

Can Digital Tools Predict Future Health Risks in Family Medicine Using Ontomorph?

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Abstract

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Family doctors are trained to prevent disease, not just treat it. Yet prevention often depends on predicting what might happen in the future. Will this patient develop diabetes? Will that patient have a heart attack? Who is at risk for cancer, and who needs screening? In recent years, digital tools have emerged that attempt to answer these questions using patient data, genomic information, and machine learning. These tools project future health risks and simulate the effects of different interventions. This narrative review examines whether such tools may help family doctors prevent and manage chronic diseases. Ontomorph is used as a case example of a platform that proposes "what-if" simulations and ten-year risk projections based on a patient's genome, laboratory results, and lifestyle data. The review also considers the practical and ethical issues of using future-risk projections in primary care, drawing on recent literature. The evidence suggests that digital risk prediction may improve case finding, support shared decision-making, and enhance preventive care. However, challenges remain, including validation, bias, patient anxiety, workflow integration, and unclear liability. Family doctors should engage with these tools critically, ensuring that they serve patient care rather than adding to the burden of practice.

Keywords: Predictive tools, Ontomorph, Family Medicine, Clinical work flow, Digital Twins

Introduction

The goal of family medicine is not only to treat illness but to prevent it. A family doctor who identifies a patient at risk for diabetes can offer lifestyle counseling before the disease develops. A doctor who recognizes a patient at risk for heart disease can prescribe a statin before a heart attack occurs. Prevention depends on prediction. It requires looking ahead and asking what might happen.¹

Traditionally, prediction has relied on clinical judgment and simple risk scores. A doctor might use age, blood pressure, cholesterol, and smoking status to estimate cardiovascular risk. These tools are useful but limited. They do not account for genetic factors, lifestyle changes over time, or the complex interactions between different health conditions.²

In recent years, digital tools have emerged that attempt to improve prediction. These tools use machine learning algorithms, large datasets, and genomic information to project future health risks. They can simulate the effect of changing a single variable, such as starting a medication or losing weight. They can show patients what their risk might look like in ten years if they act now versus if they do nothing.³

Ontomorph is one example of this approach. Its platform proposes simulation features that project a patient's health trajectory over time. A patient with a ten-year cardiovascular risk of 12% can see how that risk might change with lifestyle modifications. A patient with a BRCA1 variant can see the organs affected and the screening recommendations timed to that risk.⁴ The platform's stated goal is to catch conditions before they become diagnoses.

This review asks a practical question: Can digital risk prediction and simulation tools help family medicine? To answer this, the article examines how such tools work, what benefits they may offer, and what problems they may create. Ontomorph is used throughout as a case example to ground the discussion in a real system.

This article is a narrative review. Literature was identified through searches of PubMed, Google Scholar, and institutional databases using key concepts including "risk prediction," "machine learning," "primary care," "family medicine," "digital twin," "clinical decision support," "genomic risk," and "chronic disease prevention." The search period focused on 2021 to 2026. Articles were selected based on relevance to primary care, methodological quality, and contribution to understanding the benefits and challenges of digital risk prediction tools. Platform-specific information about Ontomorph was obtained from publicly available company materials and the platform website. The review does not claim to be exhaustive but aims to provide a balanced overview of the topic for family medicine readers.

How Digital Risk Prediction and Simulation Tools Work The Basics of Risk Prediction

Risk prediction is the process of estimating the likelihood that a future event will occur. In medicine, this often means estimating the probability that a patient will develop a disease within a certain time frame. A ten-year cardiovascular risk of 12%, for example, means that a patient has a 12% chance of having a heart attack or stroke in the next ten years.⁵

