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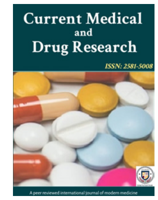

Artificial Intelligence-Enabled Clinical Decision Support for Chronic Disease Management in Primary Care: Implications for Family Nurse Practitioner Practice

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ABSTRACT

Artificial intelligence-enabled clinical decision support is increasingly being applied to chronic disease management in primary care. This structured integrative review examined how AI supports risk prediction, complication detection, patient prioritisation, screening, education, and care coordination, with emphasis on implications for family nurse practitioner practice. PubMed was used as the principal information source, with studies limited to English-language, human, free full-text publications from January 2018 to July 2026. Seventy-one records were identified, one duplicate was removed, and 70 unique records were screened. Seventeen publications were retained, including 15 AI-related studies and two contextual digital decision-support studies. The evidence showed that AI can improve case finding for diabetes, predict chronic kidney disease and cardiovascular risk, identify complications in free-text records, support diabetic-retinopathy screening, and assist with patient segmentation and self-management education. However, performance varied across settings, and several models were limited by poor calibration, internal validation, workflow burden, and uncertain transferability to primary care. Direct evidence involving family nurse practitioners was limited, but the findings were highly relevant to screening, monitoring, referral, patient education, and care coordination. AI should therefore be used as a support tool rather than an independent decision-maker. Safe implementation requires clinical oversight, local validation, transparency, privacy protection, equity monitoring, and appropriate professional training.

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INTRODUCTION

Chronic diseases such as diabetes mellitus, hypertension, cardiovascular disease, chronic kidney disease, chronic obstructive pulmonary disease, obesity, and heart failure account for a substantial proportion of long-term illness managed in primary care. These conditions require continuous assessment, medication management, preventive counselling, laboratory monitoring, early identification of complications, and coordination across healthcare services. Effective management is especially important because many patients present with multimorbidity, social challenges, limited health literacy, or difficulties adhering to treatment. Primary-care professionals often manage large patient populations within limited consultation periods. Important information may be distributed across laboratory systems, medication records, clinical notes, home-monitoring devices, and referral documents. This fragmentation can delay the identification of deterioration or care gaps. Additional challenges include inconsistent application of clinical guidelines, limited access to specialists, medication non-adherence, workforce shortages, and unequal access to preventive services. These pressures increase the need for tools that can organise clinical information and support timely decisions.

Artificial intelligence-enabled clinical decision-support systems have emerged as one possible response. Artificial intelligence can analyse large datasets, identify patterns, estimate disease risk, extract information from clinical documentation, and provide patient-specific alerts or recommendations. Recent applications include diabetes case finding, cardiovascular risk prediction, chronic kidney disease prediction, diabetic complication detection, retinal screening, patient segmentation, and personalised health education (Cheng et al., 2024; Hewner et al., 2023; Kresnowati et al., 2026; Saban et al., 2025). These systems may support earlier intervention and more efficient use of primary-care resources. However, strong predictive performance does not automatically produce improved clinical outcomes. Calibration problems, limited external validation, workflow disruption, algorithmic bias, and poor data quality may reduce their usefulness. Family nurse practitioners are well positioned to evaluate and apply AI-supported information because they provide comprehensive and continuous primary care. Their responsibilities commonly include assessment, diagnosis, prescribing, chronic disease monitoring, patient education, preventive care, referral, and care coordination. They also consider social, behavioural, and cultural factors that may not be fully represented in algorithmic data. Hewner et al. (2023), for example, showed that machine-learning patient segmentation became more clinically meaningful when expert nursing knowledge guided variable selection and interpretation.

Despite growing interest in healthcare AI, direct evidence concerning its use by family nurse practitioners remains limited. Many studies focus on model performance rather than implementation, professional accountability, patient communication, or long-term outcomes. This creates uncertainty regarding how AI should be incorporated into FNP-led chronic disease care. The aim of this review is to examine the applications, benefits, challenges, and professional implications of AI-enabled clinical decision support in primary-care chronic disease management. Its objectives are to identify major clinical applications, evaluate their relevance to FNP practice, examine ethical and implementation risks, assess required professional competencies, and propose a practical framework for responsible integration.

Conceptual and Theoretical Foundations

Artificial intelligence in healthcare refers to computer-based methods capable of performing tasks that ordinarily require human interpretation, such as recognising patterns, predicting outcomes, processing language, or generating recommendations. Common approaches include machine learning, deep learning, natural language processing, predictive analytics, and rule-supported clinical decision systems. These approaches differ from conventional electronic health records, which primarily store and display information. AI-enabled systems use available data to estimate risk, classify patients, detect abnormalities, or recommend possible actions. Clinical decision-support systems provide information intended to assist healthcare professionals in making patient-care decisions. Their functions may include diagnostic assistance, medication alerts, preventive reminders, risk stratification, identification of care gaps, and monitoring of disease progression. Some systems use predefined clinical rules, while others use machine-learning models developed from large datasets. The distinction is important because not every automated alert or digital tool qualifies as artificial intelligence. AI-supported decision systems should therefore be described according to their actual methods rather than assumed technological sophistication.

The Chronic Care Model provides a useful foundation for understanding how AI may contribute to long-term disease management. The model emphasises productive interaction between informed patients and prepared healthcare teams, supported by clinical information systems, decision support, self-management assistance, organised care delivery, and community resources (Wagner et al., 2001). AI may strengthen several of these components by identifying high-risk patients, supporting planned follow-up, personalising education, and revealing gaps in treatment. However, technology cannot replace coordinated teams, accessible services, or patient participation. The Evidence-Based Practice Framework is also relevant. Evidence-based care combines the best available research evidence with professional expertise and patient values (Sackett et al., 1996). AI-generated recommendations represent one source of information within this process. Family nurse practitioners must determine whether a model is valid, applicable to the patient population, consistent with current guidelines, and acceptable to the patient. This prevents algorithmic output from being treated as an unquestionable instruction. The Technology Acceptance Model explains why technically accurate systems may still fail in practice. It proposes that adoption is strongly influenced by perceived usefulness and perceived ease of use (Davis, 1989). This is reflected in the reviewed evidence. Saman et al. (2022) found that clinicians recognised the clinical value of decision support but reported limited satisfaction and time savings. Training, workflow compatibility, transparency, and technical support are therefore central to adoption.

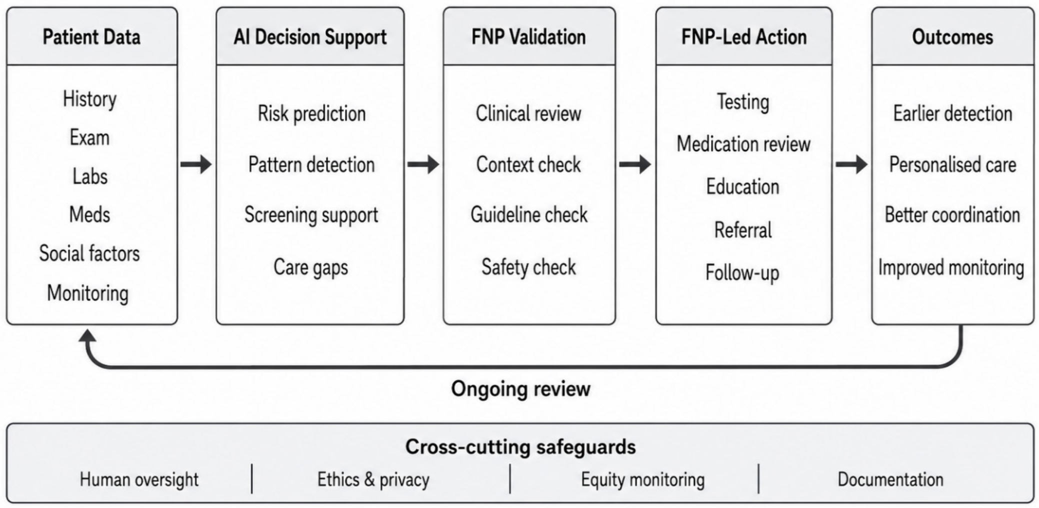
Together, these frameworks position AI as a supportive component within patient-centred chronic care. Patient data are analysed by the system, interpreted by the FNP, discussed with the patient, and translated into personalised action. Outcomes are then monitored and used to revise the care plan. This relationship is presented in Figure 1, with human oversight, ethical governance, privacy protection, and equity monitoring operating across the entire process.

