eHealth in the Promotion of Health Literacy after Acute Myocardial Infarction

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Abstract. Introduction: Acute Myocardial Infarction (AMI) remains one of the leading causes of morbidity and mortality, requiring effective secondary prevention strategies focused on individuals' needs. Health literacy and health beliefs influence outcomes following a cardiac event, and targeted health education is a key mechanism through which digital tools can improve post-AMI outcomes. At the same time, eHealth solutions and Artificial Intelligence-based tools have shown potential to support personalized interventions, although gaps remain in the integrated characterization of this population. Objective: To characterize the Portuguese population affected by AMI and to develop a therapeutic adherence predictive model, based on Machine Learning, to support personalized health education and early intervention strategies. Methods: An ambispective cross-sectional observational descriptive-analytical study will be conducted across different healthcare settings within two Local Health Units in northern Portugal. Adults with a documented history of AMI, followed in Primary Health Care, Outpatient Cardiology Clinics, or hospital inpatient settings, will be consecutively included. Data collection will include structured face-to-face questionnaires, namely the HLS19-Q12 for health literacy assessment and a questionnaire based on the Health Belief Model, complemented by retrospective consultation of electronic health records. The data will be used to develop Machine Learning models to predict adherence to the post-AMI therapeutic regimen, informing the design of tailored health education programmes. Expected results: A detailed and integrated characterization of the population affected by AMI is expected, enabling the identification of relevant patterns and risk subgroups, and supporting the development of a predictive model for therapeutic adherence with direct implications for health education and patient empowerment.

Keywords: Person with Acute Myocardial Infarction; Health Literacy; Health Education; eHealth; Machine Learning

1 Background

The increasing prevalence of Acute Myocardial Infarction (AMI), together with the growing complexity of available therapeutic options, has driven a transition towards more personalized approaches in healthcare delivery [1]. This context reinforces the need to invest in health literacy and structured prevention programs, recognized as fundamental determinants for improving health outcomes [2].

The ability to understand, interpret, and use health information is strongly associated with healthier behaviours, greater adherence to therapeutic regimens, higher satisfaction with healthcare received, and better perceptions of self-management, while simultaneously contributing to the reduction of suffering associated with the clinical condition [3]; [4]; [5]; [6]. Additionally, social determinants of health, such as educational level, employment status, and lifetime income, exert a significant influence on health literacy levels and on individuals' ability to manage chronic diseases [3]; [7]. Evidence demonstrates that low levels of health literacy reduce the likelihood of adherence to health education programmes, use of preventive services, and effective disease management over time [1]; [8]. Consequently, health education — whether delivered in person or through digital channels — plays a central role in equipping individuals with the knowledge and skills needed to manage their condition, representing a foundational component of any eHealth intervention aimed at improving post-AMI outcomes.

Within this framework, the World Health Organization defines eHealth as the safe and cost-effective use of information and communication technologies in health and health-related fields, including healthcare delivery, clinical monitoring, health education, knowledge dissemination, and research [9]. The literature highlights the growing impact of eHealth solutions in improving the efficiency, accessibility, and responsiveness of healthcare systems to individuals' needs and expectations [9]. Despite these advances, face-to-face interaction with healthcare professionals remains the predominant approach in the prevention and cardiac rehabilitation programmes described in the literature [1]. Concurrently, there has been sustained growth in the development of mobile applications and digital solutions aimed at improving health communication, with eHealth emerging as an effective strategy for operationalizing digital technologies to support patients [9]. Previous studies have shown that tele-nursing interventions contribute to increased treatment adherence and enhanced self-efficacy in managing clinical conditions [10]; [11]. However, evidence suggests that isolated interventions — exclusively face-to-face or exclusively digital — provide limited benefits in sustaining long-term behavioural change. Consequently, combining in-person and remote strategies has been recommended to expand the options available to patients and enhance adherence to therapeutic regimens [12]; [13]. The use of smartphones and mobile applications for individualized health parameter monitoring, integrated into hospital-based cardiac rehabilitation programmes with face-to-face sessions, has demonstrated potential to overcome logistical and organizational barriers, contributing to improved physical and functional outcomes [10]; [7].

