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Clinical Practice Implementation to Address ASCVD Risk: A Practice Change in Primary Care

Elizabeth Wooten
University of St. Augustine for Health Sciences

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Elizabeth Wooten, ANP-BC, AACC

School of Nursing, University of St. Augustine for Health Sciences

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David Liguori, DNP

Preceptor: Eileen Meyer, DNP

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University of St. Augustine for Health Sciences
DNP Scholarly Project
Signature Form

Student Last Name:	**First Name:**	**Middle Initial:**
Wooten	Elizabeth	C

E-mail: e.wooten@usa.edu
Title of DNP Project: Clinical Practice Implementation to Address ASCVD Risk: A Practice Change in Primary Care

My signature confirms I have reviewed and approved this final written DNP Scholarly Project.
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DNP Project Primary Faculty:	David Liguori	DocuSigned by: David Liguori [illegible]	11/21/2023
DNP Project Preceptor:	Eileen Meyer	DocuSigned by: 22BFDB5C08BB443...	11/27/2023
DNP Project Preceptor:			

Abstract

Practice Problem: Heart disease stands as the leading cause of mortality in the United States. While healthcare providers strive to identify and optimize prevention strategies, particularly in high-risk patient populations, notable gaps in care persist, notably in the management of modifiable risk factors such as low-density lipoprotein cholesterol (LDL). By harnessing the power of artificial intelligence (AI) integrated software within clinical settings, we can revolutionize the landscape of this devastating chronic disease.

PICOT: The PICOT question that guided this project was: In Primary Care Advanced Practice Providers (APP) caring for high-risk and/or very high-risk patients with atherosclerotic cardiovascular disease (ASCVD) (P), how do automated electronic alerts with guideline-based recommendations (I) compare to standard notification practice (C) affect referral initiation to cardiology or prompt medication change (O) within 10 weeks (T)?

Evidence: In the realm of modern healthcare, it is crucial to recognize the impact of AI on Electronic Health Records (EHRs). This fusion of data analysis and health information technology provides an opportunity for healthcare treatments to become much more effective, resulting in better patient outcomes. Fifteen studies that matched the inclusion criteria were collected and used as substantiating evidence for this project.

Intervention: AI software integrated into the EHR system computed comprehensive data analytics, consequently discovering a substantial cohort of patients with an elevated risk profile for ASCVD, accompanied by an LDL-C level that exceeded established clinical guidelines. Subsequently, an automated communication was sent to the APP, furnishing them with pertinent notifications and offering referral recommendations.

Outcome: By integrating AI processes into the EHR, data management is streamlined and real-time disease prevention analysis is achieved. The primary goal was to identify high-risk ASCVD patient groups using AI within the EHR and assess the effectiveness of AI-generated electronic alerts with clinical guidance in encouraging behavior change. The clinical significance of this data collection and implementation was substantial. While the statistical analysis produced relevant metrics, it also exhibited applicability in the clinical context. The data exposed a patient population lacking aggressive medical management or referrals, a concern noted by APPs.

Conclusion: Introducing AI-based tools can direct the pathway of care and bridge crucial gaps in care in high-risk populations. The result of this technology utilization and integration offers timely screening strategies, education, clinical decision support, and opportunities to address vital pathways for providers and health systems to address ASCVD treatment gaps.

A Clinical Practice Implementation to Address ASCVD Risk: A Practice Change in Primary Care

Dyslipidemia is a recognized and well-established risk factor for developing cardiovascular disease, which is the leading cause of death in the United States (Drago et al., 2020). Primary care providers spend substantial time and effort on preventative medicine, including risk factor management for at-risk patients. A patient's overall risk associated with high cholesterol levels is cumulative over a patient's life span and primary prevention initiatives started earlier in this equation are paramount.

Lipid management is multifaceted, and complex and is the cornerstone of the standard of care for patients at risk of ASCVD or in effectively managing those diagnosed with cardiovascular disease. The foundation of pharmacologic therapy is using statins with the addition of ezetimibe and proprotein convertase subtilisin/kexin type 9 inhibitors to achieve lipid goals, according to the American College of Cardiology and American Heart Association (ACC/AHA) guidelines (Reiter-Brennan et al., 2020). As the guidelines are modified and published, they are not being applied thoroughly in clinical practice.

The opportunity for improvement is to detect these patients earlier in the disease progression so that they are not undertreated or miss out on cardiovascular prevention strategies (Shah, 2020). Another significant unresolved problem in current practice is the issue of residual risk. Despite the comprehensive guidelines and transition of care processes within the institution, high-risk patients are not always on the appropriate medication post-discharge after a cardiovascular event or hospitalization. There are substantial gaps in lipid treatment and goal attainment among patients and providers. In follow-up, patients are not routinely on guideline-recommended statin therapy, and a limited number of providers are applying evidence-based lipid-lowering therapies to the patient's regimens in a consistent manner (Kolkailah et al., 2022).

This project aimed to identify and address the gaps in care around treating patients with elevated LDL-C and associated ASCVD risk. By evaluating and uncovering current modalities within the institution, a software-based platform powered by AI using natural language processing (NLP) and screening strategies helps guide practitioners to earlier identification, prompt referral, and encourage guideline-based approaches for the treatment of dyslipidemia. The goal was to generate a new standard of care for this patient population. Using AI-based machine learning algorithms, estimations of prevalence and gaps in care will be deduced (Shah, 2020). Considerable work is ongoing to identify residual risk as well so that significant changes occur in the treatment approach for dyslipidemia.

Significance of the Practice Problem

Properly managing cardiovascular risk factors in those that are considered high risk significantly reduces the progression of cardiovascular disease and death (Reiter-Brennan et al., 2020). Modifiable risk factors such as dyslipidemia are considered one of the highest adjustable risk factors that are tremendously effective when treated early and appropriately with available medications and lifestyle adjustments. The reason this is so important to address is that high cholesterol has no symptoms, and consequently, patients are not aware of their risk burden or likelihood of a major event until it is too late. It also leads to the further development of other chronic diseases if left untreated (Butalia et al., 2022). As health care providers, the variances in patient care delivery should inspire questions about the evidence behind the current practice.

There is an alarming trend in healthcare and within the current health system, of patients who are not identified early, treated aggressively, or not adequately optimized in this regard. According to statistics from the Center for Disease Control and Prevention's (CDC) recent update, there are 94 million adults over the age of 20 that have total cholesterol levels above 200 mg/dL (Reiter-Brennan et al., 2020). The top quintile of highest cholesterol prevalence is in the southern region including Alabama, Mississippi, Louisiana, Arkansas, Oklahoma, Texas, Kentucky, and Tennessee. Only two-thirds of U.S. adults report having their cholesterol checked routinely (Tsao et al., 2022).

An alternate approach is needed to fill the population gap of achieving target levels of LDL-C in high-risk patients within the institution (Butalia et al., 2022). Providers must conduct a detailed risk assessment, paying special attention to patient subgroups who are at elevated risk and reflect on the overall value of a particular therapy to effectively treat patients (Reiter-Brennan et al., 2020). Of the different types of hyperlipidemias, heterozygous familial hypercholesterolemia (HeFH) is an autosomal dominant inherited condition that leads to extreme elevations in LDL cholesterol. This group is at a much higher risk for having a devastating cardiovascular event at a much younger age with an estimated prevalence of 1 in 220 based on large genetic studies (Shah, 2020).

When reviewing the current guidelines, there is an advocation for the practitioner to take on a more complex method for primary prevention of ASCVD through cholesterol management. The updated cholesterol guidelines have set progressively lower target threshold levels to achieve a more impactful reduction of ASCVD. Lifestyle therapy for primary prevention at all ages is strongly encouraged and practitioners do not often emphasize the importance that this change carries. Additionally, it is crucial to pay close attention to the ASCVD burden based on race and ethnicity, as both factors play a significant role in risk classification (Reiter-Brennan et al., 2020).

There are noted variations in statin use for secondary prevention and even more importantly the role medical therapy plays in the primary prevention of high-risk patient populations. Identifying cardiovascular patients at risk for recurrent events or subsequent adverse sequelae of an event is important to patient outcomes and to reduce the readmission rates for treatable and preventable risk factors (Shah, 2020).

In the practice setting, there was evidence that high-risk patients were not optimized in regards to LDL management or treatment from a review of documented history, quality metric data analysis, and the utilization of AI-integrated software and NLP. Data analytics revealed a need for clinical implementation of early detection, better transition of the care process, and assurance patients are provided the right medical therapy by their primary care team.

In assessing the cost and value considerations of lipid management, pharmacologic therapy is much less costly overall than hospitalization for a stroke or MI (Reiter-Brennan et al., 2020). The cost of utilizing novel screening strategies with the EHR is being investigated to help improve identification.

PICOT Question

In Primary Care Advanced Practice Providers (APP) caring for high-risk and/or very high-risk ASCVD patients (P), how do automated electronic alerts with guideline-based recommendations (I) compare to standard notification practice (C) affect referral initiation to cardiology or prompt medication change (O) within 10 weeks (T)?

Population

The project population was APPs practicing primary care medicine within an academic health system. The detailed patient population reviewed were patients at high risk for ASCVD events, and also those with known or suspected HeFH documented within the EHR and who were currently receiving treatment for this disease. The provider population was selected due to the overwhelming evidence that many do not aggressively treat these patients in their practice; they often time under treat or miss referral to a specialist thus delaying treatment initiation. The patient population age range was ≥18 years of age with no divergence of race, ethnicity, body mass index, comorbidities, or socioeconomic status. Within this particular patient population, greater than 50% of the reduction in cardiovascular disease mortality is directly associated with the development and application of early dyslipidemia treatment (Drago et al., 2020).