METHODOLOVGY

Review Design

This study used a structured integrative literature review to examine artificial intelligence-enabled clinical decision support in chronic disease management and its implications for family nurse practitioner practice. The design was appropriate because the available evidence included model-development

Figure 1. Conceptual Framework Linking AI, Family Nurse Practitioner Practice, and Patient Outcomes.



studies, external validation studies, qualitative research, implementation studies, reviews, and consensus publications. A narrative approach was used because the studies differed in population, disease focus, AI method, clinical purpose, and outcome measures.

Information Sources

PubMed was the principal database because of its coverage of medicine, nursing, primary care, digital health, and chronic disease research. Google Scholar was explored as a supplementary source, but its results were not formally exported, deduplicated, or included in the numerical screening count. Two PubMed searches were retained. The first focused broadly on AI, clinical decision support, chronic disease management, and primary care. The second focused more narrowly on nurse practitioners, nurse-led care, chronic disease, and clinical decision support.

Search Strategy

The search combined four concepts:

- Artificial intelligence and clinical decision support
- Chronic disease management
- Primary care
- Nursing and nurse practitioner practice

Search terms included "artificial intelligence," "machine learning," "predictive analytics," "clinical decision support," "chronic disease management," diabetes, hypertension, cardiovascular disease, chronic kidney disease, COPD, primary care, family practice, nurse practitioner, advanced practice nursing, and nurse-led care.

The search covered publications from 1 January 2018 to 15 July 2026. Filters were applied for English language, human studies, and free full-text availability. Broader and disease-specific combinations were used where necessary to avoid excluding multidisciplinary primary-care studies that did not mention nurse practitioners in the title or abstract.

Eligibility Criteria

Studies were included when they examined AI, machine learning, natural language processing, predictive analytics, or clinically relevant decision support; addressed chronic disease prevention, detection, treatment, monitoring, or management; had clear primary-care relevance; and reported sufficient information on design, population, technology, and findings. Studies were excluded when they had no relevant AI or decision-support component, focused only on unrelated conditions or acute hospital care, were protocols without results, were editorials or commentaries, presented technical models without a clinical pathway, contained insufficient information, or duplicated another record.Non-AI digital decision-support studies were retained only as contextual evidence when they informed workflow, nurse practitioner involvement, patient communication, or implementation challenges.

Screening Process

The main PubMed export contained 69 records, while the supplementary search added two records. After one duplicate was removed, 70 unique records were screened by title and abstract. Screening involved removal of clearly irrelevant records, assessment of relevance to AI, chronic disease, and primary care, abstract-level review, and classification of eligible publications. Fifteen AI-related publications were retained for the central synthesis, together with two contextual non-AI digital decision-support studies.

Data Extraction and Evidence Classification

Extracted information included author, year, country, setting, design, sample size, chronic disease, AI method, clinical purpose, outcomes, limitations, DOI or PMID, and relevance

Table 1: Search Strategy and Eligibility Criteria

Component	*Description*
Review design	Structured integrative literature review
Primary source	PubMed
Supplementary source	Google Scholar was explored for additional literature, but its results were not included in the formal screening count
Search period	1 January 2018 to 15 July 2026
Filters	English, human studies, and free full text
Main search concepts	Artificial intelligence, machine learning, clinical decision support, chronic disease management, primary care, nursing, and nurse practitioner practice
Inclusion criteria	Studies examining AI-related or clinically relevant decision support for chronic disease management in primary care, with sufficient methodological and outcome information
Exclusion criteria	Protocols without results, unrelated conditions, nonclinical technical studies, duplicate records, and studies without clear primary-care or decision-support relevance
Screening method	Title and abstract screening using predefined eligibility criteria
Evidence classification	Core AI studies, implementation studies, reviews and consensus papers, and contextual non-AI digital decision-support studies
Synthesis method	Narrative and thematic synthesis
Records identified	71
Duplicates removed	1
Records screened	70
Records excluded	53
Publications retained	17, comprising 15 AI-related publications and 2 contextual digital decision-support studies

to family nurse practitioner practice. Numerical findings were recorded only when explicitly reported in the available abstracts.

The retained publications were grouped into core empirical AI studies, implementation and professional-use studies, reviews and consensus papers, and contextual non-AI digital decision-support studies.

Data Synthesis

Because the studies were heterogeneous, findings were synthesised narratively rather than statistically. Themes included risk prediction, patient segmentation, complication detection, screening, education, implementation, explainability, health equity, and professional accountability.

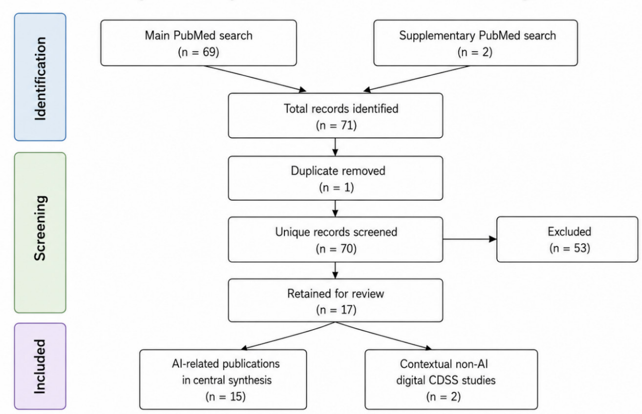
Methodological Limitations

The review relied mainly on PubMed and free full-text studies, so relevant subscription-only publications may have been missed. Google Scholar results were not formally screened. Most evidence was assessed at title and abstract level, and full risk-of-bias appraisal was not completed for every study. Direct FNP evidence was also limited, so some implications were inferred cautiously from related primary-care and nursing roles.

Characteristics of the Included Literature

Seventeen publications were retained for the review, comprising 15 AI-related papers and two contextual digital clinical decision-support studies. The evidence base included empirical machine-learning studies, external validation studies, qualitative research, clinician implementation surveys,

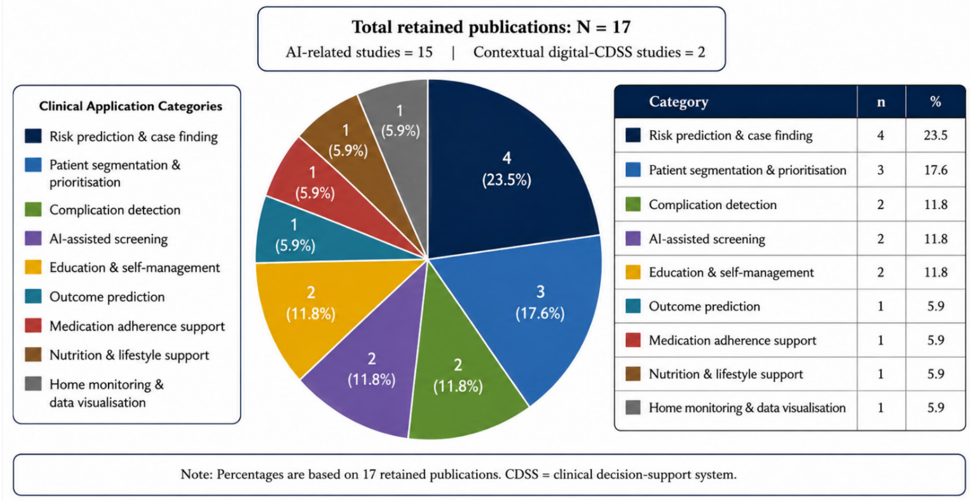
Figure 2. Study Identification and Selection Flow Diagram.