More recently, the integration of Artificial Intelligence (AI) into eHealth initiatives has represented a paradigm shift in the delivery of personalized care, particularly in the management of individuals after AMI [14]; [15]. AI-based solutions play a relevant role in promoting health literacy and health education by enabling the provision of personalized educational content and real-time decision support, fostering individuals' active involvement in their own care [16]. This intersection of technology and education is particularly relevant at a conference focused on Information Technology and Education, as it illustrates how AI-driven tools can function as adaptive educational platforms, tailoring content to individual learning needs and health profiles. Through predictive analytics models, AI enables the processing of large volumes of clinical and sociodemographic data to identify risk patterns, anticipate complications, and formulate individualized recommendations, thereby optimizing secondary prevention strategies [17]. Furthermore, AI-supported continuous monitoring systems facilitate the early detection of clinically relevant changes, enabling timely interventions and more efficient use of healthcare resources [18]. Nevertheless, the literature identifies important limitations, namely difficulties in recruiting older individuals, people with low digital literacy, and the underrepresentation of women in existing studies [19]. There is also a scarcity of research exploring in depth the relationship between individuals' information needs and their adaptation to different risk profiles, motivations, and prevention strategies [5]. Identified methodological approaches reveal a predominance of quantitative and cross-sectional designs, with limited use of prospective and mixed-methods studies, restricting the understanding of how patients' needs evolve over time [1]; [5]; [20].

Considering this evidence, the present study addresses the identified methodological gaps and current advances in digital health. This work aims to develop a predictive digital prototype based on Machine Learning, intended for the early identification of individuals affected by AMI who are at greater risk of poor adherence to therapeutic regimens.

The initial stage focuses on a comprehensive characterization of the population affected by AMI within a region of the country, including the assessment of social and health determinants, health behaviours, health literacy levels, perceived risks, and motivation for behavioural change. For this purpose, a validated questionnaire adapted to the Portuguese population and grounded on the different constructs of the Health Belief Model (HBM) will be used [21].

Beyond health literacy, it is recognized that the information provided to patients should consider different levels of perceived risk and motivation for change, with a direct impact on the adoption and maintenance of healthy behaviours. Variables such as perceived susceptibility to disease, perceived severity of the event, perceived effectiveness of preventive behaviours, and self-efficacy for change constitute central determinants of health behaviours. This methodological approach, supported by social marketing specialists, ensures a robust understanding of the target population, which is essential for the subsequent development of personalized and effective digital interventions.

1.1 Objectives

The study aims to comprehensively describe the characteristics of the Portuguese population affected by AMI and to develop a predictive therapeutic adherence model, based on Machine Learning models, capable of supporting healthcare professionals in providing personalized early intervention strategies. The following specific objectives are also defined:

- To identify social determinants of health within the sample;
- To assess the general level of health literacy among participants;
- To identify perceived benefits regarding adherence to therapeutic regimens;
- To identify perceived self-efficacy related to adherence to therapeutic regimens;
- To identify perceived barriers to adherence to therapeutic regimens;
- To identify perceived susceptibility to AMI among individuals;
- To identify the perceived severity of the event;
- To identify cues to action perceived by individuals in the context of adherence to therapeutic regimens and secondary prevention;
- To identify predictors of therapeutic adherence in post-AMI individuals.

The study will be conducted in two stages: i) Phase I: Characterization of the post-AMI population; ii) Phase II: Development of a Machine Learning-Based Predictive Model.

2 Methodology

2.1 Phase I: Characterization of the post-AMI population

The study design follows a mixed quantitative and qualitative paradigm. In the initial phase of the project, an ambispective cross-sectional observational study (retrospective and prospective data collection) with a descriptive-analytical nature will be conducted. The retrospective component will be based on consultation of participants' electronic clinical records, allowing the collection of relevant clinical information related to the AMI event, associated comorbidities, and prescribed therapeutic regimens. The prospective component will correspond to data collection at the time of recruitment through face-to-face assessment and the administration of validated questionnaires for participant characterization, including assessment of health literacy, health beliefs, and adherence to therapeutic regimens. The cross-sectional design aims to provide a comprehensive characterization of the study population at a specific point in time, as well as exploratory analyses to identify relevant patterns and risk profiles, without any intervention being assigned by the researchers. The constructs analysed are framed within the Health Belief Model (HBM), with the objective of generating empirical knowledge to support the subsequent development of a predictive model and personalized digital interventions in later stages of the project.

Considering the nature of the study and in accordance with reporting guidelines recommended by the EQUATOR Network, the present protocol is guided by the SPIROS 2023 Checklist (Recommended Items to Address in the Observational Study Protocol and Related Documents), while the conduct of the study and reporting of results will follow the recommendations of the STROBE Statement (Strengthening the Reporting of Observational Studies in Epidemiology).

At this stage of the project, the construction of the Machine Learning-based predictive model will begin, requiring the evaluation and testing of the proposed digital solution through a qualitative approach involving two focus groups (FGs) selected by convenience sampling. One group will consist of six patients and six caregivers, while the other will include six physicians and six nurses from cardiology units and primary healthcare settings. The combination of quantitative and qualitative methods ensures a comprehensive assessment of the feasibility, usability, and real-world applicability of the solution.