Intervention

To identify and treat high-risk ASCVD patients with congruent cardiovascular disease, the provider must physically see the patient in the clinic, extrapolate the pertinent information from the medical record regarding diagnosis, and then provide treatment and appropriate follow-up. Documentation also must be done meticulously. This was labor intensive. A better method to identify patients earlier was to create an AI-based integration into the EHR through real-time data analytics/queries to subsequently generate structured data sets, notifications, and recommendations that align with current guidelines. Strategically implemented tactics like this one will improve care, close the gaps noted, and increase adherence, boosting the population's health (Drago et al., 2020).

Comparison

Within this evidence-based practice (EBP) project, the comparative measures specifically address the early identification of high-risk patients and how the providers are notified through the process. The current modalities of recognizing high-risk patients within primary care practice are labor-intensive and conducted at an individual provider level. This provides room for error. The current practice depended heavily on individual providers' attention to detail, consistent assessment of risk factor development, and dependence on succinct and comprehensive documentation from other practitioners. The current system was set up for reactive responses rather than proactive responses that are more tailored. There was missed information and pull-through discrepancies.

Outcome

The outcome of this project was to improve prompt identification, referral, and guideline-directed optimized medical therapy initiation to confidently decrease variability in deviation of ACC/AHA guidelines, preventing recurrent ASCVD events. The literature showed that efficacious control of cardiovascular disease risk factors, like dyslipidemia, decreases probable disease progression and the likelihood of related death (Drago et al., 2020). Sub-optimal management of dyslipidemia in those at risk for ASCVD was noted and there was a lack of evidence of successful utilization of statin therapy and LDL levels achieved (Butalia et al., 2022).

Healthcare providers within primary care medicine need to take prompt and necessary preventive measures with medical therapy and prompt referral to reduce the risk of cardiovascular disease-related events. The desired outcome of this project was to advance guideline-directed optimized medical therapy initiation, with an AI-integrated platform within the EHR that will quickly identify the patient population and generate a notification of at-risk patients to the primary care clinic. Thus, optimal therapy can be initiated and patients are followed accordingly throughout the health system.

Timing

The time frame for implementation and data gathering was 10 weeks. During this time, a population-based, real-time observational study was utilized using hospital-wide, clinical, and administrative health data from the hospital EHR, shedding light on barriers between dyslipidemia identification and drug therapy recommendations in clinical practice (Santi et al., 2021).

Evidence-Based Practice Framework & Change Theory

Establishing an EBP framework serves as the vehicle to create the interconnection of evidence-based practices into the delivery of care (Harris et al., 2020). The utility of evidence within the practice was necessary for the change to occur. Without having clarity around the definitions and uncovering reputable evidence found in the literature, the scope of the change project, reproduction, and reliability of the outcomes will suffer (Harris et al., 2020).

For this project, the Johns Hopkins evidence-based practice framework was utilized. This framework illustrates how EBP is an interprofessional activity to improve patient care coordination, help providers identify best practices, and integrate them into the delivery of care such as establishing a coordinated effort and prompt identification of high-risk ASCVD patients within primary care. The framework starts with an inquiry that develops into a well-developed practice question. It uses a three-step process called PET: practice question, evidence, and translation. Through evidence generating, translation, and ongoing reflection, best practices develop. This is when practice improvements can be applied through careful consideration with this powerful problem-solving approach (Dang et al., 2022).

Implementing change within a healthcare organization is inevitable and is directly impacted by how well the processes are managed. Healthcare is too important to remain status quo, therefore providers, stakeholders, and policymakers have an important role in ensuring operative change (Barrow et al., 2020). This change process must be grounded in theory and properly managed. Most providers desire to be evidence-based in their methods however often lack the resources, and the confidence to implement change or have misconceptions about the change, thus the need for a theoretical model is essential to guide and structure the change process (Melnyk & Fineout-Overholt, 2019).

The approach to the implementation and dissemination of clinical practice guideline change is complex, therefore, it will be theoretically constructed on Rogers' Diffusion of Innovation Theory. This theory serves as the foundation for the project due to its innovative concept design and five-phase structure and is very useful when embarking on organizational change around EBP (Melnyk & Fineout-Overholt, 2019). Rogers' theoretical model of diffusion is used to develop an environment for the creation of multifaceted interventions to foster provider awareness and behavior change consistent with clinical practice guideline recommendations. The guiding principles of the theory are detailed in the five change phases: Knowledge, Persuasion, Decision, Implementation, and Confirmation. Rogers states that by targeting the early adopters in the change effort, the focus and energy around the proposed change will progress the innovative idea and practice change (Dearing & Cox, 2018).

This model will help develop the structure for sustainability and scale up the level of synchronized quality improvement change. When stakeholders within the organization communicate the reason for the change and support an innovative project such as the AI integration within the EHR for prompt identification and notification for ASCVD patients, social systems convert to a standardizing state (Dearing & Cox, 2018).

Evidence Search Strategy

To locate answers to the clinical question, an evidence-based literature search was conducted using electronic databases PubMed, CINAHL Complete, and Google Scholar from 2016 to 2022. Text words, medical subject headings, or a combination of both were applied. Keywords used depended on the PICOT elements and were used in various groupings in the initial search. These include: “hyperlipidemia” OR “high-risk ASCVD” OR “dyslipidemia” OR “familial hypercholesterolemia” AND “treatment” OR “ACC guidelines” OR “medical treatment” OR “gaps in treatment” OR “lipid management” AND “early identification” OR “AI integration” OR “EHR notification” OR “gaps in care.” A few relevant journals specific to ACC/AHA guidelines were selected through a manual hand-searching method.

Full-text articles in English were chosen. The search techniques utilized were Boolean operators, truncation, subject headings, and filters. Studies that met the inclusion criteria included (a) quantitative and qualitative research articles, (b) articles relating to clinical care and outcomes, (c) articles involving guideline recommendations and general management of dyslipidemia, and (d) articles about cardiovascular risk factors and gaps in guideline-directed medical therapy for hyperlipidemia. Non-English publications, studies reviewing the pediatric population, and articles that provided education without formal data collection were excluded from the appraisal. The index terms and keywords from 15 studies that matched the inclusion criteria were collected and used for the literature review.

Evidence Search Results

A methodical search was carried out in January 2023. The review verified the eligibility criteria, eliminated duplicate studies, critically reviewed the full text, and recounted the articles finally selected for review. Only original comparative studies exploring outcomes were chosen based on the inclusion and exclusion criteria. This yielded 392 academic journals that evaluated evidence-based recommendations for identifying, assessing, and treating hyperlipidemia. Two hundred and forty-six records were removed as duplicates from the retrieval. An additional screening process was conducted to narrow the particular focus of the project based on their titles and abstracts. This resulted in 88 articles that did not demonstrate associated results that were discarded. The remaining 58 reports were deemed suitable for further screening and analysis. Twenty-seven articles were excluded due to the focus being on the pediatric population, being too broad and not addressing the PICOT, or not providing a conclusion or evidence through formal data collection (educational-only content).

Initial search results yielded 15 scholarly articles outlined according to the PRISMA model (see Figure 1). Of these articles, eight primary articles contained evidence associated with the PICOT question for the qualitative analysis (see Appendix A). Appendix A reviews the design, level, quality grade, intervention and comparison, outcome definitions, usefulness, and key findings. A manual search of the bibliographies of these studies was also conducted, yielding five more studies related to the overall project.

The Johns Hopkins EBP Model rating hierarchy was used to grade the strength of evidence and the level of research evidence (Dang et al., 2022). All of the primary research articles included resulted in Level III grade criteria of research (Kolkailah et al., 2022; Petrov et al., 2021; Safarova et al., 2016; Sarraju et al., 2022). One study was an expert analysis design (Shah, 2020), while the others were either quasi-experimental, retrospective, or quantitative analyses. There are two level II studies reviewed (Drago et al., 2020; Patel et al., 2019) and one ACC/AHA guideline (Reiter-Brennan et al., 2021). In the focus and analysis of this project, there were no primary research studies identified in the literature that allowed for randomized control studies or Level I research evidence.

Most of the articles referred to the impact of implementing lipid management guidelines, early identification with algorithms within electronic databases, personalized care to prevent ASCVD, and notable gaps in care. The quality rating of the articles is class A quality and B quality. There was a total of five articles of high quality (Drago et al., 2020; Kolkailah et al., 2022; Patel et al., 2019; Reiter-Brennan et al., 2021; Safarova et al., 2016) and three that were

Quality B rating (Petrov et al., 2021; Sarraju et al., 2022; Shah, 2020). These ratings demonstrate consistency, generalizable results, sufficient sample sizes, and definitive or fairly definitive conclusions or recommendations based on a thorough and comprehensive literature review (Dang et al., 2022).

Themes with Practice Recommendations

A synthesis of the literature was conducted, extrapolating the scientific evidence from each related article in pursuit of answering the clinical question. Seven articles were reviewed and appraised for their quality and content. They included: one guideline review (Reiter-Brennan et al., 2021); five quantitative articles (Kolkailah et al., 2022; Patel et al., 2019; Petrov et al., 2021; Safarova et al., 2016; Sarraju et al., 2022), one quasi-experimental study (Drago et al., 2020), and one expert analysis (Shah, 2020). The focus was to classify patterns in the literature with guidelines and objective data analysis that reinforced the significance of the question.