Note: Google Scholar was explored but not included in the numerical screening count.

structured and scoping reviews, and expert consensus work. Most publications appeared between 2022 and 2026, showing that the use of artificial intelligence in chronic disease management is a recent and rapidly developing area. The retained studies were conducted across diverse healthcare settings, including the United States, Hong Kong, China, Indonesia, Israel, Denmark, and broader international or European contexts. Primary-care and community-based studies were particularly relevant, although some hospital-derived evidence was retained where it had clear implications for follow-up, risk stratification, or continuity of care. Sample sizes varied considerably, from small qualitative and professional surveys to large analyses of electronic health

Figure 3. Distribution of Retained Studies by Clinical Application



records. Hewner et al. (2023), for example, analysed 3,438 high-need primary-care patients, including 1,233 people with diabetes, while Saban et al. (2025) examined 2.3 million free-text records from 41,469 patients with diabetes.

Diabetes was the most frequently represented condition, either as the primary disease or as the basis for complications such as chronic kidney disease, diabetic retinopathy, and cardiovascular risk. Other areas included hypertension, heart failure, multimorbidity, medication adherence, nutrition, preventive care, and health equity. This concentration reflects the availability of structured clinical, laboratory, monitoring, and electronic-record data that can support AI-based analysis and prediction.

The technologies studied included supervised and unsupervised machine learning, natural language processing, risk-prediction models, patient-clustering methods, explainable AI, AI-supported image screening, and mobile health education tools. Some studies focused mainly on predictive performance, while others examined usability, workflow integration, clinician acceptance, or patient experience. The evidence also reflected different levels of clinical maturity. For instance, Kresnowati et al. (2026) reported promising predictive performance for chronic kidney disease risk in adults with type 2 diabetes, but the model remained limited by internal validation and required testing in other populations. Direct evidence involving family nurse practitioners was limited. However, several studies examined clinical functions that closely align with FNP responsibilities, including screening, risk assessment, care coordination, patient education, monitoring, and referral. Nursing knowledge also contributed directly to patient segmentation in the study by Hewner et al. (2023). Table 2 summarises the main characteristics of the retained publications.

Applications of AI-Enabled Clinical Decision Support in Chronic Disease Management

Artificial intelligence-enabled clinical decision support is being applied across chronic disease care to improve risk identification, patient prioritisation, complication detection, screening, and self-management. The reviewed evidence shows different levels of clinical maturity. Some systems have been externally validated in primary-care populations, while others remain internally validated models that require broader testing before routine use.

Risk Prediction and Early Case Identification

Risk prediction was the most common application identified. Machine-learning models were used to estimate the likelihood of diabetes, cardiovascular disease, chronic kidney disease, and adverse heart-failure outcomes using demographic, laboratory, medication, and electronic health-record data.

Cheng et al. (2024) externally validated machine-learning and logistic-regression models for identifying undiagnosed prediabetes and diabetes in primary care. The machine-learning model achieved an AUROC of 0.744 and sensitivity of 0.70. However, it underestimated observed risk, showing that acceptable discrimination does not guarantee adequate calibration. For family nurse practitioners, such models may support decisions about glucose testing, lifestyle intervention, and follow-up, but they should not replace clinical assessment.

Kresnowati et al. (2026) evaluated six algorithms for predicting chronic kidney disease among 7,581 adults with type 2 diabetes. CatBoost performed best, with an AUC of 0.847, and SHAP analysis was used to explain the contribution of individual variables. The resulting web-based calculator may help identify patients who require renal testing, medication review, or earlier referral. However, the model was internally validated and requires testing in other populations.

Cardiovascular risk prediction also showed strong performance. Zhou et al. (2025) reported a C-statistic of 0.87 for an AI-supported cardiovascular model. Such systems may assist FNPs in determining the intensity of preventive counselling, monitoring, and referral. Nevertheless, predictive performance alone does not prove that the model improves patient outcomes.

Table 2: Characteristics of the Retained Publications

Author/year	*Country or setting*	*Design/sample*	*Chronic disease or focus*	*AI/CDSS application*	*Main verified finding*
Hewner et al. (2023)	United States; primary-care dataset	Unsupervised ML analysis; 3,438 high-need patients, including 1,233 with diabetes	Diabetes and multimorbidity	K-means patient segmentation informed by nursing knowledge	Four clinically meaningful clusters were linked to actionable medical and social care plans.
Cheng et al. (2024)	Hong Kong primary care	External validation; 1,237 recruited and 919 completed glucose testing	Prediabetes and diabetes	ML and logistic-regression risk models	The ML model showed an AUROC of 0.744 and sensitivity of 0.70, but calibration was inadequate.
Zhou et al. (2025)	Hong Kong healthcare population	Prediction-model development and validation using large EHR cohorts	Cardiovascular disease prevention	XGBoost Cox, LASSO and conventional risk modelling	The full model achieved a C-statistic of 0.87 and outperformed comparator risk models.
Wang et al. (2026)	China; 45 community settings	Qualitative study; 17 adults with type 2 diabetes	Diabetes self-management	AI-enabled health education, reminders and chatbot support	Participants reported improved awareness and self-management support, although chatbot use was limited.
Kresnowati et al. (2026)	Indonesia; national chronic-disease data	Multicentre prediction study; 7,581 adults with type 2 diabetes	CKD risk in diabetes	CatBoost and five comparator algorithms with SHAP	CatBoost performed best, with an AUC of 0.847 and accuracy of 0.797.
Chae et al. (2026)	Hong Kong; 43 hospitals	Multimodal prediction study; 2,868 patients	Heart failure	ML using demographic, medication, laboratory and ECG data	The best model achieved an AUC of 0.881 for 30-day mortality and 0.709 for readmission.
Saban et al. (2025)	Israel; health-service records	NLP development and validation using 2.3 million records from 41,469 patients	Diabetes complications	Rule-based and ML natural language processing	NLP achieved a mean F-score of 86%, compared with 51% for diagnostic codes.
Krogh et al. (2026)	Denmark; 10 primary-care clinics	Prospective validation; 183 patients and 336 retinal images	Diabetic retinopathy	AI-assisted retinal screening	Sensitivity was 73.7%, specificity 90.2%, NPV 98.3% and AUC 0.82; performance improved after poor-quality images were excluded.
Saman et al. (2022)	United States; 36 primary-care clinics	Pre- and post-implementation clinician surveys	Cardiovascular risk in prediabetes	Clinical decision-support system	Most clinicians perceived clinical value, but satisfaction and time-saving ratings were low.
Scheideman et al. (2026)	United States; diabetes professionals	Observational survey; 28 clinicians	Diabetes monitoring	Glycemia Risk Index as a decision-support score	Seventy-five percent were willing to integrate the score into practice, but training and standardisation were required.
Yousefi et al. (2025)	International evidence base	Rapid review; 22 studies	Health promotion and disease reduction	AI-supported preventive and behavioural interventions	AI was commonly applied to diet, physical activity, smoking cessation and mental-health support.
Osonuga et al. (2025)	International primary-care evidence	Structured review; 89 eligible studies and 52 synthesised	Health equity	AI risk stratification, telehealth and NLP	AI may improve access and personalised care, but bias, digital exclusion and poor representation remain major concerns.
Tse et al. (2024)	Hong Kong	Narrative review of healthcare big-data applications	Cardiovascular disease and diabetes	AI-enhanced EHR prediction and risk stratification	Routine EHR data can support large-scale predictive models, but implementation and validation remain essential.
Bajramagic et al. (2026)	European diabetes-care context	Delphi consensus study	Diabetes	AI-enabled clinical decision support	Experts developed 14 recommendations for safe and effective clinical implementation.

Ngo et al. (2025)	International primary-care evidence	Scoping review; 97 studies	Nutrition and chronic disease care	Chatbots, recommendation systems and image or audio recognition	Potential benefits included efficiency and engagement, although effectiveness and safety findings were mixed.
Blecker et al. (2025)	United States; 10 primary-care sites	Cluster RCT; 1,726 adults	Hypertension and medication adherence	Automated identification and digital CDSS alerts	The intervention did not significantly improve medication adherence or blood pressure.
Cohen et al. (2022)	United States primary care	Video-based observational study; 73 visits involving 15 physicians	Hypertension	EHR-integrated home blood-pressure visualisation	Visualisation supported patient–clinician interpretation and decision-making without prolonging discussions.

