground testing and spacecraft operations. For example, monitored item thresholds can be adjusted, and recovery actions can be updated to reflect evolving recovery requirements.

V. THE FUTURE EVOLUTION OF THE EHR SYSTEM

Certain problems with the present FEHR system design methodologies have been highlighted by recent projects produced at OHB System AG. These results open the door for creative approaches that complement established industrial procedures rather than replacing them. This paragraph aims to describe these deficiencies and offer some potential fixes. Future space missions will typically have high performance and availability requirements due to their ambitious ambitions. Interplanetary spacecraft missions present an extra problem due to the time delay between command transmission and spacecraft reception, which ground management teams must manage as telemetry data quantities grow. Furthermore, the lack of a well-established analytical methodology to support FTA/FMECA activities, system-level EHR conception down to its implementation causes serious discontinuities throughout all project phases and hinders the process of a stable and consistent EHR design. The FDIR toolset environment plays a central role in providing a seamless support throughout the various FDIR development phases, and the space and scientific communities are well aware of all these issues. From a technical perspective, efforts concentrate on novel mechanisms that are coupled with tried-and-true conventional FDIR techniques in an effort to decrease the quantity of safe mode occurrences while lengthening the spacecraft's operational duration.

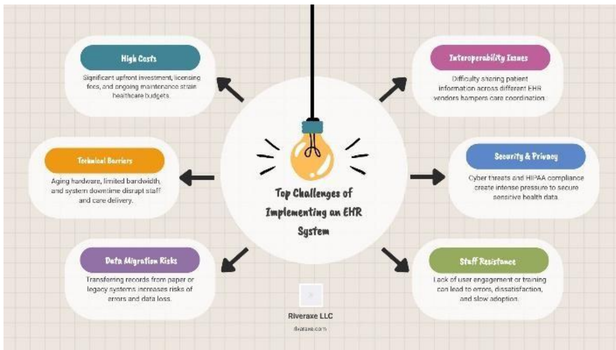

Fig.3 concept of hardware redundancy and analytical redundancy for EHR

The current method for defining an EHR function is to map one or more failure modes to a telemetry point (discrepancy), which will cause an isolation or recovery action in the event that the telemetry data's FDIR threshold is surpassed. Failure modes, however, could impact not just the telemetry point to which it is assigned, but also other telemetry points that are designated for the identification of various failure modes and various recovery strategies. This could result in a recovery that doesn't address the issue in the initial EHR stage. This is because the EHR techniques that are now in use are predicated on strict and inflexible protocols. Basic diagnostic procedures typically handle symptoms separately, which can lead to inconsistent conclusions or inaccurate diagnosis. They are also unable to deal with the space environment, which is time-variant and only partially observable by the EHR monitoring function. Therefore, in order to evaluate the health of the system, a model-based EHR that can combine data from many sources and reason about anomalous observations in the presence of uncertainties, system dynamic dynamics, and partial observability is required. The next steps, which are backed by some initial evaluation at OHB System AG, are to maintain the EHR hierarchical structure as it is shown in II-B and to provide the EHR system with more potent and efficient ways of detection and recovery . When choosing an algorithm, it is necessary to consider three main factors: the time required for system diagnosis, the type of data to be handled (continuous, hybrid, and discrete), and the computer resources needed. The use of analytical redundancy over hardware redundancy, which provides a control-system view of the EHR with a distinct division between the fault detection and isolation (FDI) step and the controller reconfiguration step, is another crucial feature of the new EHR approaches. both the controller reconfiguration stage and the FDI (FDI isolation) step). Comparing duplicate signals produced by different hardware, such as measurements of the same signal provided by two or more sensors, is the fundamental idea of hardware redundancy.

Conversely, analytical redundancy identifies and isolates faults using an estimating technique in conjunction with a mathematical model of the system. Generally speaking, the analytical redundancy strategy is less expensive than the hardware redundancy because it doesn't call for extra hardware. But because the analytical redundancy strategy must be guaranteed to be robust in the face of noise, unforeseen disruptions, and model uncertainties, it is more difficult... In general, there are two types of model-based methodologies in the analytical redundancy approach: qualitative and quantitative. The quantitative model-based techniques, like the observer-based techniques, produce FDI residuals by utilizing control theories and explicit mathematical models. Conversely, the methods based on qualitative models employ artificial intelligence techniques like pattern differences between the behavior observed and the behavior anticipated by the model. Approach