These articles generated significant interest and impact on the disease, the population, guideline-directed therapy, and innovative recommendations. A table summarizes the evidence investigated and evaluated (see Appendix A). The key themes identified in synthesizing these seven articles were (1) population, (2) utilization of electronic health records for identification, and (3) dyslipidemia management according to guidelines.

Population

The population identified for this project were patients with dyslipidemia inclusive of heterozygous familial hypercholesterolemia, who were also diagnosed with ASCVD with LDL-C levels above the threshold according to guidelines. Individualized cholesterol management is complex therefore a detailed risk assessment, value consideration of appropriate therapy, and personalized treatment plans are paramount for lifelong management (Reiter-Brennan et al., 2020). There must be prompt identification of this patient population for them to be treated according to guidelines. Four articles revealed the underutilization of current therapy with statins and the undertreated, underdiagnosed hyperlipidemia patient population (Kolkailah et al., 2022;

Patel et al., 2019; Petrov et al., 2021; Sarraju et al., 2022). There is conclusive evidence that ASCVD causes an increase in mortality, is considered a high-risk condition associated with an increased burden of CV morbidity, and unfortunately, clinical events like myocardial infarction (MI), stroke, or peripheral arterial disease (PAD) are the first manifestation of undiagnosed hyperlipidemia (Drago et al., 2020; Patel et al., 2019; Petrov et al., 2021; Sarraju et al., 2022).

Electronic Health Records for Identification

There is a hidden burden within EHR to empirically and successfully identify at-risk patients. EHR-based algorithms can identify a cohort within an already high-risk diagnosis of dyslipidemia, as well as provide healthcare systems and clinicians better approximations around prevalence to aid in connecting gaps in care (Patel et al., 2019; Shah, 2020). For innovation and progression to occur in medicine, accessibility and feasibility of data utilization within the EHR is an important standard to set. Screening and identifying individuals for the disease before evident clinical manifestations occur changes the landscape of treatment (Safarova et al., 2016). Population-based large-scale tools and screening strategies with AI software systems or NLP can guide clinicians to earlier diagnosis and judicious treatment for this population (Sarafova et al., 2016; Sarrraju et al., 2022; Shah, 2020). Two articles touched on the downstream processes of care and application of appropriate treatment after the identification of these individuals and whether or not improved patient outcomes could be implied with EHR algorithm integration (Patel et al., 2019; Sarafova et al., 2016).

There was a notable consensus among the researchers that using NLP, EHR algorithms and AI integration is a novel and logical method of identification of high-risk ASCVD and dyslipidemia patients within the EHR database. These techniques can capture population-based high-risk patient groups, guide the initiation of guideline-based interventions, and assess the management and utilization of pharmacologic therapy for dyslipidemia in primary care practices (Patel et al., 2019; Petrov et al., 2021; Safarova et al., 2016; Sarrraju et al., 2022). When clinicians are notified within the EHR of a patient’s LDL-C and associated ASCVD risk factors, they can address the disease earlier, potentially ward off adverse cardiovascular events and mortality, and reduce the cost of care associated with this diagnosis (Patel et al., 2019).

Dyslipidemia Management

The degree to which current therapy is utilized and dosed for secondary prevention in high-risk ASCVD patients is unclear, thus causing lost opportunities for cardiovascular disease prevention (Drago et al., 2020; Kolkailah et al., 2022; Shah, 2020). There is room for better LDL-C management among high-risk ASCVD patients. The findings in the national-wide analysis of over 200,000 patients with ASCVD conducted by Kolkailah et al. (2022) demonstrated over half of these patients are not on guideline-recommended appropriate statin therapy. It also revealed that the utilization of evidence-based non-statin lipid-lowering therapy (LLT) is even fewer (Kolkailah et al., 2022). This directly counters the current updated guidelines which advocate for a multifaceted approach to primary and secondary prevention of ASCVD through aggressive cholesterol management (Kolkailah et al., 2022; Reiter-Brennan et al., 2020).

EHR-based algorithms based on the modified Dutch Lipid Criteria for a high-risk patient with hyperlipidemia or HeFH can be generated easily and provide valuable information regarding prescriptions, medication nonuse, LDL-C measurements and frequency of lab work, as well as those patients not being treated at all (Drago et al., 2020; Patel et al., 2019; Sarrraju et al., 2022; Shah, 2020). Targeted interventions to improve and create more consistency around the use of guideline-recommended LDL-lowering therapy are a direct by-product of using this process (Reiter-Brennan et al.,2020; Sarraju et al., 2022).

Practice Recommendations

The practice recommendations were founded on a thorough and rigorous examination of the current literature that was involved in the search strategy. The most notable theme that the literature supported was that innovative modalities like EHR algorithms and alerts for clinicians provide supportive education and clinical decision support and reveal potential pathways for health systems to address ASCVD treatment gaps. These studies highlighted the need for earlier diagnosis and initiation of guideline-directed lipid-lowering therapy in the management of dyslipidemia and HeFH, as this is the cornerstone of medical management in lowering ASCVD risk (Petrov et al., 2021; Shah, 2020). EHR-based alerts are used in real conditions of daily clinical practice and they are targeted with embedded ordering capability to encourage LLT intensification. The quality and depth of patient capture of information through NLP and AI was significantly more extensive than manual data extraction thus offering a promising solution.

It was recommended that AI algorithms and alerts within the EHR be developed to systematically and strategically identify and treat dyslipidemia/ high-risk ASCVD patients. This allowed wide-scale intervention at low cost which would have significant outcomes for the population, community, and health system (Drago et al., 2020). A logical intervention for the clinical question was based on an overview of all data in this synthesis and all other studies reviewed.

Setting, Stakeholders, and Systems Change

For this evidence-based change project, a large 1100-bed acute care hospital in Alabama serving a multitude of rural and outlying communities was chosen. Numerous affiliates also partner with this health system through outreach efforts providing access and innovative quality healthcare to the Alabama population. It is one of the largest institutions in the nation and is known for its clinical enterprise and research centers. The healthcare facility also has a Magnet Designation for Nursing Excellence and has held this title five times over. The setting focus for this project is specifically within the Cardiovascular Institute (CVI) as it is considered one of the top cardiovascular programs in the nation and continues to provide pioneering and a broad range of preventative care and complex procedures.

The emphasis of this project was on preventative cardiology and risk reduction for cardiovascular disease and related complications in the primary care division. The CVI saw over 86,000 patients, with 68,000 of those being clinic visits and 6,367 inpatient discharges for various cardiovascular diseases and interventions. The lipid specialists within this institution see patients with very complicated lipid disorders, both genetic like HeFH and acquired. Patients seen here can have combined hyperlipidemia, severe hypertriglyceridemia, and elevated lipoprotein(a) and are eligible for advanced non-statin therapies for those having difficulty tolerating lipid-lowering medications. The primary care group collaborates, partners, and seeks multidisciplinary patient-centered care directly with the CVI.

Stakeholders

The CVI Co-Directors, the Director of Quality, the MD lead for Clinical Practice Transformation, the CV Service Line Director, and the Primary Care and Cardiology APPs selected for the cohort project implementation were all significant stakeholders in the change project. Other stakeholders included nursing staff supporting the primary care team in clinical practice, and the Cardiology Fellows currently researching preventative cardiology. All of the stakeholders had a vested interest in the topic and the operational and clinical outcomes it would produce. There was interdisciplinary team collaboration throughout this project for the successful implementation of the evidence-based practice change. The most important stakeholders were the patients who would ultimately receive better care as a consequence of this initiative. Each stakeholder was identified and analyzed according to the Johns Hopkins Stakeholder Analysis Tool, defining their role, impact level, influence, priorities, and desired contribution to the project (Dang et al., 2022).

SWOT Analysis

A SWOT analysis was conducted of the institution and CVI specifically assessing current gaps. This was done to identify the strengths, weaknesses, opportunities, and threats (See Appendix B). Notable strengths of this project were the reputable services and legacy of the CVI with positive leadership endorsement and alignment with the CVI's vision of identifying and treating vulnerable patient populations rapidly. Opportunities recognized centered around increased access, awareness, and adaptability to integrative medicine utilizing technology advancements and upgrades to the EHR. This would ultimately improve patient outcomes with early recognition and treatment of dyslipidemia.

The analysis revealed a few problems as well. Those include silo functionality within cardiology and potential overarching priorities that conflicted between stakeholders within the institution. Also, with the integration of AI and NLP modalities only at 85% completion, there were delays with integration and full reception of the new technology. Some threats that revealed themselves through the SWOT analysis were resistance to the acknowledgment of the prompt/alert, perceptions of this type of integration, and a lack of key organizational leadership supportive of the change process.

Systems Change

The pilot cohort change occurred at the micro (individual) and meso (healthcare institute) levels congruently. From a meso-level system change, CVI and cardiovascular physicians led the way in preventative cardiology. As the institution deployed the EHR-integrated notifications, collegial support, internal communicative networks, and education were paramount. Also, information technology systems, departmental infrastructure, and management support all relate to the meso factors in the change suggested. At a micro level, the effects of such system change will greatly improve the productivity, and capabilities of the clinicians caring for this population and support interdisciplinary teamwork and shared decision-making. The patient, as well, benefited from the provider receiving prompt notification regarding high-risk criteria and subsequent earlier intervention offering guideline-directed medical management and aggressive treatment options.

Shared care between primary care, cardiac specialty, and the patient was formalized as a model of change that could ultimately allow interrelationship and further potential impact of this project into other areas outside of the CVI. Meso-level focus within this project had a significant influence on the frontline micro factors and the urgency and quality of care provided.