Table note

AI means artificial intelligence; AUC/AUROC means area under the receiver operating characteristic curve; CDSS means clinical decision-support system; CKD means chronic kidney disease; EHR means electronic health record; ML means machine learning; NLP means natural language processing; NPV means negative predictive value; and SHAP means Shapley Additive Explanations.

Blecker et al. and Cohen et al. are included as contextual digital decision-support studies, not as artificial intelligence studies. The evidence was primarily verified from the exported PubMed titles and abstracts; therefore, claims in the table are restricted to information available in those records

Patient Segmentation and Care Prioritisation

AI may also group patients according to shared medical, behavioural, and social characteristics. Hewner et al. (2023) used k-means clustering to analyse 3,438 high-need primary-care patients, including 1,233 with diabetes. Three expert nurses selected clinically meaningful variables and interpreted four patient groups based on psychosocial and medical needs.

The groups included patients with language barriers, extensive comorbidity, mental-health or substance-use concerns, and renal failure. These clusters were linked to actionable medical and social care plans. This study demonstrates that machine-learning outputs become more useful when combined with nursing knowledge. For FNPs, patient segmentation may support care coordination, follow-up planning, social-service referral, and resource allocation.

Complication Detection and AI-Assisted Screening

Natural language processing can identify information in clinical notes that may not be captured by diagnostic codes. Saban et al. (2025) applied rule-based and machine-learning NLP methods to 2.3 million records from 41,469 patients with diabetes. The system identified complications such as neuropathy, nephropathy, retinopathy, diabetic foot disease, cardiovascular disease, and hypoglycaemia.

The NLP approach achieved a mean F-score of 86%, compared with 51% for diagnostic codes. This suggests that AI may reveal undocumented complications and care gaps. FNPs could use such summaries to support record review, but extracted findings must be checked against the original documentation before clinical action.

Krogh et al. (2026) evaluated AI-assisted diabetic-retinopathy screening in 10 primary-care clinics. The system achieved sensitivity of 73.7%, specificity of 90.2%, and a negative predictive value of 98.3%. The high negative predictive value suggests potential usefulness in ruling out referable disease. However, image quality affected performance, making staff training, quality control, and specialist referral pathways essential.

Prediction of Deterioration and Monitoring

Chae et al. (2026) developed multimodal models using demographic, medication, laboratory, and electrocardiographic data from patients with heart failure. The best model achieved an AUC of 0.881 for 30-day mortality but only 0.709 for readmission. This indicates that AI performance may vary by outcome.

Although the study was hospital-based, the findings may support post-discharge primary care. FNPs could use risk information to prioritise early review, medication reconciliation, symptom assessment, and specialist referral. However, hospital-derived models should not be transferred directly into community practice without external validation.

Cohen et al. (2022) also showed that clear visualisation of home blood-pressure data improved patient-clinician interpretation without prolonging consultations. Although this was not an AI study, it demonstrates that decision support depends partly on how information is presented and integrated into care.

Education, Adherence, and Preventive Support

AI-enabled education tools may extend chronic disease support beyond clinical visits. Wang et al. (2026) found that patients using an AI-supported diabetes education system reported improved awareness and self-management support. However, reminders and educational materials were used more often than chatbot functions, suggesting that simpler features may be more acceptable.

Review evidence also shows growing use of AI for nutrition, physical activity, smoking cessation, and preventive care, although effectiveness remains mixed (Ngo et al., 2025; Yousefi et al., 2025). FNPs may use these tools to reinforce counselling, but recommendations should be reviewed for accuracy, cultural relevance, affordability, and patient preference.

Blecker et al. (2025) showed that automated identification of medication non-adherence and clinical alerts did not significantly improve adherence or blood pressure among

Table 3: Applications of Artificial Intelligence in Chronic Disease Management

AI application	*Chronic disease area*	*Data source or technology*	*Clinical decision supported*	*Verified evidence*	*Implication for FNP practice*
Risk prediction and early case finding	Prediabetes, diabetes, cardiovascular disease, and CKD	EHR, demographic, laboratory, medication, and clinical data analysed with machine-learning models	Identification of patients who require further testing, closer monitoring, preventive treatment, or referral	Cheng et al. reported an AUROC of 0.744 for diabetes case finding, while Kresnowati et al. reported an AUC of 0.847 for CKD prediction in adults with type 2 diabetes	FNPs may use risk estimates to prioritise screening and follow-up, but should confirm predictions with clinical assessment and diagnostic testing
Patient segmentation and care prioritisation	Diabetes and multimorbidity	K-means clustering using psychosocial and clinical variables selected with expert nursing input	Classification of high-need patients into clinically meaningful groups	Hewner et al. identified four patient clusters that were linked to actionable medical and social care plans	Supports care coordination, resource allocation, individualised follow-up, and identification of social needs
Cardiovascular risk stratification	Cardiovascular disease and prediabetes	XGBoost, LASSO, EHR-based prediction models, and cardiovascular clinical decision-support tools	Estimation of future cardiovascular risk and selection of preventive interventions	Zhou et al. reported a C-statistic of 0.87 for the full prediction model; Saman et al. found that most clinicians perceived added clinical value, although satisfaction was limited	FNPs may use risk scores to guide counselling, medication review, referral, and preventive-care intensity
Detection of chronic disease complications	Diabetes and related complications	Natural language processing applied to free-text electronic medical records	Identification of complications not consistently captured by diagnostic codes	Saban et al. reported a mean F-score of 86% for NLP, compared with 51% for diagnostic codes	May help FNPs identify undocumented complications and care gaps, but extracted findings must be reviewed for accuracy
AI-assisted diagnostic screening	Diabetic retinopathy	AI analysis of retinal images obtained in primary-care clinics	Determination of whether ophthalmology referral is required	Krogh et al. reported sensitivity of 73.7%, specificity of 90.2%, and a negative predictive value of 98.3%	Can extend screening access in primary care, although poor-quality images and false-positive results require clear referral and quality-control procedures
Prediction of deterioration and adverse outcomes	Heart failure	Multimodal ML using laboratory, ECG, medication, and demographic data	Prediction of short-term mortality and hospital readmission	Chae et al. reported an AUC of 0.881 for 30-day mortality and 0.709 for readmission	May support post-discharge follow-up and referral prioritisation, but the evidence was derived from hospital data rather than routine FNP-led primary care
Personalised education and self-management support	Type 2 diabetes and preventive care	AI-enabled mobile education, reminders, chatbots, and recommendation systems	Selection and delivery of personalised health information and self-management support	Wang et al. found that patients reported improved awareness and self-management support, although chatbot use was limited; review evidence also showed mixed effects across interventions	FNPs may use AI-supported education between consultations while considering digital literacy, accessibility, and patient preference
Nutrition and lifestyle support	Diabetes, obesity, and other chronic diseases	Chatbots, recommendation systems, and image or audio recognition	Delivery of personalised dietary and behavioural recommendations	Ngo et al. identified potential benefits for efficiency and engagement, but reported mixed evidence regarding effectiveness and safety	AI may supplement FNP counselling, but recommendations should be checked for clinical appropriateness, cultural relevance, and feasibility
Medication adherence and treatment support	Hypertension	Automated identification of non-adherence and EHR-based clinical alerts	Recognition of adherence problems and initiation of patient discussion	Blecker et al. found no significant improvement in medication adherence or blood pressure compared with usual care	Demonstrates that automated alerts alone are insufficient; effective FNP communication, follow-up, and barrier assessment remain necessary

Home monitoring and data visualisation	Hypertension	EHR-integrated presentation of home blood-pressure readings	Interpretation of trends and shared treatment decisions	Cohen et al. found that visualisation supported patient–clinician interpretation without prolonging consultations	FNPs can use clear visual summaries to support shared decision-making, although this study involved digital decision support rather than AI
Health-equity and population-level decision support	Multiple chronic diseases	AI risk stratification, telehealth, NLP, and population-health analytics	Identification of underserved groups, care gaps, and unequal access	Osonuga et al. found potential benefits for access and personalised care but identified risks from bias, digital exclusion, and unrepresentative data	FNPs should consider whether AI tools perform fairly across demographic groups and avoid relying on outputs that may worsen disparities
Professional and organisational decision support	Diabetes and chronic disease management	AI-CDSS roadmaps, risk indices, and implementation frameworks	Safe adoption, workflow integration, and interpretation of AI recommendations	Bajramagic et al. developed 14 consensus recommendations, while Scheideman et al. found that clinicians were generally willing to use a glycaemic risk index but required training and standardisation	FNP adoption requires AI literacy, clear governance, workflow compatibility, and continued professional accountability

Table note: AI means artificial intelligence; AUC/AUROC means area under the receiver operating characteristic curve; CDSS means clinical decision-support system; CKD means chronic kidney disease; ECG means electrocardiography; EHR means electronic health record; FNP means family nurse practitioner; ML means machine learning; and NLP means natural language processing. Blecker et al. and Cohen et al. are included as contextual digital decision-support evidence and should not be described as AI studies.