Traditional risk scores use a small number of variables. The

Framingham Risk Score, for example, uses age, sex, blood pressure, cholesterol, smoking status, and diabetes status.⁵ These scores are easy to calculate and have been validated in large populations. However, they do not capture the full complexity of individual risk. Machine learning models can use many more variables. They can incorporate data from electronic health records, wearables, genomic tests, and social determinants of health. They can identify patterns that are not obvious to human clinicians. A systematic review of machine learning in primary care found that these models can predict the risk of chronic conditions including cardiovascular disease, diabetic retinopathy, and chronic kidney disease.²

Simulation and Digital Twins

Simulation goes a step further than prediction. It allows clinicians and patients to explore what might happen under different scenarios. What if the patient starts a statin? What if they lose ten pounds? What if they stop smoking? Simulation tools can model these scenarios and show the projected impact on future risk.⁷ However, simulated changes in predicted risk are model outputs rather than evidence that an individual patient will experience the projected benefit. Prediction should not be confused with causal inference or treatment-effect estimation.

Ontomorph's platform proposes simulation features that are built on this principle. The patient's twin integrates genome, laboratory results, and lifestyle data into a projected trajectory.⁴ The user can adjust a single variable and see the projection re-resolve. For example, a patient can see how their ten-year cardiovascular risk changes if they start exercising regularly.

This approach is sometimes called a "digital twin." A digital twin is a dynamic, virtual representation of a physical system that is updated with real-time data. In healthcare, a digital twin can simulate, monitor, and predict the behavior of health entities to reduce the risk of complications.⁸ A review of AI in family medicine identified digital twins as a promising tool for managing chronic conditions such as diabetes, hypertension, and heart disease.⁸

Integration with Clinical Workflows

For risk prediction to be useful, it must be integrated into clinical workflows. A prediction tool that sits on a shelf is of no help to a busy family doctor. The information must appear at the point of care, when it is needed, in a form that is easy to understand.⁹

Clinical decision support systems are designed to do this. They use predictive models and patient data to provide recommendations, alerts, and reminders.¹⁰ A systematic review of clinical decision support systems in primary care found that they can improve the quality and safety of care.⁹ However, the same review found that the greatest barrier to use was increased workload. If the system adds clicks, interrupts workflow, or produces too many alerts, it will not be used.

Ontomorph proposes to address this by embedding prediction and simulation directly into the patient's record. When a clinician views a patient's twin, risk projections are already calculated. When a new medication is considered, the simulation is updated automatically.⁴ The prediction is not a separate tool. It is part of the record itself.

Benefits for Family Medicine

Predicting Chronic Disease Risk

Chronic diseases are the leading cause of death and disability worldwide. Conditions such as diabetes, heart disease, and chronic

kidney disease develop slowly and often silently. By the time symptoms appear, the disease may be advanced. Early identification of at-risk patients is essential for prevention.¹¹

Digital risk prediction tools can help. A systematic review of population risk stratification tools in primary care found that implementing these tools can lead to better health outcomes, reduced hospitalizations, and improved quality of life for patients with chronic diseases.¹¹ A study of AI-based clinical decision support in a resource-constrained setting found that risk assessment improved by 27% and statin prescription by 29% among doctors using the tool.¹²

Ontomorph's platform is designed to support this kind of early identification. The twin integrates data from multiple sources, including genomic variants that may indicate inherited risk. A patient with a BRCA1 mutation, for example, can see the organs affected and the screening recommendations timed to that risk.⁴ This kind of personalized risk assessment is not possible with traditional risk scores.

Supporting Personalized Prevention

Prevention is not one-size-fits-all. A patient with a strong family history of heart disease may need earlier and more aggressive intervention than a patient without such a history. A patient with a genetic variant that affects drug metabolism may need a different medication than a patient without that variant.¹³

Digital risk prediction tools may support personalized prevention. They can incorporate genomic data, lifestyle factors, and biomarkers to generate individual risk estimates. A narrative review of precision medicine in primary care found that clinical prediction tools incorporating genomic markers are increasingly used to stratify patients' risk for conditions like cardiovascular disease and osteoporosis.¹⁴

Ontomorph's platform includes genomic data as a core component. The twin resolves variants onto the organs they affect and uses them to inform risk projections.⁴ This approach may help family doctors identify patients who need earlier screening, more frequent monitoring, or different treatments.