Meso and micro-level system change had a noteworthy impact on the quality of CVI services, and patient outcomes.

Implementation Plan with Timeline and Budget

Electronic alerts using NLP and screening strategies integrated into the EHR improve patient outcomes and create a partnership between primary care and cardiology. AI-based machine learning algorithms provide estimations of prevalence and gaps in care which produces opportunities for the institution to take action on treating these high-risk patients (Shah, 2020). The success of a project occurs when informatics and technology are at the base to provide context. It is the central construction for meaningful projects (Harris et al.,2020). The following SMART goals were constructed to support the successful implementation and evaluation of this project. They are specific, measurable, attainable, realistic, and timed. They included:

- *Goal 1:* To determine the implication of AI integration and electronic alerts to providers for early identification of at-risk patients, comparing the referral rate to cardiology, and the number of patients who receive medical management changes subsequently from the prompt alert.
- *Goal 2:* Leverage and improve the EBP electronic feedback process to interconnect gaps in provider clinical documentation, thus closing the loop on unconfirmed ASCVD diagnoses found within EHR.
- *Goal 3:* Data collection will occur ambispective, looking specifically at retrospective analytics and prospective data on the timeliness of referrals based on electronic alerts.
- *Goal 4*: Generate a practical plan focused on improving the management of dyslipidemia using immediate, customized, informational, automated electronic alerts which will improve clinical decision-making and optimize the use of evidence-based lipid-lowering therapies.

- *Goal 5*: Clinical data review using NLP algorithm modules will be completed by the physician and analysis team of Clinical Practice Transformation team to identify the prospective patients. Also, directly consulting with the primary care team to ensure 100% of the data is captured and effectiveness is measurable.
- *Goal 6*: Use this project as the framework for a proof of concept to implement with other patient populations.

Clinical decision-making was reinforced with the concepts around an effective problem-solving mindset. The Johns Hopkins Nursing Evidence-Based Practice (JHNEBP) model was useful when approaching such decisions within the clinical space and in creating change (Dang et al., 2022). This project was designed to meet the needs of a practicing clinician seeking to identify the practice question, acquire the supporting evidence, and translate it to applicable methods. The JHNEBP framework uses a three-step process, called PET, that involves identifying a practice question, acquiring and appraising the evidence, and through translation, applying the findings to practice (Dang et al., 2022). Translation is the final phase in the PET process and this is when the implementation of this project will occur. A succinct diagram of the AI-based integration process is detailed in Appendix C.

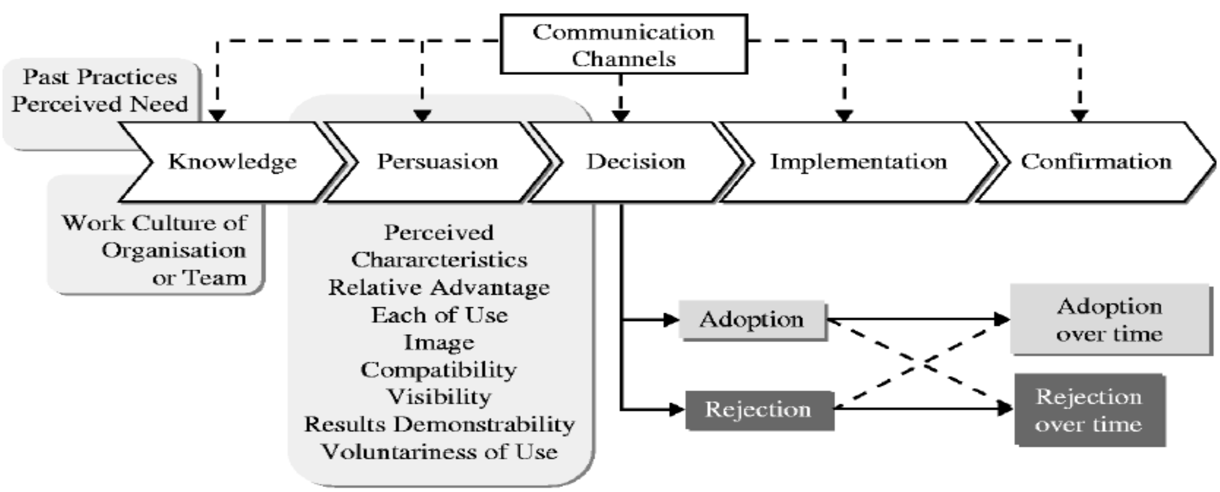
Rogers' Theoretical Model of Diffusion Theory

There are common goals and complex issues requiring problem-solving skills from various people within the institution regarding this project. Evidence-based practice, education, and clinical practice are interrelated. Interprofessional collaboration binds those working together to improve outcomes for clinicians, patients, and the ASCVD population alike. This project allowed for innovative thinking and application, the sharing of ideas around a specific patient population, and access to newly implemented technology within the EHR.

Rogers' theoretical model of diffusion was ideal for this project's innovative nature as a new evidence-based approach for extending and improving health care is created. The essence of this theory reflects on the continuum of adoption and motivation of those in the health system, assessing patterns of diffusion of relational work, and then adopting the innovation noting the important advantages it has over current practice. Through implementing a change project like this one, the real-time, AI-based assessments of external validity revealed effective and realistic practice conditions and thus reflected as a decent entrant for dissemination.

The five stages of Rogers' diffusion theory foster change through knowledge, persuasion, decision, implementation, and confirmation (see Figure 2). Communication channels throughout are a significant component. Communication allowed for the creation and sharing of information thus fostering adoption. Every step in this process was used to clarify the openness to healthcare practice change by clinicians and the institution. These principles also allow for additional opportunities with operational integration and can quicken the rate of adoption and broaden the reach of health modernizations (Dearing & Cox, 2018). Rogers also noted that there is a correlative curve showing the slow rate of adoption at the beginning of innovation, then progressing to a fast-accelerating rate, which then decelerates with fewer nonadopters remaining at the decision-making table (Dearing & Cox, 2018).

Figure 2 *A Model of Five Stages in the Innovation-Decision Process*



Source: Rogers (2003)

Note. Reprinted from: *Diffusion of Innovations*, (5th ed.), by Everett M. Rogers, 2003, the Free Press. Copyright (c) 2003 by the Free Press.

Knowledge

The decision process starts with gaining knowledge, which is the first step in the diffusion of innovation. In this phase, the individual experiences awareness-knowledge representing the process where the individual becomes aware of the AI-platform integration within the EHR for the ASCVD patient population. Also in this phase, the individual attempts to determine what the innovation is and how and why it will work within their practice. According to Rogers, this is a very important process in this phase as it increases the chances of successful adoption of the innovation (Dearing & Cox, 2018). To decrease the probability of discontinuance, teaching clinicians (end-users) how to integrate the features of this technology into their practice was key.

Persuasion

With anything new and different, there is often resistance to change. There may be negative or positive attitudes toward this change integration when perceptions are formed, thus the persuasion phase follows the knowledge phase. This stage is more about feelings rather than knowledge and is quite impressive with the level of uncertainty that may reveal itself. Questions regarding support, peer assessments, individual opinions, and beliefs about the AI-based integration alerts were asked at this point. Throughout this phase, individuals search for additional supportive information that helps guide them to a formal decision (Dearing & Cox, 2018). Clinicians using this EHR integration were educated on the benefits of such innovation.

Decision

At this phase, the individual chooses to adopt or reject the algorithmic integrative alerts in the EHR. Individuals used the AI modules on a trial basis, testing out the processes and system changes to see how it works. This can speed up the process of decision. Thoughtful consideration occurs at this phase when the individual chooses to adopt the innovation or not. When a positive decision is made, the individual will change their behavior to use the innovation in practice, however, it is important to note that the end-users are often not the choosers of an innovation. This makes implementation quite captivating and begs us to consider the full scope of sustainability and full organizational change (Dearing & Cox, 2018).

Implementation

When the institution and decision-makers have accepted the concept and are ready to adopt it, this is when innovation is put into practice. Uncertainty resurfaces in this context, particularly concerning the anticipated results and procedural sequence. This is when the project manager, key stakeholders, and implementors of change recruit others to soften the level of hesitation. Changes and modifications occur at this phase and as the project evolves, reinvention occurs. As the innovative idea continues to be modified and adapted, adoption becomes institutionalized (Dearing & Cox, 2018).

Confirmation

The decision has been made at this phase and sustainable support is pursued. Evaluation and recurrent analysis occur as the individuals involved seek congruent attitudes of others that either support or disagree with the integration. As healthcare systems find appropriate patients for proactive care and disease management using this innovative process and AI-based algorithms, valuable insights for care teams are gained and converted to action. Rogers states that this is an important step in the decision process, as many times discontinuance may occur due to replacement or disenchantment discontinuance because the individual isn’t content with the result or doesn’t see a comparative benefit (Dearing & Cox, 2018).

Project Timeline

The Gantt chart (see Appendix D) provided a schedule of activities completed during the project. The project duration for the implementation phase was 10 weeks, with an additional 2-week window for modifications and evaluation completion. The details of individual responsibilities of data collection, provider education, touch-point meetings, project implementation, evaluation, and dissemination were detailed in the chart over a 12-week time frame. It was important to note that the process of data collection was very specific. This was detailed in the initial phase of implementation, paying special attention to particulars of the data to ensure early issues were addressed that warranted change. After thorough collection and analysis of the data, results were judiciously interpreted using the conceptual framework with subsequent dissemination of the findings in the form of a grand round lecture and/or oral presentation (Melnyk & Fineout-Overholt, 2019).