1,726 patients with hypertension. Although the system was not explicitly AI-based, the finding demonstrates that alerts alone are insufficient. Effective communication, assessment of adherence barriers, shared decision-making, and continued follow-up remain essential.

Overall, AI-enabled clinical decision support is most useful when it converts complex data into clear and actionable information. Family nurse practitioners remain responsible for validating outputs, considering the wider clinical and social context, and deciding whether the recommendation is appropriate. Table 3 summarises the principal applications.

Benefits for Family Nurse Practitioner Practice

Artificial intelligence-enabled clinical decision support offers important benefits for family nurse practitioner practice, particularly in screening, risk assessment, monitoring, care coordination, and patient education. The reviewed evidence suggests that AI is most useful when it helps practitioners interpret complex clinical information and identify patients who may need earlier or more intensive intervention. These benefits, however, depend on accurate data, appropriate workflow integration, and continued clinical oversight.

Improved Clinical Decision-Making

AI systems can organise patient information, generate risk estimates, and identify patterns that may be difficult to recognise during a brief consultation. Cheng et al. (2024) demonstrated that machine-learning models could support the identification of patients at risk of prediabetes and diabetes in primary care. Zhou et al. (2025) similarly reported that an AI-supported cardiovascular prediction model showed stronger discrimination than conventional risk models in the population studied.

For FNPs, these systems may inform decisions about diagnostic testing, preventive counselling, medication review, follow-up intensity, and specialist referral. They may also reduce the burden of manually reviewing large electronic health records. Nevertheless, AI output should be considered alongside clinical examination, patient history, current guidelines, and patient preferences. Poor calibration or incomplete data may produce recommendations that are not appropriate for an individual patient.

Earlier Identification of High-Risk Patients

Early recognition of disease progression is essential to preventing chronic disease complications. AI-supported prediction may help FNPs identify patients whose clinical results appear stable but whose combined risk factors suggest a greater likelihood of deterioration. Kresnowati et al. (2026) developed a machine-learning model for predicting chronic kidney disease among adults with type 2 diabetes. The model could support decisions concerning renal-function testing, medication review, nephroprotective interventions, and referral. Natural language processing may also identify complications that are not consistently represented in diagnostic codes. Saban et al. (2025) reported that NLP detected diabetes-related complications more effectively than structured diagnostic coding alone. This could help FNPs recognise possible neuropathy, nephropathy, retinopathy, diabetic foot disease, cardiovascular complications, or hypoglycaemia that might otherwise be overlooked. However, AI-generated findings must be confirmed against the original clinical record.

Personalised Care and Patient Prioritisation

Family nurse practitioners frequently manage patients with multimorbidity, social challenges, and different levels of healthcare need. Hewner et al. (2023) showed that machine learning combined with expert nursing knowledge could classify high-need primary-care patients into clinically meaningful groups. The resulting clusters reflected factors such as comorbidity, language barriers, mental-health concerns, substance use, and renal disease. Such segmentation may help FNPs determine which patients require intensive follow-up, social-service referral, medication support, or multidisciplinary care. It also recognises that chronic disease outcomes are influenced by social and behavioural circumstances, not only laboratory measurements. AI may therefore support more efficient allocation of limited primary-care resources while allowing interventions to be adapted to individual needs.

Improved Screening and Referral

AI-assisted screening may expand access to preventive services within primary care. Krogh et al. (2026) reported that an AI-supported diabetic-retinopathy screening system achieved high specificity and a negative predictive value of 98.3%. This suggests that the technology may help distinguish patients who are unlikely to have referable disease from those requiring ophthalmological assessment. For FNPs, primary-care screening could support earlier detection and reduce delays in referral. However, image quality affected system performance, meaning that staff training, equipment standards, and specialist referral pathways remain necessary. Practitioners must also consider the consequences of false-positive and false-negative classifications.

Patient Education and Self-Management

Chronic disease outcomes depend greatly on patient behaviour between consultations. AI-supported educational platforms can provide reminders, personalised information, monitoring prompts, and lifestyle guidance. Wang et al. (2026) found that patients using an AI-enabled diabetes education system reported improved awareness and self-management support. However, patients used simple reminders and educational materials more frequently than chatbot functions. FNPs may use these tools to reinforce medication routines, dietary goals, physical activity, symptom awareness, and monitoring schedules. Their suitability should be evaluated according to health literacy, language, cultural background, affordability, digital skills, and access to technology. AI-based education should strengthen, rather than replace, direct patient communication.

Workflow Support and Professional Efficiency

AI may assist FNPs by summarising records, prioritising high-risk cases, and identifying care gaps. However, implementation evidence shows that clinical usefulness does not always translate into time savings or improved outcomes. Saman et al. (2022) found that many clinicians perceived value in decision support, but satisfaction and reported efficiency remained limited. Similarly, automated adherence alerts did not significantly improve medication adherence or blood pressure in the trial by Blecker et al. (2025). This shows that technology alone cannot resolve behavioural, financial, or social barriers to treatment. Effective FNP communication, shared decision-making, and continued follow-up remain essential.

Overall, AI can strengthen FNP practice through earlier detection, personalised care, improved screening, and better prioritisation. Its benefits are greatest when it complements professional judgement and patient-centred care rather than wreplacing them.

Implications for Family Nurse Practitioner Roles and Responsibilities

The integration of artificial intelligence into chronic disease management is likely to expand, rather than reduce, the responsibilities of family nurse practitioners. AI can assist with risk prediction, patient prioritisation, screening, documentation, and self-management support, but it also introduces new duties related to interpretation, validation, communication, and accountability. Family nurse practitioners must therefore combine digital competence with established clinical judgement and patient-centred care.

Changing Clinical Responsibilities

AI-supported systems may shift some aspects of practice from routine data review toward interpretation of risk scores, verification of alerts, and coordination of complex care. For example, patient-segmentation methods can identify groups with different medical and social needs, allowing practitioners to prioritise follow-up and referrals more efficiently. Hewner et al. (2023) showed that machine-learning clusters became clinically meaningful when expert nurses selected relevant variables and interpreted the results. This suggests that nurses should participate actively in AI design and implementation rather than serve only as end users. Family nurse practitioners may also assume a larger role in deciding whether AI-generated recommendations are clinically appropriate. A high-risk classification may prompt additional laboratory testing, medication review, preventive counselling, or referral, but the practitioner must consider symptoms, comorbidities, social circumstances, and patient preferences before acting.

Clinical Judgement and Accountability

AI does not remove professional accountability. Prediction models may perform well at the population level while remaining inaccurate for individual patients. Cheng et al. (2024), for instance, reported acceptable discrimination for diabetes case finding but also identified calibration problems. This means that a model may rank risk reasonably well while still underestimating or overestimating the probability of disease. Family nurse practitioners must understand these limitations and document how AI outputs influenced clinical decisions. They should record whether a recommendation was accepted, modified, or rejected and explain the clinical reasoning behind that decision. This is particularly important where algorithmic advice conflicts with the patient's presentation or established clinical guidelines. Over-reliance on automated recommendations may lead to automation bias, while ignoring useful alerts may result in missed opportunities for early intervention.

Patient Communication and Shared Decision-Making

The use of AI also affects the relationship between practitioners and patients. Risk scores and automated recommendations may appear authoritative, even when they contain uncertainty. FNPs must explain outputs in language patients can understand and clarify that AI provides support rather than a final diagnosis.

