



Mind Genomics as a Framework for Investigating Human Engagement with AI-Enabled Population Health Interventions

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Abstract

Artificial intelligence (AI) is increasingly being used to support population-health activities such as risk identification, prevention, monitoring, and intervention planning. However, identifying a health risk or an intervention opportunity does not necessarily mean that people will understand, trust, accept, or engage with the resulting intervention. This conceptual and methodological paper proposes Mind Genomics as a framework for studying how different people respond to AI-enabled population-health interventions. The framework organizes potential intervention features into four conceptual domains: Trust and Transparency, Convenience and Delivery, Social and Contextual Fit, and Autonomy and Human Support, comprising 16 proposed elements. In a future Mind Genomics study, these elements could be incorporated into BimiLeap, a web-based platform for designing, conducting, and analyzing Mind Genomics studies. BimiLeap would combine the proposed elements to generate experimentally designed vignettes, which respondents would evaluate according to their willingness to engage with the proposed population-health programme. BimiLeap would then process the resulting ratings through its integrated Mind Genomics analytical workflow to identify the relative contribution of intervention elements and potential response-based mindsets.

These findings could help identify which intervention features are more strongly associated with engagement among different groups of people and could support the development of more appropriately tailored communication or intervention strategies. Future empirically identified mindsets could also provide a basis for developing a Personal Viewpoint Identifier (PVI) to support more personalized communication. A hypothetical AI-enabled diabetes prevention and management programme is used to illustrate how the framework could be applied, with potential applications across other population-health contexts. Overall, the paper presents a conceptual pathway linking population-health needs, AI-supported intervention opportunities, Mind Genomics, and human engagement, with future empirical research needed to determine its practical value.

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Introduction

Population Health and the Emerging Role of Artificial Intelligence

Population health concerns the health outcomes of groups of individuals, including the distribution of those outcomes within a group, and encompasses attention to health determinants together with policies and interventions that connect determinants to outcomes [1].

The growing availability of health data has created opportunities for artificial intelligence (AI) and machine-learning approaches to contribute to healthcare and population-health activities. A systematic review of AI in healthcare describes applications across organizational, clinical, patient, and sector-level functions, including data processing, machine learning, clinical decision support, resource allocation, diagnosis, treatment, consultation, monitoring, and other technology-enabled activities [2].

Within population health, AI has been discussed as a supporting technology across multiple stages of care delivery. Mutharasan and Walradt (2024) describe applications involving population-level health management, preventive care, chronic-disease management, patient identification, and other stages of the care-delivery continuum [3]. They also describe examples in which augmented intelligence was used to identify patients with advanced heart failure within an integrated health system.

AI-supported predictive analytics has also been discussed in relation to patient risk stratification. Sharma et al. (2023) describe the use of predictive analytics to analyze large datasets, identify higher-risk individuals, and support preventive-care and resource-allocation strategies [4]. Their paper specifically discusses integration of sources such as electronic

health records, demographics, environmental factors, and social determinants of health in predictive models.

Clinical risk-prediction literature illustrates both the potential and the complexity of this area. Narasimhan et al. (2025) discuss AI and machine learning in clinical risk prediction and patient monitoring while highlighting questions concerning model performance and the challenges involved in translating predictive approaches into clinical use [5].

AI applications in public health have also been discussed in relation to prediction, health records, health education, disease prevention, remote access, and analysis of complex health information. Gore and Olawade (2024) specifically discuss these possibilities within the context of public health in India while also noting the possibility of misinterpretation and problems arising from inappropriate reliance on AI systems [6].

Taken together, these sources support a view of AI as a potential analytical and operational support technology within population-health and healthcare systems. They do not establish that AI should independently determine population-health decisions.

This distinction leads to a further question: Once a population-health intervention has been identified or prioritized, how will people respond to it?

From AI Capability to Human Engagement

The ability to identify a potential health risk does not necessarily establish that a resulting intervention will be accepted or used.

AI implementation in healthcare has been associated with multiple categories of barriers. Ahmed et al. (2023) identified six broad areas of barriers: ethical, technological, liability and regulatory, workforce, social, and patient-safety barriers [7]. Their review

also emphasizes that implementation has been uneven despite the potential attributed to AI technologies.

Trust represents another important implementation consideration. Steerling et al. (2023) conducted a scoping review of trust in AI implementation in healthcare and identified three broad themes influencing trust: individual characteristics, AI characteristics, and contextual characteristics. Their review also noted that trust may be conceptualized in different ways, including relational forms of trust involving people within the context of AI use [8].