Budget Plan

In studying the budget related to the project, there were anticipated direct and indirect costs involving salaries and benefits, training costs, AI-based software and supplies, and office space allocated for data analytics from the live production the of EHR module (see Table 1). The budget was nominal as the costs to the current organization did not change regarding what was already in place. There was no additional staffing needed for this project. Suitable staff within the organization including physicians, research nurses, research fellows, and health IT personnel were already employed at the institution congruently working in this space and topic. Potential incurred costs to sustain the project, such as AI-based software updates, additional IT support, and additional technology or EHR upgrades may be needed prospectively for long-term sustainability.

Table 1 *Budget*

EXPENSES		**REVENUE**	
Direct		Billing	
▪ Salary: 80 hours (2 MD, 1 NP, 1 RN)	$34,500	Grants	
▪ Computer	$2,500	Institutional budget support	
▪ Software (AI platform)	Already purchased		
- Monthly fee	$250		
Indirect			
Equipment upgrade	$6,000		

Total Expenses	$43,250	Total Revenue:	
Net Balance:			$43,250

Role of the DNP Student

This project required close collaboration and project planning with those within the institution. The DNP student was the primary project manager for this change project and was responsible for efficacious initiation, planning, and management of staff, and directed the project timeline and goals. The project manager was in charge of involving others on the project who a had specific set of skills and AI-based tools available to contribute to the project goals and outcomes. It was important for the project manager to also set meaningful and realistic scheduled meetings to keep everyone informed and encourage open communication with team members as the project moved through its lifecycle.

Engaging the stakeholders and active contributors in the change project produced shared accountability, transparency, and valued contributions. As the project manager, the DNP student led the team through effective communication, planning, and implementation of the desired project goals, inspiring others to become involved in the overall project focus to raise awareness for future projects.

Results

Integrating AI-based NLP processes within the EHR helped automate processes, organize data, and conduct real-time analysis for disease prevention. The principal outcome measure was to identify high-risk ASCVD patient populations using AI software in an EHR and secondly, evaluate the usefulness of AI-directed electronic alerts with clinical recommendations and whether there was a correlation in prompting behavior change. The purpose of these alerts was to provide the clinician with the practicability of ordering a subspecialty referral or modifying the patient’s current treatment plan promptly.

Data Collection

There were multiple streams of data collected during this project.

- Number of patients who met criteria for high-risk ASCVD and very high-risk ASCVD and their congruent comorbidities
- Number of patients who were being followed and treated by the primary care team, cardiology team individually, or both
- Number of APPs selected for participation in the project pilot
- LDL-C values and current medical regimen including statin therapy; bucketed into LDL-C > 70 and LDL-C > 55 distinctly.
- APPs perception, utility, and response to the AI-generated message sent

The EBP Project Review Council (EPRC) at the University of St. Augustine for Health Sciences and the clinical site preceptor at the institution approved the project proposal and implementation. Data was collected for 12 weeks consecutively during the project implementation phase from July 2023 to September 2023 (see Appendix D). The current literature and assessment of the institution demonstrated the absence of a streamlined process to identify high-risk ASCVD patients and highlighted the need for urgency, offering an option for specialty referral sooner, and a need for a multidisciplinary team approach to care, which supports face validity for these measures.

Individual data constituents also collected were the age of the patient, LDL-C level, HgbA1c +/- diabetes mellitus (DM), hypertension (HTN), PAD, ST-elevated myocardial infarction (STEMI), non-ST elevated myocardial infarction (NSTEMI), MI, transient ischemic attack (TIA), stroke, percutaneous coronary intervention (PCI) +/- coronary artery bypass grafting (CABG), and current statin regimen. Appendix F details the tool used for this data collection.

The lead MD in Clinical Practice Transformation along with the AI software analytic team ran all data analysis to ensure reliability and accuracy. The data collection was iterative, as it required an ongoing computational process and refining of data metrics and values for each query to ensure the correct patients were identified within the specified range of LDL-C, risk factors, and by specialty. Data was validated in conjunction with the organization's information technology staff. For HIPPA concerns, all patient identifiers were removed before inputting the data values into Microsoft Excel for statistical analysis organization. Final data points used for this project were collected by the project manager (DNP Student) and were stored within the project manager's personal computer in the cloud drive on an Excel spreadsheet that is password locked. This project does involve collecting unidentified patient information from the EHR; however, no direct patient contact occurred and the probability of any assumed risk to their safety and privacy was null.

The project investigation successfully identified 230 high-risk ASCVD patients. Ninety were considered very high risk (VHR) with LDL-C above 70 mg/dL and 125 patients were considered very high risk (VHR) with an LDL-C above 55 mg/dL and subsequently highlighted the gap in current care. These patients were followed by primary care outpatient providers and/or various cardiology subspecialties within the health system and were flagged as meeting the initial criteria with LDL-C > 55. Twenty-five APPs from primary care and cardiology were selected to participate in the pilot to receive one electronic alert about a patient's diagnosis, LDL-C level, and whether or not they were considered high-risk. The alerts were direct messages to the current provider or to the provider that ordered the patient's last lipid panel. An example of this notification is detailed in Appendix E. The integrity of the data source was through EHR and AI-integrated software analysis.

Data Analysis

The project used a pre- and post-evaluation design for evaluating outcomes, processes, and supportive measurements. Fifteen of the twenty-five APPs responded to the post-implementation survey. Data investigation was performed using Intellectus software, employing a two-tailed paired samples t-test to examine whether the mean difference between AI message relevance and AI message utility was significantly different from zero. The result of the two-tailed paired samples t-test was not significant based on an alpha value of .05, $t(14) = 1.72$, $p = .108$, indicating the null hypothesis cannot be rejected. This finding suggested the difference in the mean of AI relevance and the mean of AI utility was not significantly different from zero (Intellectus, 2019). The results are presented in Table 1. A bar plot of the means is presented in Figure 3.

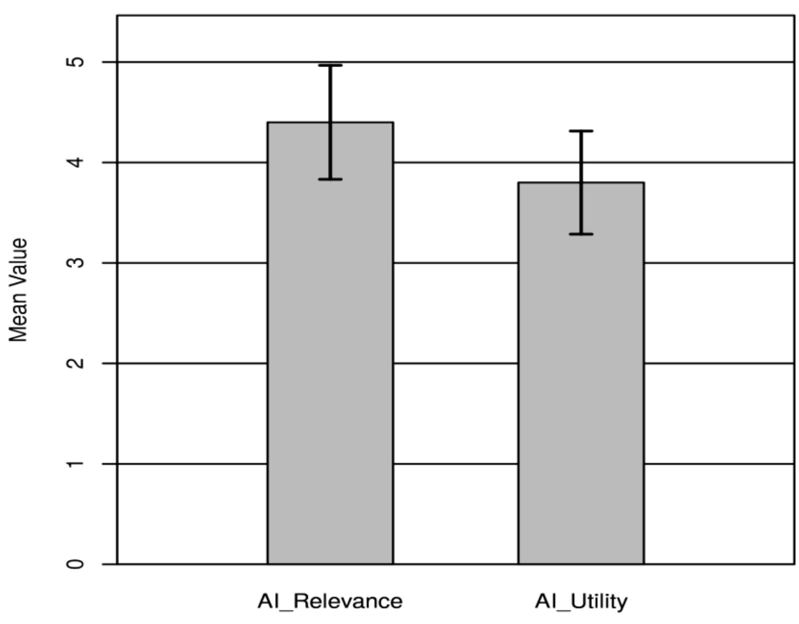
Table 2 Two-Tailed Paired Samples t-Test Difference Between AI Relevance and AI Utility

AI Relevance		AI Utility				
M	*SD*	*M*	*SD*	*t*	*p*	*d*
4.40	1.12	3.80	1.01	1.72	.108	0.44

Note. N = 15. Degrees of Freedom for the *t*-statistic = 14. *d* represents Cohen's *d*.

A Shapiro-Wilk test was conducted to determine whether the differences in AI relevance and AI utility could have been produced by a normal distribution (Razali & Wah, 2011). The results of the Shapiro-Wilk test were significant based on an alpha value of .05, $W = 0.53$, $p < .001$. This result suggested the differences in AI relevance and AI utility are unlikely to have been produced by a normal distribution, indicating the normality assumption is violated.

Figure 3 *The means of AI Relevance and AI Utility with 95% CI Error Bars*



The secondary data analysis was descriptive, looking at the patient variables for the project. Summary statistics were calculated for each interval and ratio variable that the AI software generated. Frequencies and percentages were calculated for each nominal variable.

The most frequently observed variable was MI in 66.4% of patients and 97.60% had documented hypertensive disease. Regarding PCI vs CABG, 36.80% were noted to have had a CABG and many had observed a stroke, which was unspecified. The most frequently observed statin was atorvastatin at 69.60%; dose not specified. There were also notable data fields that were missing information; the AI software didn’t find any documentation of these variables. Frequencies and percentages are presented in Table 3.