Patient education should remain individualised. Wang et al. (2026) found that patients valued AI-supported diabetes education, although simple reminders and educational materials were used more often than chatbot functions. This indicates that technology should be matched to patient preferences, health literacy, digital skills, and access. Practitioners should also discuss privacy concerns and obtain informed agreement when patient data are used in AI-supported systems.

Interprofessional Collaboration

Effective AI implementation requires collaboration among FNPs, physicians, pharmacists, information-technology professionals, data scientists, administrators, and specialists. Family nurse practitioners can contribute practical knowledge about clinical workflow, patient communication, and continuity of care. Their involvement may help prevent systems from generating alerts that are difficult to interpret or impossible to act upon. Implementation evidence shows why this is necessary. Saman et al. (2022) found that many clinicians recognised the value of a cardiovascular decision-support system, but satisfaction and perceived time savings remained limited. This suggests that technical accuracy alone does not ensure adoption. Systems must fit routine practice, provide clear recommendations, and avoid unnecessary disruption.

Scope of Practice and Human Oversight

Healthcare organisations should define who may act on AI recommendations, when specialist consultation is required, and how errors should be reported. FNPs should not use AI beyond their legal scope of practice or rely on tools that have not been validated for the relevant population. Human oversight remains essential because AI may reproduce bias, misinterpret incomplete records, or generate unsuitable recommendations. The role of the FNP is therefore not simply to follow algorithmic output, but to evaluate it critically, communicate uncertainty, and protect patient safety. Table 4 summarises the principal implications for practice.

Implementation Challenges and Risks

The implementation of artificial intelligence in chronic disease management introduces clinical, technical, ethical, and organisational challenges that may limit its value in family nurse practitioner practice. Although several reviewed studies reported promising predictive performance, successful adoption depends on more than algorithm accuracy. Data quality, workflow integration, fairness, transparency, privacy, infrastructure, and professional accountability must all be addressed before AI-enabled systems can be used safely in routine primary care.

Data Quality and Interoperability

AI systems depend on the accuracy, completeness, and consistency of the data used for training and clinical prediction. Missing laboratory results, outdated medication lists, inconsistent diagnostic coding, and incomplete documentation may lead to unreliable recommendations. This concern is particularly important in chronic disease care, where risk estimates often depend on trends observed across several visits rather than a single measurement. Saban et al. (2025) showed that natural language processing could identify diabetes-related complications more effectively than diagnostic codes alone, indicating that important clinical information may remain hidden in free-text notes. However, such systems may also misinterpret abbreviations, ambiguous statements, copied documentation, or negated findings. Family nurse practitioners must therefore confirm AI-generated summaries against the original record before acting on them. Interoperability presents an additional barrier. AI tools may need to connect with electronic health records, laboratory systems, pharmacy databases, remote-monitoring devices, and referral platforms. When these systems cannot exchange information effectively, clinicians may need to enter the same data repeatedly or review several disconnected interfaces. This can increase workload and reduce confidence in the technology. AI adoption should therefore be accompanied by reliable data standards, structured documentation practices, and technical integration with existing clinical workflows.

Algorithmic Bias and Health Equity

AI systems may reproduce or intensify inequalities present in the data used to develop them. If training datasets underrepresent rural communities, racial and ethnic minority groups, low-income populations, older adults, women, or patients with multiple chronic conditions, model performance may vary across groups. Osonuga et al. (2025) found that AI may improve access and personalised care in underserved populations, but also identified risks related to algorithmic bias, digital exclusion, and poor representation in training data.

This issue is especially relevant to FNP practice because family nurse practitioners often serve populations with limited access to specialists, transportation, internet services, or digital devices. A system that assumes regular internet access or continuous device use may be unsuitable for some patients. Similarly, a prediction model developed in one country or ethnic population may not be reliable in another. Cheng et al. (2024) demonstrated this concern by reporting calibration limitations in a diabetes risk model, despite acceptable discrimination. Health-equity safeguards should therefore

Table 4: Implications for Family Nurse Practitioner Practice

FNP responsibility	*Potential AI contribution*	*Required FNP action*	*Main risk or limitation*
Comprehensive assessment	Identifies hidden patterns across symptoms, laboratory data, medications, and social factors	Compare AI output with history, examination, and current evidence	Incomplete or inaccurate data may produce misleading recommendations
Risk stratification	Estimates the likelihood of diabetes, cardiovascular events, CKD, deterioration, or complications	Use scores to prioritise testing, monitoring, and referral	Poor calibration or limited external validation may reduce reliability
Screening and case finding	Supports identification of patients requiring glucose testing, retinal screening, or further evaluation	Confirm results and follow established diagnostic pathways	False-positive or false-negative classifications
Treatment planning	Generates patient-specific recommendations based on clinical patterns and risk	Consider comorbidities, patient preferences, affordability, and guidelines before acting	Automation bias and over-reliance on system recommendations
Medication management	Flags adherence problems, possible risks, or patients requiring medication review	Assess barriers, reconcile medicines, and discuss options with the patient	Alerts alone may not improve adherence or outcomes
Monitoring and follow-up	Detects changes in risk, symptoms, laboratory results, or home-monitoring data	Determine urgency, arrange follow-up, and escalate care when necessary	Alert fatigue and unnecessary interventions
Patient prioritisation	Groups patients according to clinical, behavioural, and social needs	Allocate follow-up intensity and coordinate multidisciplinary support	Clusters may oversimplify individual circumstances
Patient education	Delivers reminders and personalised self-management information	Check accuracy, explain recommendations, and adapt content to patient needs	Digital exclusion, low health literacy, and culturally unsuitable advice
Care coordination	Identifies care gaps and supports referral planning	Communicate with physicians, pharmacists, specialists, and social services	Poor interoperability may fragment care further
Clinical documentation	Extracts complications and relevant information from free-text records	Verify extracted information before documenting or acting	NLP errors, missing context, and misclassification
Shared decision-making	Presents risks and options in a structured form	Explain uncertainty and involve the patient in final decisions	Patients may misunderstand AI outputs as definite conclusions
Professional accountability	Supports evidence-informed reasoning but does not replace judgement	Document how AI output was reviewed and why recommendations were accepted or rejected	Unclear legal responsibility when AI contributes to an error
Health-equity protection	May identify underserved patients and population-level care gaps	Examine performance across demographic groups and challenge biased outputs	Biased training data may reinforce existing disparities
Quality improvement	Enables monitoring of care gaps, outcomes, and system performance	Report errors, evaluate outcomes, and participate in audits	Weak governance may allow unsafe systems to remain in use

Table note: AI means artificial intelligence; CKD means chronic kidney disease; FNP means family nurse practitioner; and NLP means natural language processing. AI should be used as a support tool, while final responsibility for assessment, interpretation, communication, and clinical action remains with the FNP.

include subgroup performance testing, transparent reporting of population characteristics, and ongoing monitoring after implementation. FNPs should question whether a model has been validated in patients similar to those they serve.

Explainability and Transparency

Many AI models produce risk scores without clearly showing how the recommendation was generated. This lack of transparency can reduce clinician trust and make it difficult to explain decisions to patients. Explainable methods, such as SHAP, may help identify which variables contributed most to a prediction. Kresnowati et al. (2026) used SHAP analysis in a chronic kidney disease prediction model, which may improve clinical interpretation. However, explainability does not guarantee correctness. A system may provide a clear explanation for a prediction that is still based on biased or incomplete data. FNPs need sufficient AI literacy to interpret model outputs, recognise uncertainty, and avoid presenting predictions as definitive conclusions.

Privacy and Data Security

AI systems often require large amounts of sensitive patient information, including diagnoses, medication histories, laboratory values, social factors, and remote-monitoring data. This creates risks related to unauthorised access, cyberattacks, secondary data use, and third-party vendors. Patients may not understand how their information is collected, stored, or used to train algorithms. Healthcare organisations should establish clear consent procedures, access controls, encryption standards, and data-sharing agreements. FNPs should be able to explain how patient information is used and identify situations in which privacy concerns outweigh potential benefits.