Improving Clinical Decisions

Risk prediction may improve clinical decisions in several ways. It may help clinicians decide who needs treatment. It may help them choose between different treatment options. It may help them communicate risk to patients in a way that supports shared decision-making.¹⁵

A study of machine learning-based clinical decision support for type 2 diabetes found that predictive models could generate treatment pathway graphs, helping clinicians and patients review alternative treatment strategies.⁷ A systematic review of AI in primary care found that these tools supported chronic disease management by enabling earlier risk stratification, safer prescribing, and more consistent patient follow-up.¹

Ontomorph's simulation features may strengthen this benefit. When a clinician and patient can see the projected impact of different interventions, they can make more informed decisions together. The platform's visualization tools allow patients to see how their risk might change with lifestyle modifications or medication.⁴ This kind of shared decision-making is a core principle of family medicine.

Enhancing Patient Engagement

Patients who understand their risk are more likely to take action. A systematic review of patient-centered digital health records found that these tools are associated with benefits in health care utilization, treatment adherence, and self-management.¹⁶ Another study found that patients who saw their clinical notes felt more empowered and better understood their treatment plans.¹⁷

Ontomorph's platform is designed to support patient engagement. Patients can view their twin, see what each result means, and simulate the effects of lifestyle changes.⁴ The platform includes features for logging symptoms, setting alerts, and sharing access with family members. These tools may help patients become active partners in their care rather than passive recipients.

Limitations and Challenges

Validation and Accuracy

Risk prediction models are only as good as the data they are built on. A model developed in one population may not perform well in another. A review of machine learning-based cardiovascular risk prediction found that models are often developed by researchers in Western countries and focused on white ethnicity, which could result in bias and compromise health equality.¹⁸

External validation is essential before a model can be used in clinical practice. Adequate clinical validation requires assessment of both discrimination (the ability to distinguish between patients who will and will not experience an event) and calibration (the agreement between predicted and observed event rates). Model performance may deteriorate when applied to populations that differ from the development cohort. A scoping review of cardiovascular disease risk calculators recommended that healthcare settings use feasible, accurate, and user-friendly tools tailored to the population and health system.⁵ Ontomorph's platform uses its own knowledge system, HOLON, to resolve risk estimates.⁴ The platform has not published external validation studies, and its clinical accuracy remains unproven.

Bias and Equity

Machine learning models can perpetuate and amplify existing biases. If the training data underrepresents certain groups, the model may perform poorly for those groups. A study of bias in healthcare prediction models found clear evidence of racial, gender-based, and age-related biases that profoundly impact prediction performance and lead to unfair outcomes.¹⁹

A framework for assessing and addressing bias in predictive models found that models can under predict hospitalization risk for minoritized patients, leading to inadequate care.²⁰ This is a serious concern for family medicine, where equity is a core value. If digital risk prediction tools are not carefully designed and validated, they may widen existing disparities.

Applicability to Nigerian and African Primary Care

For family medicine in Nigeria and similar low-resource settings, several additional considerations apply. First, most risk prediction models have been developed and validated in high-income countries with predominantly white populations. Their applicability to African populations is uncertain without local external validation. Second, the availability and representativeness of local electronic health data remain limited. Many primary care facilities in Nigeria still rely partly or predominantly on paper records, which limits the data available for risk prediction. Third, access to genomic data and

genetic counselling services is limited, raising questions about the feasibility of genomic risk prediction in routine practice. Fourth, digital literacy, internet connectivity, and cost may restrict the use of digital tools. Fifth, interoperability between existing health information systems is often poor. These factors suggest that while digital risk prediction holds promise for Nigerian family medicine, implementation must be context-sensitive and accompanied by investment in data infrastructure, training, and equitable access.