Table 3 *Frequency Table for Nominal Variables*

Variable	*n*	%
MI		
NSTEMI	24	19.20
MI	25	20.00
myocardial infarction	16	12.80
MI 1989	1	0.80
MI in 2016	1	0.80
STEMI	8	6.40
Heart attack	6	4.80
MI in 2007	1	0.80
MI in 2008	1	0.80
Missing	42	33.60
IC		
CABG	46	36.80
PCI/stent	42	33.60
Missing	37	29.60
HTN		
Hypertension	122	97.60
hypertension	2	1.60
Missing	1	0.80
STROKE		
unspecified	21	16.80
ischemic	2	1.60

TIA	8	6.40
hemorrhagic	1	0.80
Missing	93	74.40
STATIN		
atorvastatin	87	69.60
Rosuvastatin	22	17.60
Missing	16	12.80
VISIT		
Clinic Visit	81	64.80
Return Clinic Visit	3	2.40
New Patient	16	12.80
Heart Failure Discharge	5	4.00
Telehealth New	2	1.60
Device Discharge Visit	1	0.80
New Cardiology Oncology	1	0.80
New Previous Patient	1	0.80
Discharge	2	1.60
Missing	13	10.40

Note. Due to rounding errors, percentages may not equal 100%.

The average age was 64.89 (SD = 12.16, SEM = 1.09, Min = 32.52, Max = 90.73, Skewness = -0.23, Kurtosis = -0.36). The observations for LDL had an average of 99.62 (SD = 39.82, SEM = 3.56, Min = 55.00, Max = 221.00, Skewness = 1.14, Kurtosis = 0.55). The summary statistics can be found in Table 4.

Table 4

Summary Statistics Table for Interval and Ratio Variables

Variable	*M*	*SD*	*n*	SE_M	Min	Max	Skewness	Kurtosis
AGE	64.89	12.16	125	1.09	32.52	90.73	-0.23	-0.36
LDL	99.62	39.82	125	3.56	55.00	221.00	1.14	0.55

Note. '-' indicates the statistic is undefined due to constant data or an insufficient sample size.

Outcome Measures

Clinical significance was quite notable with this data collection and implementation. Through the statistical analysis, the metrics by which project results were measured were relevant, however, statistical significance revealed little application in the clinical setting (Carpenter et al., 2021). From a practical standpoint, this data reveals a population of patients who are not receiving aggressive medical management or referral. The primary outcome measure also assessed the change in provider behavior influenced using AI technology. To measure the impact and motivated change, a survey was sent to each provider after they had received the message (see Appendix G). It had 6 questions and 1 free-text box for additional comments. Over 80% of respondents found the AI-generated message to be relevant to practice, and nearly all found it helpful in aiding in clinical decision-making. 93% of the respondents stated it prompted them to take action on behalf of the patient or make a change in treatment. There were mixed results on the frequency of messaging, but the majority felt that the more frequent the better. See Table 5 for the subjective feedback provided by the APPs.

Table 5 *Subjective Comments about AI-Generated messages for ASCVD patients*

Positive Comments	**Negative Comments**
▪ Aids in coordinating the care between the providers ▪ No excessive time spent digging through the chart for patient information ▪ Identifies a problem, provides guidelines, and suggests modifications-checks all the boxes ▪ The AI-generated messages remind providers to look again when needed for those high-risk patients ▪ Has the potential to change overall practice ▪ Good reminder to ‘take another look’ at my patients identified	▪ Frequency is a concern; we are already overloaded with messages in the EHR ▪ The message was lengthy; bullet points and a more succinct message are preferred ▪ Would want the message to be optional, not mandatory, to open or check ▪ Received the message at random, not associated with a clinic visit or event. Would prefer for it to be tied to an encounter

Impact

The emphasis of this project was to enhance patient outcomes and contribute to generalizable knowledge in this therapeutic area. The findings of this project advocate that using AI software with NLP applications and AI-generated alerts embedded within the EHR can help identify, standardize, inform, and progress the quality of care for patients with ASCVD. The highly sophisticated technology and the efficiency of its processes promote consistency and system-wide integration, with the ability to alert all providers of any specialty caring for high-risk patients. Such an intervention could be widely scaled and paired with other quality improvement initiatives to optimize outcomes and generate collaborative care for ASCVD patients who are undertreated.

The impact of this project was limited by the ongoing iteration of the AI programming and the short duration time frame. AI systems incorporate mechanisms for continuous learning over a significant amount of time, so as new patient data becomes available and treatment outcomes are observed, AI can update its algorithms to improve accuracy and relevance. AI software for patient identification and treatment recommendation leverages the power of data analysis, machine learning, and predictive modeling to support providers in delivering tailored and evidence-based care to patients. It enhances their decision-making process and has the potential to improve patient outcomes while optimizing resource allocation in healthcare systems.

The future implications of this project could include efficient data management, powerful clinical decision support, predictive analysis, and smart AI algorithms constructed to enhance population health management for at-risk populations.

Dissemination Plan

As part of the informative dissemination of the project results, details and outcomes will be presented to the primary care team, CVI APPs, and the lead MD over Clinical Practice Transformation. The meeting invitation will be sent via email to all of the physicians, APPs, and Directors who are a part of the CVI and Primary Care. By displaying the results of this study, the healthcare system and providers will gain knowledge that will improve healthcare outcomes for their patient population and enhance the care provided.

In January 2024, The Alabama ACC will hold its winter meeting, and presenting the results of this project in a breakout session attended by APPs, RNs, and clinical pharmacists would be informative and relevant to those who care for patients with ASCVD. This meeting is interdisciplinary and session topics embody innovative ideas for improving patient outcomes. This would be an applicable meeting to share the results widely with those who practice outside of this particular institution as well. Successful dissemination will result in an engaged audience with a newfound awareness of the clinical question and outcomes. Both internal and external distribution of information will enhance the decision-making capabilities of those who care for the ASCVD patient and allow for constructive feedback from those in practice to allow for improvements before full implementation.

The scholarly manuscript will be published to SOAR@USA, which is an academic institutional location that houses many successful DNP projects. This allows for extensive public exposure and increased awareness around the topic of AI integration in nursing and healthcare. The project will be reviewed and evaluated by the institutions' EBRC to ensure quality work has been completed. Lastly, asking for a formal peer review within the institution will allow for a collaborative presence in the final review.

Conclusion

One highly modifiable and well-established risk factor for developing cardiovascular disease is dyslipidemia (Drago et al., 2020). Cardiovascular disease is the main cause of death in the United States, therefore, employing aggressive risk reduction is the name of the treatment game. In the context of risk reduction at the primary care level, prompt identification of these patients with up-to-date LDL levels and expedited referral to a specialist is essential. There is a tremendous opportunity for individual clinicians and institutions alike to improve their processes around the detection and initiation of prevention strategies (Shah, 2020). The literature and results of this project suggest there are still substantial gaps in lipid treatment and goal attainment among patients and providers despite updated guidelines.

Introducing AI-based tools using deep learning NLP classifiers can direct the pathway of care and bridge crucial gaps in care in high-risk populations. Timely screening strategies, education, clinical decision support, and opportunities to address vital pathways for health systems to address ASCVD treatment gaps will result from this technology utilization and integration. The project employed the Johns Hopkins EBP model PET framework and Roger's diffusion of innovation change theory to transform the way ASCVD patients are identified, referred, and treated medically. The utility of AI-based integration support, sustainability, and potential for widespread implementation around proof of concept was based on numerous key findings from this EBP change project. The change project offered a chance to tap into innovative technology using relevant, informative, electronic alerts within the EHR to identify an at-risk patient population, improve clinical decision-making, and optimize referral utilization and medical management.

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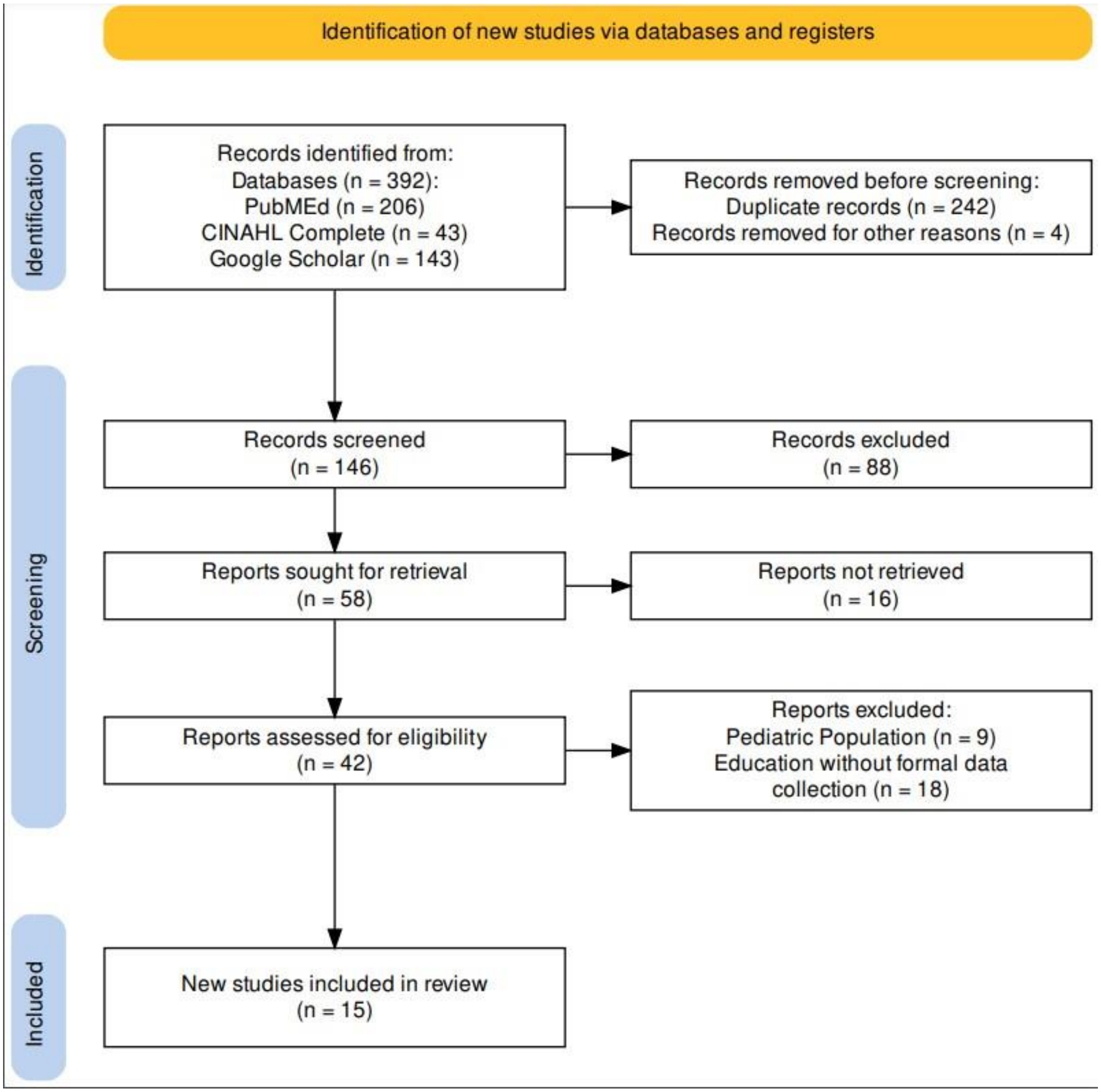
Figure 1 *PRISMA Flowchart*