Alert Fatigue and Automation Bias

Poorly designed systems may generate excessive alerts, many of which may be irrelevant or low priority. Over time, clinicians may ignore warnings, including those that are clinically important. Saman et al. (2022) found that clinicians recognised the value of decision support but reported limited satisfaction and time savings, suggesting that workflow burden can weaken adoption. Automation bias presents the opposite risk. Clinicians may accept recommendations without sufficient review because the output appears objective or technologically advanced. Blecker et al. (2025) showed that automated adherence alerts did not improve medication adherence or blood pressure, demonstrating that alerts alone cannot replace communication, counselling, and continued follow-up.

Cost, Infrastructure, and Organisational Readiness

AI implementation may require software licensing, staff training, system maintenance, technical support, cybersecurity investment, and reliable internet access. Smaller practices and rural clinics may struggle to meet these requirements. Even a high-performing model may fail if staff lack training or if the system interrupts established workflows.

Organisations should assess readiness before adoption and introduce systems gradually. Pilot testing, staff consultation, performance auditing, and technical support are necessary to reduce disruption and identify unintended consequences.

Legal and Regulatory Concerns

Uncertainty remains regarding responsibility when an AI-supported decision contributes to patient harm. It may be unclear whether liability rests with the practitioner, healthcare organisation, software developer, or data provider. FNPs remain professionally responsible for the decisions they make, even when those decisions are informed by AI. Healthcare institutions should establish policies on documentation, validation, escalation, and error reporting. AI systems should operate within professional scope-of-practice requirements and should not be used as substitutes for clinical judgement. Table 5 summarises the major implementation barriers and the competencies required for safe use.

Proposed AI-Enabled Family Nurse Practitioner Practice Framework

The proposed framework presents a practical pathway for integrating artificial intelligence-enabled clinical decision support into family nurse practitioner-led chronic disease care. It is designed to preserve human oversight while using AI to strengthen assessment, risk identification, care planning, and follow-up.

Patient Assessment and Data Collection

The process begins with a comprehensive patient assessment. Relevant information may include medical history, symptoms, physical findings, laboratory results, medication records, social determinants of health, patient-reported outcomes, and data from remote-monitoring devices. Accurate data collection is essential because incomplete or outdated information can weaken the quality of AI-generated recommendations.

Family nurse practitioners should also identify contextual factors that may not be fully captured in electronic systems, such as financial barriers, health literacy, family support, cultural beliefs, and access to transportation or technology.

Data Integration and AI-Supported Analysis

The collected information is then integrated into an AI-enabled clinical decision-support system. Depending on the application, the system may perform risk prediction, patient segmentation, pattern recognition, complication detection, or identification of care gaps. For example, machine-learning models may estimate the risk of diabetes, chronic kidney disease, cardiovascular events, or deterioration, while natural language processing may extract complications from clinical notes. Evidence from Hewner et al. (2023), Cheng et al. (2024), and Kresnowati et al. (2026) shows that these tools can support patient prioritisation and risk assessment when used cautiously.

FNP Validation and Contextual Judgement

AI output should never move directly into clinical action without professional review. The FNP must compare the recommendation with the patient's current condition, history, comorbidities, medications, preferences, and available resources. This stage is critical because a model may perform well overall but remain poorly calibrated for certain patients or populations. The practitioner should determine whether the output is clinically plausible, whether confirmatory testing is required, and whether the recommendation falls within professional scope of practice.

Shared Decision-Making

Once the output has been reviewed, the FNP should explain the findings to the patient in clear language. Risk scores and predictions should be presented as estimates rather than certain outcomes. The patient should be involved in deciding whether to proceed with testing, referral, medication adjustment, lifestyle intervention, or monitoring. This preserves autonomy and reduces the risk that AI recommendations are treated as unquestionable instructions.

Personalised Intervention

The next stage involves selecting an intervention based on the combined evidence from the AI system, clinical judgement, and patient preference. Possible actions include:

- Diagnostic testing
- Medication review or adjustment
- Preventive counselling
- Referral to a specialist
- Remote monitoring
- Self-management education
- Social-service coordination
- More frequent follow-up

The intervention should be realistic, affordable, culturally appropriate, and suited to the patient's level of digital access.

Table 5: Implementation Barriers and Required Competencies

Implementation barrier	*Likely consequence for practice*	*Required FNP competency*	*Recommended organisational response*
Poor data quality	Inaccurate risk estimates, missed complications, or inappropriate recommendations	Ability to assess data completeness and question unreliable outputs	Routine data-quality checks, standardised documentation, and regular EHR audits
Limited interoperability	Fragmented information, repeated data entry, and workflow delays	Competence in navigating integrated digital systems and identifying missing information	Connect AI tools with EHR, laboratory, pharmacy, referral, and remote-monitoring systems
Algorithmic bias	Unequal performance across demographic or socioeconomic groups	Ability to recognise bias and assess whether a model is suitable for the patient population	Test model performance across subgroups and conduct regular fairness audits
Digital exclusion	Reduced access for patients with limited internet, devices, literacy, or technical skills	Ability to assess digital readiness and provide alternative care options	Offer non-digital pathways, accessible interfaces, language support, and patient training
Limited explainability	Reduced clinician trust and difficulty explaining recommendations to patients	Ability to interpret risk scores, model limitations, and uncertainty	Prefer transparent systems and provide clear explanations of influential variables
Privacy and cybersecurity risks	Breach of confidentiality, loss of patient trust, and unauthorised data use	Knowledge of consent, confidentiality, and secure data handling	Use encryption, access controls, vendor agreements, and incident-response procedures
Alert fatigue	Important warnings may be overlooked because of excessive notifications	Ability to prioritise alerts according to clinical urgency	Reduce low-value alerts and tailor thresholds to clinical workflow
Automation bias	Uncritical acceptance of incorrect or unsuitable recommendations	Critical appraisal and independent clinical judgement	Require human review before clinical action and audit AI-related decisions
Workflow disruption	Increased workload, longer consultations, and poor user acceptance	Ability to incorporate AI into routine assessment without weakening patient interaction	Conduct pilot testing and involve FNPs in system design and implementation
Insufficient training	Misinterpretation of outputs and unsafe use of AI tools	AI literacy, digital competence, and ethical decision-making	Provide continuing education, simulation, and competency assessment
Cost and infrastructure limitations	Unequal adoption across rural, community, and low-resource practices	Ability to evaluate whether the technology is feasible and clinically valuable	Assess cost-effectiveness and provide technical, financial, and internet support
Unclear legal responsibility	Uncertainty regarding liability when AI contributes to harm	Knowledge of professional accountability and scope of practice	Establish clear policies for validation, documentation, escalation, and error reporting
Weak clinical validation	Use of models that perform poorly outside their original population	Ability to examine external validation and population relevance	Require local testing before implementation and monitor real-world performance
Patient mistrust or misunderstanding	Refusal to use the technology or overconfidence in AI-generated results	Clear communication, shared decision-making, and explanation of uncertainty	Provide transparent patient information and obtain informed agreement where appropriate
Inadequate governance	Continued use of unsafe, outdated, or biased systems	Ability to report problems and participate in quality improvement	Create multidisciplinary AI-governance committees and schedule regular system reviews

Table note: AI means artificial intelligence; EHR means electronic health record; and FNP means family nurse practitioner. Safe implementation requires both practitioner competence and organisational safeguards. Final clinical responsibility remains with the healthcare professional using the system.

Monitoring and Outcome Evaluation

After implementation, the FNP should monitor clinical outcomes, adherence, symptoms, laboratory trends, and patient experience. AI-supported systems may help identify changes over time, but they should not replace direct reassessment. The final stage is outcome evaluation and care-plan adjustment. If the patient improves, the current plan may continue. If risk increases or the intervention is ineffective, the FNP should reassess the patient, review the AI output, and modify the plan.

Across all stages, the framework requires three safeguards: human clinical oversight, privacy and ethical governance, and continuous monitoring for bias and unequal performance.

Education and Organizational Preparedness

Safe use of AI in family nurse practitioner practice requires both individual competence and organizational readiness. Technology should not be introduced without training, governance, and clear clinical procedures.

AI Literacy

Family nurse practitioners need a basic understanding of how AI systems are developed, what data they use, and what their outputs mean. This does not require advanced programming knowledge, but practitioners should understand concepts such as model training, validation, discrimination, calibration, sensitivity, specificity, and predictive value.