Study Setting

The study will be conducted in two Local Health Units located in northern Portugal, encompassing different healthcare settings, namely Primary Healthcare, outpatient cardiology clinics, and cardiology inpatient services.

Participants

Given the exploratory nature of the initial phase of the project and its role as a preparatory stage for the development of a predictive algorithm based on Machine Learning (ML), no formal sample size calculation based on specific inferential hypotheses was performed. A consecutive inclusion strategy will be adopted during the recruitment period to maximize the clinical, sociodemographic, and behavioural variability of the sample, considered essential for the future training and validation of ML algorithms. This approach is consistent with methodological recommendations for studies aimed at developing predictive healthcare models, in which data diversity and representativeness are more relevant than statistical power associated with specific group comparisons. Accordingly, individuals with a documented history of AMI who meet eligibility criteria and agree to participate during the data collection period will be included, with an estimated sample size sufficient to allow robust descriptive analyses and exploratory identification of relevant patterns and risk profiles. Sample adequacy will be assessed a posteriori, considering the number of included variables, data completeness, and the technical requirements of subsequent predictive modelling stages.

Sampling Method

A non-probabilistic consecutive sampling strategy will be used, based on the systematic inclusion of all eligible individuals approached in the different healthcare settings involved in the study during the recruitment period. This sampling strategy is considered appropriate for the observational design of the study and its primary objective of characterizing the population with a history of AMI, enabling the inclusion of participants with diverse clinical profiles, healthcare trajectories, and sociodemographic contexts. Furthermore, consecutive sampling reduces the risk of selection bias associated with arbitrary participant selection and promotes the inclusion of a heterogeneous sample, which is essential for exploratory analyses and future development of a Machine Learning-based predictive algorithm. Including participants from multiple levels of care and different stages of the healthcare pathway contributes to increasing data variability and the external validity of the findings.

Participant Selection

All male and female individuals meeting the following cumulative criteria will be considered eligible:

- Age ≥18 years;
- Documented history of AMI confirmed through electronic clinical records;
- Clinical follow-up within one of the healthcare services included in the study.

The following individuals will be excluded:

- Severe sensory or motor impairments preventing questionnaire completion;

- Cognitive impairments or language barriers compromising understanding of the study objectives and procedures;
- Inability to provide autonomous informed consent.

Recruitment will occur consecutively within the context of routine clinical practice by healthcare professionals integrated into the research team. Formal inclusion in the study and data collection procedures will only begin after informed consent has been signed, and participants will be assigned an alphanumeric code.

Data Collection

Data collection will occur at two complementary moments, according to the ambispective design of the study. The prospective component will consist of face-to-face administration of structured and validated questionnaires to eligible participants after informed consent is obtained and during attendance at healthcare services within routine clinical practice. Instruments will be administered by trained researchers in a clinical setting, ensuring privacy and confidentiality. The retrospective component will involve consultation of participants' electronic clinical records to collect relevant clinical data related to the AMI episode, comorbidities, and prescribed therapeutic regimens, strictly limited to variables previously defined in the protocol.

All processed data will be pseudonymized, and the data analysis team will only have access to data in this format. Data processing will strictly comply with the principles of lawfulness, transparency, minimization, purpose limitation, accuracy, integrity, and confidentiality, in accordance with the General Data Protection Regulation (GDPR).

2.2 Phase II: Development of a Machine Learning-Based Predictive Model

This phase of the project focuses on the development, refinement, and optimization of a predictive algorithm based on ML models aimed at predicting adherence to therapeutic regimens among post-AMI patients. A highly accurate and valid algorithm capable of predicting adherence trajectories among post-AMI patients is expected. Development will follow the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology adapted to the clinical context, ensuring scientific rigour, reproducibility, and interpretability of results. Main Components: i) Data preparation and quality module; ii) Feature engineering module; iii) Modelling and algorithm selection module; iv) Validation and performance evaluation module; v) Interpretability and explainability module.

The solution will be developed using data collected in Phase I, applying ML techniques and, when appropriate, deep learning (DL), to identify adherence patterns and support the implementation of personalized interventions. The methodology includes preparation and harmonization of sociodemographic and clinical datasets derived from population characterization, as well as data quality control procedures (consistency, missing values, and outliers). This will be followed by feature selection and feature engineering to identify the main predictors of therapeutic adherence while ensuring clinical relevance and statistical robustness of the indicators included in the model.