(Haddaway et al., 2022)

Note. Prisma flow chart diagram from "Preferred Reporting Items for Systematic Reviews and Meta-analyses: The PRISMA Statement," by D. Moher, A. Liberati, J. Tetzlaff, & D.G. Altman, 2009, Annals of Internal Medicine, 151(4), p.267 (http://dx.doi.org/10.7326/0003-4819-151-4-200908180-00135).

Appendix A

Summary of Primary Research Evidence

Citation	Design, Level, Quality Grade	Sample Sample size	Intervention Comparison	Theoretical Foundation	Outcome Definition	Usefulness Results Key Findings
Reiter-Brennan et al., (2020).	Guidelines LEVEL IV Quality A	n/a	Review of the recent guidelines and important changes for clinical practice	none	Statins are the foundation of lipid management Grouped by risk (high risk vs very high risk) Nonstatin therapies as add-on, evidence-based treatment options when low-density lipoprotein (LDL-C) remains above the 70 mg/dL threshold. Primary Prevention Secondary Prevention: The reduction in risk is proportional to the decrease of LDL-C levels	2018/2019 guidelines recommend primary preventive therapy for children and young adults. After initiating or changing the dose of LDL-C-lowering medications and lifestyle changes, repeat lipid measurements should be in 4 to 12 weeks after therapy Special treatment algorithms are outlined for certain patient subgroups

Shah, (2020).	Expert Analysis LEVEL V Quality B	n/a	Early diagnosis and treatment with AI, machine learning, Dutch Lipid Network criteria, and genetic testing; treatment with *Versus* Standard assessments with family hx, physical exam, lipid panel; Treatment w/ GDMT	none	FH imposes a significant public health burden Early screening modalities to improve identification Identify clinical red flags to prevent CV complications	Tools and screening strategies developed to help guide clinicians to earlier diagnosis and treatment of FH EMR data can be extrapolated by use of AI and machine learning algorithms to identify patients and provide better insights into gaps in care
Kolkailah et al., (2022).	Quantitative, non-experimental LEVEL III Quality A	227,824 patients ASCVD patients included median age 65 years	Appropriate GDMT statin therapy Versus lower-than recommended therapy and no statin therapy	none	Statin therapy utilization Secondary prevention statin utilization and dosing Those not on statins were female and less likely to have private insurance Utilization of non-statin LLT was low across all groups	Half of ASCVD patients are not on guideline-recommended appropriate statin therapy, few are utilizing evidence-based non-statin LLT, and many are utilizing non-evidence-based LLT. Further work is urgently needed to improve utilization of guideline-based LLT in clinical practice .
Drago et al., (2020).	A quasi-experimental, uncontrolled, before-and-after study LEVEL II	1151 patients with IHD (ischemic heart disease)	Face-to-face training and online course phase, feedback Versus no formal training on management guidelines	none	LDL-C control according to current guidelines, classified as ‘good’	Cholesterol control of IHD patients was influenced by the type training activity that the physicians underwent

	Quality A				Control CVD risk factors like dyslipidemia, reduce their mortality rate Application of the recent targets of the European guideline, which establish a lower level of LDL-C control, the percentage of good control could be worse than observed in this study	Being female and being older were risk factors, while being diabetic and having suffered a stroke were protective factors for LDL-C control and identification. Physicians who participated in the program attributed as a protective factor for their patients
Petrov et al., (2021).	Quantitative study LEVEL III Quality B	11,090 hospital records of patients admitted for treatment of acute events with ICD codes for ASCVD	Proportion and management of FH patients from those admitted to the hospital for treatment of acute ASCD AND Achievement of LDL-C targets	none	The proportion of patients classified as FH as defined by the Dutch Lipid Network Criteria (DLNC), use of lipid-lowering therapy, LDL-C achieved by 1, 3, 6, and 12 months post-index event, and public resources spent on hospital and ambulatory treatment Need for aggressive LLT and use the	Less than half of those discharged for ASCVD event were placed on a high-intensity statin, and vast majority had poorly controlled LDL-C

					efficiency of EMR search tools to support early diagnosis	
Patel et al., (2019).	Quantitative analysis, multivariate analyses LEVEL II Quality A	EHR database query of over 1.5 million Geisinger Health System (GHS) patients (January 2000 to August 2016) with (ICD-9) codes for hyperlipidemia (272.0, 272.1, 272.2, 272.3, 272.4)	population-based approach using electronic health record (EHR)-based algorithms to identify FH	none	Major adverse cardiovascular events Mortality Cost of medical care	There are novel ways of identifying and examining the sequelae of familial hypercholesterolemia in a population-based manner Using an electronic health record–based algorithm for detection and risk stratification allows for usability of cost of cost-of-care assessment
Safarova et al., (2016).	Quantitative, Cross-sectional study LEVEL III Quality A	5992 patients with low-density lipoprotein cholesterol (LDL-C) ≥190 mg/dL and without secondary causes of hyperlipidemia	Development of an ePhenotyping algorithm for rapid identification of FH in electronic health records (EHRs) AND deployed it in the Screening Employees And Residents in the Community for Hypercholesterolemia (SEARCH) study	None	EHR data may be useful to assess both the epidemiology and management of severe hypercholesterolemia in primary care practices Algorithm use in ascertaining FH cases	EHR-based phenotyping algorithm identified FH cases with accuracy prevalence of clinical FH to be higher than the commonly reported projected estimate of 1:500 Significant under-recognition of clinical FH with less

		mean age 52 ± 13 years,			DLNC for FH using structured data sets and natural language processing LDL-C goal per EHR algorithm ascertainment	than half of patients having a diagnosis code related to primary hypercholesterolemia and achieving LDL-C ≤100 mg/dL on treatment or LDL-C ≤70 mg/dL, when CVD was present FH may be significantly underdiagnosed and undertreated in the United States
Sarraju et al., (2022).	Retrospective study, multisite, multiethnic EHR-based health system, quantitative LEVEL III Quality B	56,530 ASCVD patients Patients diagnosed with ASCVD between the ages of 18 and 89 year	Deep learning-based natural language processing (NLP) approaches to classify statin nonuse and reasons for statin nonuse using unstructured electronic health records (EHRs) from a diverse healthcare system	none	The primary outcome was statin nonuse based on structured and unstructured EHR data. The secondary outcome was the reason for statin nonuse classified into the following categories: muscle-based side-effects, other side-effects, perceived lipid control, patient preference, and nonspecific reasons.	Real-world, multiethnic cohort of ASCVD patients, approximately 40% lacked guideline-concordant statin prescriptions A high proportion of ASCVD patients without documented statin prescriptions in a large health system, including disparities in statin prescriptions by gender, race/ethnicity, and practice setting (academic versus community-based)

Legend: LDL-C: low-density lipoprotein cholesterol; ASCVD: Atherosclerosis cardiovascular disease; GDMT: Guideline directed medical therapy; DLNC: Dutch Lipid Network criteria; CV: cardiovascular; FH: Familial hypercholesterolemia; EMR: Electronic Medical Record; AI: Artificial intelligence; LLT: lipid lowering therapy; IHD: Ischemic Heart disease; CVD: cardiovascular disease; EHR: electronic health record