Without this knowledge, there is a risk that AI outputs will be accepted uncritically or misunderstood.

Interpretation of Risk Scores

FNPs should be trained to interpret risk estimates in relation to the individual patient. A high score does not automatically confirm disease, while a low score does not eliminate risk. Practitioners should consider whether the model has been externally validated, whether it was developed in a similar population, and whether the patient's data are complete. Cheng et al. (2024) showed that acceptable discrimination can coexist with calibration problems, highlighting the need for cautious interpretation.

Recognition of Bias and Ethical Use

Training should also cover algorithmic bias, health equity, privacy, informed consent, and professional accountability. FNPs must be able to recognise when a system may underperform in underserved or underrepresented groups. Osonuga et al. (2025) emphasised that AI may improve access while also increasing digital exclusion and inequity if systems are not designed and monitored carefully.

Continuing Professional Development

AI education should be incorporated into graduate nursing programmes, clinical simulation, continuing education, and workplace training. Ongoing learning is necessary because AI tools and regulatory expectations are changing rapidly. Training should include case-based exercises, interpretation of model outputs, communication of uncertainty, and management of incorrect recommendations.

Organizational Training and Governance

Healthcare organizations should establish multidisciplinary governance structures involving clinicians, nurses, information-technology staff, data specialists, administrators, and patient representatives.

Organizational responsibilities should include:

- Local validation before implementation
- Staff training and competency assessment
- Data-quality monitoring
- Bias and fairness audits
- Cybersecurity safeguards
- Clear documentation standards
- Incident reporting and escalation procedures
- Regular review of system performance

Bajramagic et al. (2026) emphasised the importance of governance, professional education, and safe implementation when moving AI-enabled decision support into diabetes care.

Organizational preparedness should also include sufficient technical support, workflow testing, and time for staff adaptation. Without these measures, even a technically strong AI system may fail to improve care.

DISCUSSION

The reviewed evidence indicates that artificial intelligence can strengthen chronic disease management by supporting risk prediction, complication detection, patient prioritisation, screening, and self-management. The strongest evidence was found in diabetes-related applications, including case finding, chronic kidney disease prediction, diabetic complication detection, and retinal screening. This concentration likely reflects the availability of structured laboratory, medication, and electronic health-record data suitable for algorithmic analysis. Several studies reported promising predictive performance. Cheng et al. (2024) demonstrated that machine learning could support diabetes case finding in primary care, while Kresnowati et al. (2026) reported strong discrimination for chronic kidney disease prediction among adults with type 2 diabetes. Zhou et al. (2025) also found that an AI-based cardiovascular risk model outperformed conventional comparators. However, model performance alone does not demonstrate improved clinical outcomes. Calibration problems, internal validation, population differences, and limited implementation testing reduce the certainty that these tools will perform equally well in routine practice.

The evidence also shows that clinical expertise remains essential. Hewner et al. (2023) demonstrated that machine-learning patient clusters became more useful when expert nurses selected relevant variables and translated the findings into practical care plans. This is particularly important for family nurse practitioners because chronic disease management involves social, behavioural, and clinical factors that may not be fully represented in algorithmic data. AI can organise information, but FNPs must determine whether the output is appropriate for the individual patient. Implementation findings were mixed. Saman et al. (2022) found that clinicians recognised the value of clinical decision support, although satisfaction and perceived time savings were limited. Blecker et al. (2025) similarly reported that automated adherence identification and alerts did not improve medication adherence or blood pressure. These findings suggest that technology cannot replace patient communication, shared decision-making, and sustained follow-up.

AI-supported education and screening may offer practical benefits. Wang et al. (2026) found that patients valued personalised diabetes education, although simpler reminders were more acceptable than chatbot functions. Krogh et al. (2026) reported promising results for AI-assisted diabetic-retinopathy screening, but performance depended on image quality and appropriate referral pathways. For FNP practice, the main benefit of AI lies in supporting earlier detection and better prioritisation rather than replacing professional judgement. The evidence is strongest for predictive accuracy and information processing but remains limited regarding long-term outcomes, cost-effectiveness, workload reduction, and direct FNP-led implementation. Future studies should therefore evaluate AI systems in real primary-care settings and measure patient outcomes, equity, workflow effects, and professional accountability.

RECOMMENDATIONS FOR PRACTICE, POLICY, AND RESEARCH

Clinical Practice

Family nurse practitioners should use AI-enabled clinical decision support as an aid to assessment, screening, monitoring, and care planning, not as a replacement for professional judgement. Risk scores and recommendations should be checked against patient history, examination findings, comorbidities, preferences, and current guidelines. Where validation is limited, confirmatory testing and closer review are necessary. FNPs should also explain AI-supported findings clearly and involve patients in decisions about testing, treatment, referral, and remote monitoring. Digital tools should be selected with attention to health literacy, language, culture, affordability, and access to technology.

Healthcare Organizations

Healthcare organizations should validate AI systems in local populations before routine use. Implementation should include pilot testing, staff consultation, workflow assessment, cybersecurity safeguards, and continuous outcome monitoring. Multidisciplinary governance committees should oversee data quality, algorithmic bias, privacy, incident reporting, and system updates. Organizations should also provide training in AI literacy, risk interpretation, documentation, and professional accountability. Alert systems should prioritise clinically important information and reduce unnecessary notifications.

Professional Bodies and Policymakers

Professional organizations and regulators should develop clear standards for AI use in advanced practice nursing. These should address scope of practice, informed consent, documentation, human oversight, competency requirements, and responsibility when AI contributes to harm. Policymakers should require transparent reporting of model development, validation populations, subgroup performance, and known limitations. Support is also needed to prevent rural and low-resource practices from being excluded because of poor infrastructure.

Future Research

Future studies should evaluate AI in real-world FNP-led and multidisciplinary primary-care settings. Research should measure patient outcomes, workload, consultation time, cost-effectiveness, clinician acceptance, and unintended effects rather than focusing only on predictive accuracy. Longitudinal studies should also examine whether AI reduces complications, hospitalisations, and health disparities. Greater attention should be given to FNP participation in system design, implementation, and evaluation.

LIMITATIONS

This review relied mainly on PubMed, so studies indexed only in CINAHL, Scopus, Web of Science, IEEE Xplore, or other databases may have been missed. The free full-text filter may also have excluded relevant subscription-only publications. Google Scholar was explored, but its results were not formally exported, deduplicated, or included in the numerical screening process. The evidence audit was conducted mainly at the title and abstract level, and a complete full-text risk-of-bias appraisal was not performed for every retained study. Direct evidence involving family nurse practitioners was limited. Some implications were therefore inferred cautiously from studies involving nurses, primary-care clinicians, multidisciplinary teams, or tasks commonly performed by FNPs. The included studies also differed widely in design, population, chronic disease, AI method, setting, and outcomes. This heterogeneity made meta-analysis inappropriate. The findings should therefore be interpreted as a structured synthesis rather than a comprehensive review of all available evidence.

CONCLUSION

Artificial intelligence-enabled clinical decision support has strong potential to improve chronic disease management in primary care. The reviewed evidence shows that AI can support risk prediction, patient segmentation, complication detection, screening, education, and prioritisation of high-need patients. The most developed applications were found in diabetes, cardiovascular risk, chronic kidney disease, and diabetes-related complications. For family nurse practitioners, AI may support earlier intervention, personalised follow-up, referral, and care coordination. However, predictive accuracy alone does not guarantee better outcomes. Poor calibration, weak external validation, data-quality problems, workflow disruption, bias, and digital exclusion may limit clinical value. Human oversight therefore remains essential. FNPs must interpret AI recommendations within the patient's full clinical and social context, communicate uncertainty, and remain responsible for final decisions. Technology cannot replace empathy, professional accountability, shared decision-making, or sustained patient engagement. Safe implementation requires training, transparent governance, privacy protection, local validation, fairness monitoring, and clear documentation standards. AI should be treated as a clinical support resource, not an independent decision-maker. Its value will depend on whether it strengthens evidence-based, equitable, and patient-centred care.

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