Patient Anxiety and Communication

Telling a patient that they are at high risk for a serious disease can cause anxiety. A qualitative study of dementia risk prediction in primary care found that patient fear was a primary factor to consider when implementing these tools.²¹ Another study found that risk prediction tools could cause unnecessary anxiety, especially when the risk is uncertain or when the patient feels powerless to change it.²²

Communicating risk is difficult. Risk estimates are probabilistic, not certain. A ten-year cardiovascular risk of 12% means that 12 out of 100 people with similar characteristics will have an event. It does not mean that this particular patient will have an event.²³ A review of uncertainty in risk estimates found that patient and public involvement groups have argued that providing this information is ethically mandatory.²³ Risk should generally be communicated using understandable absolute risks, appropriate time horizons, and clear acknowledgement of uncertainty. Deterministic language should be avoided, particularly when model confidence and population validity are uncertain.

Ontomorph's platform includes AI lab interpretation and simulation features that may help explain risk.⁴ However, the platform cannot eliminate the emotional impact of receiving bad news. Family doctors will need to support patients in understanding and coping with what they see.

Workflow and Time Burden

Adding risk prediction to family medicine creates work. Physicians are already burdened with documentation, inbox management, and administrative tasks. A systematic review of clinical decision support systems in primary care found that increased workload was the greatest barrier to use.⁹

If Ontomorph requires physicians to learn a new interface, review risk projections, and discuss them with patients, it may add to this burden. A qualitative study of primary care providers found that concerns about workflow burden and incompatibility with a whole-patient approach contributed to slow adoption of risk prediction tools.²⁴

Ethical and Legal Issues

Using future-risk projections raises ethical and legal questions. Who is responsible if a prediction is wrong? What happens if a patient is told they are low risk and then develops the disease? What happens if a patient is told they are high risk and receives unnecessary treatment? A review of legal and ethical considerations in AI in healthcare found that there is a lack of well-defined regulations to manage these issues.²⁵

AI-generated risk estimates and genomic interpretations require appropriate clinical validation, clinician oversight, and, where relevant, genetic counselling. Predictions should not replace clinical judgement, guideline-based risk assessment, or shared decision-

making.

A review of risk prediction tools in multiple long-term conditions found that unclear liability for legal risks, poorly defined ownership and governance of data, and concerns over privacy, security, and consent were significant barriers.²⁶ Clinicians will need support and training to use these tools effectively and will need clarification regarding liability for harms arising from their use.²⁷ Additional governance considerations include data provenance, accountability for erroneous predictions, secondary use of patient data, commercial governance, cybersecurity, and responsibility when a model changes over time.

Ontomorph's governance model gives patients control over disclosure.⁴ However, the platform's white paper acknowledges that transferred copies cannot be recalled.²⁸ Once a risk projection is shared, it may persist. This raises questions about who owns the prediction and who is responsible for acting on it.

Discussion

The idea of predicting future health risks is compelling. It aligns with the preventive focus of family medicine and the growing emphasis on personalized care. Digital tools like Ontomorph offer the promise of more accurate risk assessment, better-targeted interventions, and more engaged patients.

The benefits are clear in theory. Risk prediction may help identify patients who need early intervention. Simulation may help clinicians and patients explore different scenarios. Visualization may make risk understandable and actionable. For family medicine, where prevention is a core task, these benefits could be substantial. But the challenges are also real. Validation must be rigorous. Bias must be addressed. Patient anxiety must be managed. Workflow must be designed to reduce, not increase, burden. Ethical and legal issues must be resolved.

Ontomorph is not the first system to attempt this. Traditional risk scores, machine learning models, and clinical decision support systems have been used for years. What distinguishes Ontomorph is its integration of genomic data, simulation, and a patient-owned record. These features may address some of the limitations seen in earlier systems. For example, the inclusion of genomic data may improve risk prediction for inherited conditions. The simulation features may support shared decision-making in a way that traditional risk scores cannot.