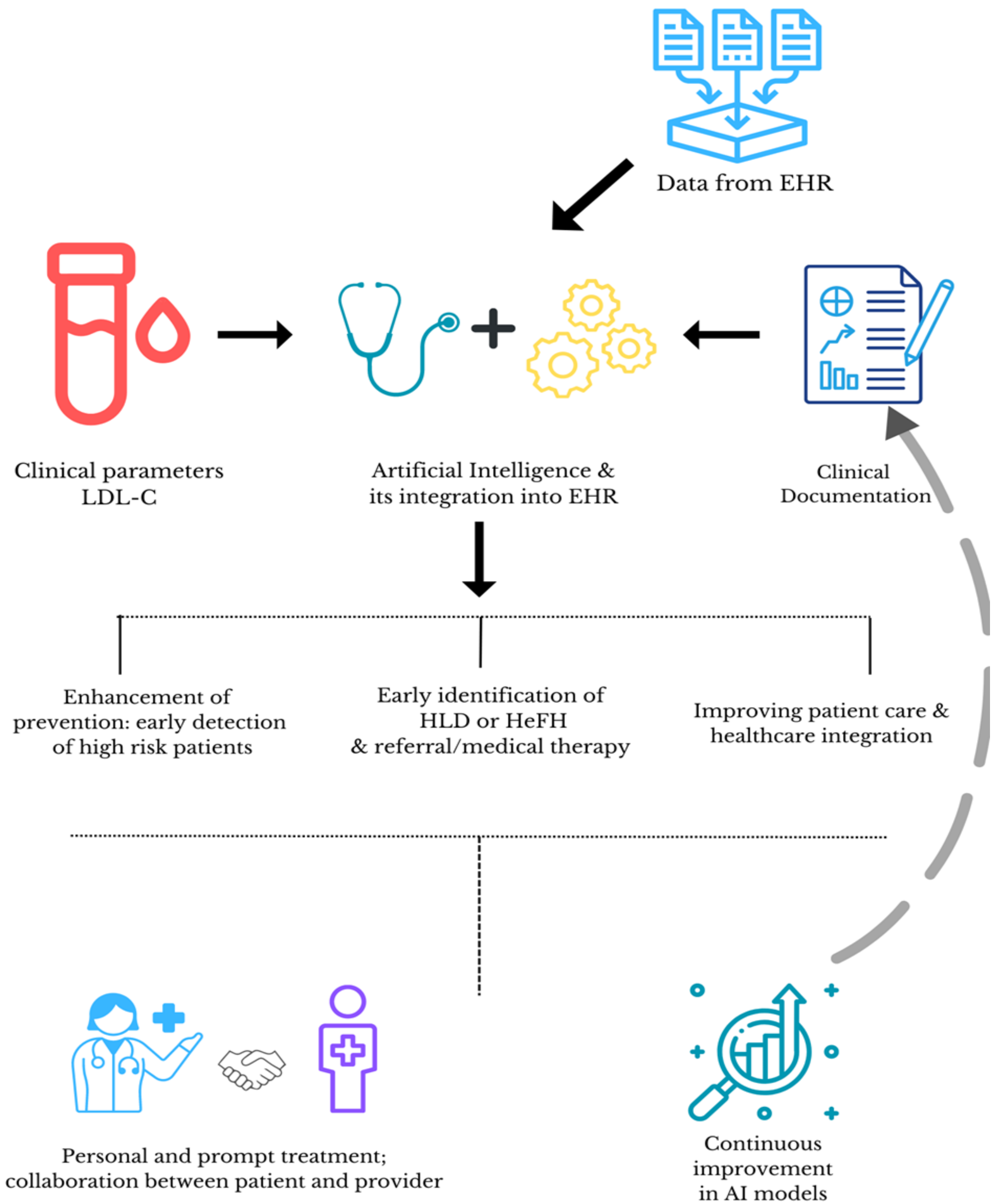
Appendix B

SWOT Analysis

STRENGTHS: • New innovative service: Timely and quick notification of identified at-risk patients • CVI director and Transformative director endorsement • CVI reputation: services are top-notch and of the highest standards • Lipid specialist enthusiastic about process improvement	WEAKNESSES: • AI and NLP integration into EHR is an emerging technology and • Priorities that conflict between stakeholders • Module and infrastructure with AI-based software not fully integrated into the EHR yet • Gaps in capabilities between disciplines; lack of cohesive communication plan
OPPORTUNITIES: • Speedy identification of patients with rapid and direct communication with providers • Access to abundant health statistics and data within the CVI population • New service: Prompts possible specialty referral or quick medical management changes at the primary care level • Better coordinated care: Provide care seamlessly in line with guidelines • Technolog**y** upgrade	THREATS: • Lack of shared strategic vision of AI integration into EHR with physicians and other clinical staff • Resistance in the acknowledgment or use of the prompt/alert • Providers may prefer to identify patients individually without support notifications • Perception of increased workload • Shared responsibility

Appendix C

Example of Software Platform Algorithm



Appendix D

Project Schedule

	NUR7801								NUR7802								NUR7803							
Activity	Week 1	Week 3	Week 5	Week 7	Week 9	Week 11	Week 13	Week 15	Week 1	Week 3	Week 5	Week 7	Week 9	Week 11	Week 13	Week 15	Week 1	Week 3	Week 5	Week 7	Week 9	Week 11	Week 13	Week 15
PLANNING PHASE																								
Meet with preceptor																								
Identify Gaps in Care and fine-tune PICOT																								
Review literature/ Critical Appraisal																								
Prepare project proposal																								
Discuss project with Stakeholders																								
Identify internal resources for project																								
EHR access and system review training																								
Identify clinician support																								
Customize AI-NLP algorithm for data selection																								
Contact HSIS (Health informatics) for technical support																								

	NUR7801								NUR7802								NUR7803							
Activity	Week 1	Week 3	Week 5	Week 7	Week 9	Week 11	Week 13	Week 15	Week 1	Week 3	Week 5	Week 7	Week 9	Week 11	Week 13	Week 15	Week 1	Week 3	Week 5	Week 7	Week 9	Week 11	Week 13	Week 15
Review of Literature – add additional support																								
Establish schedule for project meetings weekly for progress checks																								
Review final Proposal with Preceptor/Faculty																								
Acquire organization IRB approval																								
IMPLEMENTATION PHASE																								
Confirm approval from EBPC, NEC from USAHS																								
Develop a standardized clinician guidelines																								
Conduct pre-implementation assessment and collection of data pre-implementation																								
Implementation of the NLP Alerts in EHR																								
Continual assessment of tool																								
DATA COLLECTION & ANALYSIS PHASE																								
Data Collection																								

	NUR7801								NUR7802								NUR7803							
Activity	Week 1	Week 3	Week 5	Week 7	Week 9	Week 11	Week 13	Week 15	Week 1	Week 3	Week 5	Week 7	Week 9	Week 11	Week 13	Week 15	Week 1	Week 3	Week 5	Week 7	Week 9	Week 11	Week 13	Week 15
Data Analysis																								
Project Evaluation																								
Present findings to preceptor for feedback																								
Submit results of manuscript to faculty																								
Dissemination of findings to stakeholders																								
Sustainability plan for Translational medicine, facility, and preceptor																								

Appendix E

Example of EHR Notification

|PROVIDER NAME|,

You are receiving this notification as part of a quality initiative project using the power of artificial intelligence and electronic health records to improve patient outcomes.

Your patient [Patient name], [patient DOB], meets the criteria for notification per the high-risk ASCVD protocol based on the LDL drawn on *|DATE|*. Per the 2018 AHA/ACC Multisociety Guideline on the Management of Blood Cholesterol, this patient is considered at high risk of ASCVD, and an evaluation of the patient's medical therapy may be indicated. In patients with clinical ASCVD, reduce low-density lipoprotein cholesterol (LDL-C) with high-intensity or maximally tolerated statin therapy. In very high-risk ASCVD, use an LDL-C threshold of 70 mg/dL to consider the addition of nonstatins to statin therapy. Please consider adjustment if your patient is not already on a statin or non-statin lipid-lowering therapy. If a cardiologist is not following them, you may order Ambulatory Referral to General Cardiology or a Lipid specialist, message the Gen Cards Clinic Pool, or call 205-934-xxxx to speak to a scheduler.

We appreciate your partnership in providing our patients with the best cardiac care possible.

If your patient is not appropriate for referral or up-titration/addition of medication at this time, please consider amending your last note to include one of the following reasons:

- This patient follows up with an outside cardiologist

- This patient is already on max tolerated medical regimen for cholesterol

- This patient has declined an evaluation by cardiology

We appreciate your partnership in using AI to harness the power of EHR data to better patient care.

Appendix F

Data Collection Tools for Evaluation

State-of-the-art AI technology by a third party was utilized to identify high-risk ASCVD patients, their comorbidities, LDL-C values, medication regimens (statin and non-statin therapies), and the groups of providers caring for them (cardiology and primary care). The institution was utilizing this AI-platform software in the background of their EHR to add an “intelligent layer” to routinely generated data to help find appropriate patients for proactive care and disease management. Permission was given to utilize the data produced from specific query searches for high-risk and very high-risk ASCVD patient populations cared for by the primary care team and cardiology. All patient identifiers were removed for this project.

The second tool used was student-created. It was a 7-question qualitative evaluation survey (see below) that measured the utility, perception, and clinical helpfulness of the AI-generated message. Face validity was conducted.

Appendix G
Subjective Post-Implementation Survey

APP Perspectives on AI-Driven ASCVD Identification and EHR-Based Messaging

1**. On a scale of 1 to 5, how relevant was the AI-generated message to your current patient's condition or treatment plan?**
(1 being not relevant at all, and 5 being highly relevant)
1
2
3
4
5

2. **Did you find the AI-generated message helpful in informing your clinical decision-making process?**
Yes/ No

3**. Did the AI-generated message prompt you to take specific actions or change the patient's treatment plan?**
Yes/ No

4. **Did the AI-generated message provide information that you were not previously aware of? (LDL thresholds and AHA/ACC guideline recommendations)**
Yes/ No

5. How would you rate the overall utility of AI-generated messages in your clinical practice?
Extremely useful
Very useful
Somewhat useful
Not so useful
Not at all useful

6. **How frequently would you like to receive AI-generated messages within the Electronic Health Record (EHR)?**
Rarely
Occasionally
Frequently
Always