Supervised ML models (e.g., logistic regression, random forests, and other appropriate models) will be trained, with internal validation through cross-validation techniques to minimize overfitting and ensure generalizability. Performance will be evaluated using metrics appropriate to the outcome type and class balance (e.g., AUC-ROC, sensitivity, specificity, and calibration measures), prioritizing a solution that is not only highly accurate but also interpretable and clinically explainable to facilitate use in clinical practice.

The resulting solution will be optimized for both accuracy and interpretability and will consider integration and interoperability requirements, incorporating standards such as Health Level 7 (HL7®) Fast Healthcare Interoperability Resources (FHIR®), Clinical Document Architecture (CDA), and openEHR. The multidisciplinary research team, including nurses and engineers, will work collaboratively to ensure the model's clinical relevance and practical applicability through iterative cycles of testing and refinement guided by predictive performance and clinical coherence of the results.

Study Monitoring Plan. Study monitoring will be ensured by the principal investigator, who will guarantee strict compliance with the approved research protocol and adherence to applicable ethical principles and GDPR requirements through regular meetings aimed at monitoring recruitment progress, data collection quality, and protocol compliance. Internal quality control mechanisms will be implemented, including periodic verification of data consistency and random review of records extracted from electronic clinical records. Any protocol deviations or relevant occurrences identified during data collection or analysis will be communicated to the competent institutional authorities, in accordance with applicable regulations, and appropriately documented.

Training of Personnel Involved in Data Collection. All professionals and researchers involved in data collection will receive prior specific training regarding the study objectives, methodological design, inclusion and exclusion criteria, and operational definitions of the analysed variables. Training will include standardization of procedures for extracting information from electronic clinical records, correct completion of data collection instruments, and consistent application of coding rules. This process aims to reduce interobserver variability, minimize errors, and ensure consistency, reliability, and reproducibility of data collection procedures throughout the study.

Quality Assurance. Quality assurance will be ensured through the use of validated instruments, standardized procedures, staff training, and continuous monitoring. Data consistency controls and internal audits will be implemented whenever necessary to guarantee the reliability and reproducibility of the results.

Communication and Dissemination. Study findings will be communicated transparently and responsibly, in accordance with open science principles, with the aim of promoting knowledge transferability and maximizing the project's impact on scientific research and clinical practice. In addition to the publication of scientific articles and presentations at conferences, citizen involvement in scientific dissemination processes will be prioritized through initiatives directed at the community, such as webinars and workshops, particularly targeting the study population. These initiatives, implemented throughout the project duration, will begin from the first stage to ensure sustainable implementation of the results obtained. Dissemination of findings to institutional bodies, including Health Ethics Committees and the Data Protection Officer, is also planned whenever requested or deemed relevant.

Where applicable, the main results may also be shared with the healthcare professionals involved, as well as with other institutional stakeholders, with the aim of informing clinical practice, resource planning, and healthcare decision-making.

3 Conclusion

The proposed scientific approach will overcome methodological gaps identified in the most recent literature by integrating qualitative and quantitative methodologies into a simultaneously mixed and longitudinal design, aligned with current advances in digital health, particularly regarding the close relationship between eHealth, Artificial Intelligence, and health education. By embedding educational components into a technology-driven intervention, the project also contributes to the broader field of technology-enhanced education, demonstrating how digital tools can be designed not only to monitor and predict clinical outcomes but also to actively educate and empower patients throughout their care trajectory. It further emphasizes the current need to develop communication and interoperability strategies between primary and hospital healthcare, highlighting the importance of promoting citizen engagement and empowerment for self-management of therapeutic regimens. The artefact will be developed with a focus on usability and accessibility, ensuring integration into the routine of both patients and healthcare professionals without compromising efficiency or data security.

The achievement of these objectives will rely on an innovative person-centred, multidisciplinary, and interorganizational interoperability strategy that will strengthen its potential. The project's multidisciplinary team will include specialist nurses in community health, medical-surgical nursing, and mental health, a cardiologist working simultaneously in a Local Health Unit in northern Portugal and in advanced scientific research, engineers specialized in decision support systems, Artificial Intelligence and interoperability, digital marketing and social marketing managers, consultants in health sciences and digital health, as well as graduate scholarship holders from nursing and engineering backgrounds. This diversity of profiles, combining clinical, technological, and strategic expertise, will foster the integration of complementary competencies, promoting an innovative and comprehensive approach to the scientific execution of the project.

In addition to the expected clinical and scientific impacts, the project is anticipated to contribute to the formulation of more effective health policies in the field of secondary prevention of cardiovascular diseases. We expect this study to significantly optimize citizen engagement and empowerment in the self-management of cardiovascular disease, promoting more effective personalized secondary prevention strategies and reducing the burden of recurrent cardiac events.

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