However, it is important to distinguish evidence supporting digital risk prediction tools in general from claims about Ontomorph specifically. Most evidence cited in this review concerns risk scores, machine learning models, clinical decision support systems, and digital records generally. Ontomorph-specific descriptions derive largely from the platform itself. Independent clinical evidence for Ontomorph is limited, and the platform has not undergone rigorous external evaluation.

These features also introduce new risks. The genomic data may create anxiety or lead to unnecessary interventions. The simulation may give false confidence in uncertain projections. The patient-owned record may not be adopted broadly enough to be useful.

Family doctors should approach digital risk prediction tools with cautious optimism. The potential benefits are significant, but the evidence base is still developing. Most studies on risk prediction have examined single-condition models, not integrated platforms

like Ontomorph. Research on Ontomorph specifically is limited. The platform is in beta, and its clinical impact has not been rigorously evaluated.

Conclusion

Looking ahead is a core task of family medicine. Digital risk prediction and simulation tools may help with this task. They may help identify patients at risk for chronic diseases, support personalized prevention, improve clinical decisions, and enhance patient engagement. Ontomorph provides a concrete example of how such a system might work. Its integration of genomic data, simulation features, and a patient-owned record is innovative.

But the path from concept to clinic is not easy. Validation, bias, anxiety, workflow, and ethical issues are all challenges that must be addressed. Family doctors should engage with these systems critically, asking questions about evidence, usability, and long-term sustainability. They should also advocate for their patients, ensuring that digital tools serve the goal of better care, not just more technology.

The future of family medicine will be shaped by how we manage information and predict risk. Digital risk prediction may be part of that future. Whether it improves care will depend on how well it is designed, implemented, and evaluated. The promise is real. The work is just beginning.

Conflict of Interest Statement

The authors declare no financial, professional, advisory, developmental, or other relationship with Ontomorph. Platform-specific information was obtained from publicly available company materials and the platform website. These sources are clearly identified in the text. The review aims to balance company claims with independent evidence and does not endorse any specific commercial product.

References

1. Katonai G, Arvai N, Mesko B. AI and primary care: scoping review. *J Med Internet Res*. 2025;27:e51234.
2. El-Sherbini AH, Hassan Virk HU, Wang Z, et al. Machine-learning-based prediction modelling in primary care: state-of-the-art review. *AI*. 2023;4(3):645-672.
3. Harrigan S. Artificial intelligence-enabled clinical decision support for chronic disease management in primary care: Implications for family nurse practitioner practice. *Curr Med Drug Res*. 2026;10(1):1-12.
4. Ontomorph. Platform overview. Available from: <https://ontomorph.com/>
5. Badawy MAEFMD, Naing L, Johar S, Ong S, et al. Evaluation of cardiovascular diseases risk calculators for CVDs prevention and management: scoping review. *BMC Public Health*. 2022;22(1):1742.
6. Grechuta K, Shokouh P, Alhussein A, et al. Benefits of clinical decision support systems for the management of noncommunicable chronic diseases: targeted literature review. *Interact J Med Res*. 2024;13:e48947.
7. Tarumi S, Takeuchi W, Chalkidis G, et al. Leveraging artificial intelligence to improve chronic disease care: methods and application to pharmacotherapy decision support for type-2 diabetes mellitus. *Methods Inf Med*. 2021;60(S01):e32-e43.