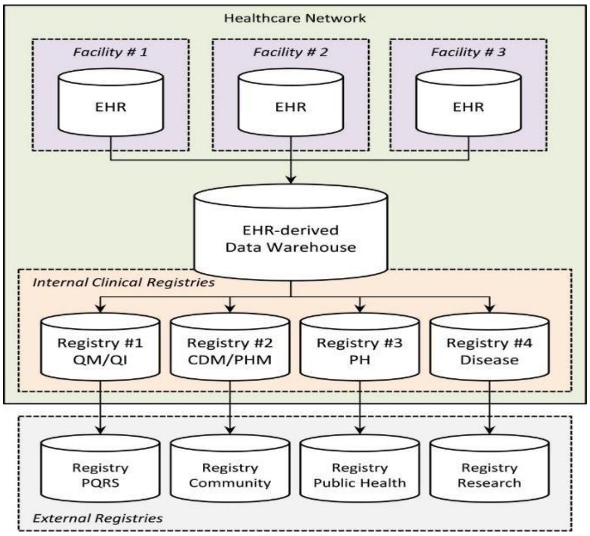

Fig.4 OBSW architecture of autonomous system

Fault diagnosis is accomplished in both situations by applying the proper decision logic last, followed by residual creation and evaluation. A crucial component of missions both now underway and in the future is autonomy. Satellites will soon be able to receive, process, and accomplish high-level objectives even in uncertain or dynamically changing environments. They will have an ergonomic interface that will make it simple for ground operators to define and send these kinds of high-level requests.

Three hierarchical levels—the decisional, operational, and functional levels—can be used to organize the OBSW architecture in order to provide autonomy, integrate planning systems, and incorporate dynamic reprogramming capabilities into the flight software.These levels are characterized by different reaction times, handle more or less abstract data representations and have different type knowledge of the system state (global or local). Ground high-level objectives can be further on-board detailed into a sequence of commands for the subsystems and can be autonomously adapted during their execution according to context changes, such as new objectives and altered on board resource profile. EHR functions are allocated to the three levels. A first set is paired to the satellite subsystems and is positioned at the functional level, which is the base of the architecture. System-level FDIR functions are implemented at the operational level, which is based on this level. Based on data from the operational level, FDIR evaluates plan execution at the decisional level and finds discrepancies.

Lastly, as optimization and model-based algorithms constitute the foundation of modern FDIR systems, particular attention must be given to their verification and validation Since FDIR systems frequently exhibit high environmental sensitivity, it is important to examine the system's behavior in a variety of realistic settings to show how robust the system is. When taken as a whole, these elements represent a quantum jump in the V&V. Verification is advised.

It is advised to verify the FDIR system's implementation's consistency, completeness, and accuracy at both the model and code levels (i.e., the data produced by the models and the reasoning engine itself). The domain models require more sophisticated V&V techniques, which are mostly based on formal or analytical methods, whereas reasoning engines can be verified by using classical V&V techniques to show that their search algorithms are right. They fall into one of the following categories and pertain to the use of methods from discrete mathematics and logic.

- ***Runtime monitoring***:
This involves analyzing the code as it executes or the artifacts it produces (like event logs).

- ***Static analysis:***
This method evaluates the properties of the code without actually running it and finds runtime faults.

- ***Model Checking :***
This involves using an executable specification language and the system's representative model to assess the system's behavior and state evolution in relation to a set of properties.

- ***Theorem Proving:***
This involves using logical induction throughout the program's execution steps to demonstrate the system requirements.

- ***Compositional Verification:***
Breaking down a system's properties into those of its constituent parts in order to determine whether each part satisfies its own propriety, then the system as a whole does as well. In order to verify complex software systems and achieve scalability, this strategy is essential.

VI. FUTURE RESEARCH

This work highlights key technical and methodological considerations for the design of AI-driven Electronic Health Record (EHR) summarization systems based on insights from existing healthcare information platforms and clinical data management practices. Several limitations in current industrial and clinical approaches can be effectively addressed by integrating traditional rule-based techniques with advanced AI-driven solutions, including qualitative and quantitative model-based reasoning methods. Future healthcare systems will increasingly require a high level of automation and intelligence in EHR processing, with the ability to manage complex clinical information and data inconsistencies with minimal human intervention. System engineers' conceptions and presumptions will no longer be as disparate from real implicitly within algorithms, system behavior can be better aligned with clinical expectations.

This will provide greater portability between missions since domain- specific knowledge will just need to be added to the models

VII. CONCLUSION

AI-driven Electronic Health Record (EHR) summarization systems are essential for ensuring efficiency, accuracy, and reliability in modern healthcare environments. These systems continuously analyze large volumes of clinical data, identify critical medical information, and support timely clinical decision-making by leveraging advanced natural language processing, data analytics, and machine learning techniques Real-Time Monitoring: Constant data collection from a range of sensors provide real-time information about the condition of spacecraft components, enabling the quick identification of anomalies.

1. Predictive Maintenance: By utilizing machine learning and predictive analytics, it is possible to anticipate probable faults before they happen, which facilitates prompt maintenance and lowers the possibility of mission-critical problems.

2. Autonomous Operations: * State-of-the-art health management systems can facilitate autonomous decision-making, which is essential for deep space missions as it enables spacecraft to respond to problems without human interference.

3. The integration of data from many subsystems into a centralized health management system improves situational awareness and offers a holistic perspective of the spacecraft's health. This is known as data integration.

4. Enhanced Mission Safety: These systems greatly increase the overall safety and success rate of space missions by detecting and reducing dangers early on.

5. Cost Efficiency: Early problem identification and resolution lowers mission failure and repair costs, increasing the cost-effectiveness of space missions.

To sum up, in order to ensure that spacecraft can function safely and effectively in the hostile environment of space, advanced health monitoring and management systems must be developed and put into place for current space missions to succeed.

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