8. Katsakiori PF, Kagadis GC, Mulita F, Marangos M. Implementing artificial intelligence in family medicine: Challenges and limitations. *Cureus*. 2024;16(2):e54216.
9. Meunier PY, Raynaud C, Guimaraes E, et al. Barriers and facilitators to the use of clinical decision support systems in primary care: a mixed-methods systematic review. *Ann Fam Med*. 2023;21(5):438-450.
10. Alexiuk M, Elgubtan H, Tangri N. Clinical decision support tools in the electronic medical record. *Kidney Int Rep*. 2024;9(4):845-854.
11. Golinelli D, Pecoraro V, Tedesco D, Negro A, et al. Population risk stratification tools and interventions for chronic disease management in primary care: a systematic literature review. *BMC Health Serv Res*. 2025;25(1):234.
12. Susanto AP, Lyell D, Widyantoro B, Juzar DA, et al. AI-assisted cardiovascular risk assessment by general practitioners in resource-constrained Indonesian settings using a conceptual prototype. *J Med Internet Res*. 2025;27:e51234.
13. Liu M, Vnencak-Jones CL, Roland BP, et al. A tutorial for pharmacogenomics implementation through end-to-end clinical decision support based on ten years of experience from PREDICT. *Clin Pharmacol Ther*. 2021;109(1):101-115.
14. Evans W, Meslin EM, Kai J, Qureshi N. Precision medicine are we there yet? A narrative review of precision medicine's applicability in primary care. *J Pers Med*. 2024;14(4):418.
15. Walsh CG, McKillop MM, Lee P, Harris JW, et al. Risky business: a scoping review for communicating results of predictive models between providers and patients. *JAMIA Open*. 2021;4(4):ooab092.
16. Brands MR, Gouw SC, Beestrum M, Cronin RM, et al. Patient-centered digital health records and their effects on health outcomes: systematic review. *J Med Internet Res*. 2022;24(12):e43086.
17. Blease C. Open AI meets open notes: surveillance capitalism, patient privacy and online record access. *J Med Ethics*. 2024;50(2):84-89.
18. Liu T, Krentz AJ, Huo Z, Čurčin V. Opportunities and challenges of cardiovascular disease risk prediction for primary prevention using machine learning and electronic health records: a review. *Rev Cardiovasc Med*. 2025;26(2):25432.
19. Gupta V, Broughton J, Rukundo A, Pinky LJ. Learning unbiased risk prediction based algorithms in healthcare: A case study with primary care patients. *Inform Med Unlocked*. 2025;45:101456.
20. Gupta R, Sasaki M, Taylor SL, Fan S, Hoch JS, et al. Developing and applying the BE-FAIR equity framework to a population health predictive model: A retrospective observational cohort study. *J Gen Intern Med*. 2025;40(3):567-576.
21. Morris RL, Schmidt-Renfree N, Joseph W, et al. Exploring the views of key stakeholders on dementia risk prediction in primary care in areas of socioeconomic deprivation: a qualitative study. *Br J Gen Pract*. 2025;75(752):e234-e242.
22. Arakelyan S, Anand A, Mercer SW, MacRae CE, et al. Risk prediction tools in multiple long-term conditions management: a qualitative study. *Br J Gen Pract*. 2025;75(751):e123-e131.
23. Riley RD, Collins GS, Kirton L, Snell KIE, Ensor J, et al. Uncertainty of risk estimates from clinical prediction models: rationale, challenges, and approaches. *BMJ*. 2025;388:e078749.
24. Takamine L, Forman J, Damschroder LJ, et al. Understanding providers' attitudes and key concerns toward incorporating CVD risk prediction into clinical practice: a qualitative study. *BMC Health Serv Res*. 2021;21(1):521.
25. Naik N, Hameed BM, Shetty DK, Swain D, Shah M, et al. Legal and ethical consideration in artificial intelligence in healthcare: who takes responsibility? *Front Surg*. 2022;9:862322.
26. Taylor LC, Peek N, Ercole A, et al. Enabling digital multifactorial risk assessment in primary care: an umbrella review and recommendations for design and implementation. *BMJ Health Care Inform*. 2026;33(1):e101234.
27. Brigden T, Mitchell C, Redrup Hill E, Hall A. Ethical and legal implications of implementing risk algorithms for early detection and screening for oesophageal cancer, now and in the future. *PLoS One*. 2023;18(9):e0290996.
28. Ontomorph. Observed and Resolved: A Structural Account of Why Health Data Requires an Open Ontological Commons. White paper. Available from: <https://ontomorph.com/>