Ethical concerns also extend beyond the technical performance of an algorithm. Hou et al. (2026), in a systematic review of qualitative studies involving healthcare professionals, identified concerns involving algorithmic bias, data privacy, accountability, and differences in ethical priorities across professional roles and cultural, resource, and policy contexts [9].

Healthcare AI governance literature similarly emphasizes that fairness, transparency, explainability, safety, privacy, accountability, human oversight, and deployment practices need to be considered together. Bailo et al. (2026) describe governance as extending across the AI lifecycle and emphasize that AI should augment rather than replace clinical judgment and institutional accountability [10].

Bias provides another reason to consider the human and social context surrounding AI. Chen et al. (2023) describe how differences across populations, demographic and genetic characteristics, healthcare data, data acquisition processes, and social determinants of health can contribute to dataset shift and disparate performance in healthcare AI [11]. They further discuss how historical healthcare inequities and under-representation of certain populations in biomedical datasets can contribute to algorithmic bias and disparities in AI performance.

Thus, AI-enabled population-health interventions can be understood not only as analytical systems but also as interventions that operate within social, organizational, and healthcare contexts.

In this framework, human engagement refers specifically to stated willingness to engage with

a proposed intervention, rather than observed participation, adherence, or subsequent health behavior.

People May Respond Differently to Different Features of AI-Enabled Healthcare

A central methodological issue is whether responses to AI-enabled healthcare can be adequately represented by a single overall attitude such as “trust” or “acceptance.”

Tang et al. (2023) systematically reviewed empirical studies of medical AI ethics and identified research addressing stakeholder knowledge and attitudes, factors associated with acceptance, and bias in medical AI [12]. Importantly, their review identified a gap between high-level ethical principles and empirical research examining how stakeholders actually perceive and respond to medical AI.

Experimental research provides a more specific illustration. Bracic et al. (2026) examined patient trust and acceptance using hypothetical AI-assisted medical scenarios in which multiple attributes were experimentally varied [13]. The study examined factors including AI performance, clinician presence, governance, and the representativeness of training data, and measured patient choice and trust.

The importance of this study for the present framework is methodological rather than predictive.

It suggests that healthcare AI can be investigated as a combination of experimentally varied attributes, rather than being treated only as a binary question of whether someone accepts or rejects “AI.”

The relevant research question therefore becomes: Which combinations of intervention characteristics are associated with stronger or weaker human responses?

That question creates an opportunity for an experimental methodology capable of studying combinations of ideas rather than isolated attributes.

The Methodological Gap

The literature reviewed above suggests a conceptual sequence:

Population Health

→ health outcomes, their distribution, determinants, policies, and interventions [1].

↓
AI-Supported Analytics

→ prediction, risk identification, monitoring, resource-related support, and intervention planning [2-5].

↓
Implementation Context

→ ethical, technological, regulatory, workforce, social, safety, trust, privacy, fairness, and governance considerations [7-10].

↓
Human Response

→ potentially heterogeneous responses to different characteristics of AI-enabled healthcare [12,13].

The resulting methodological question is:
Once an AI-enabled population-health intervention has been defined, how can combinations of its features be experimentally examined to understand how different people respond to the intervention and express willingness to engage with it?
This is where Mind Genomics becomes relevant.

Why Mind Genomics?

Several related frameworks have also addressed human engagement with digital health interventions. For example, the ENGAGE framework for precision engagement in digital health emphasizes user needs, behavioral science, and adaptive personalization to support sustained engagement and health-related behavior change. The present framework complements such approaches by proposing an experimental Mind Genomics pathway for examining responses to combinations of intervention features [14].

Mind Genomics is an experimental approach designed to study how people respond to combinations of ideas. Its development draws on experimental design and approaches related to conjoint and functional measurement [15].

The methodology uses combinations of elements rather than presenting respondents only with isolated statements. Respondents evaluate experimentally designed combinations, after which the ratings can be analyzed to estimate the contribution of individual elements [15].

Previous health-related applications demonstrate the practical use of this approach.

Gabay et al. (2019) used experimentally designed combinations of diabetes-related messages and identified three communication mindsets in their study population [16].

Coussa et al. (2024) applied Mind Genomics to public-health communication in the context of COVID-19, demonstrating the use of experimentally combined public-health communication concepts and the identification of different response patterns [17].

Kornstein et al. (2023) used Mind Genomics to present respondents with combinations of elements, obtain ratings, estimate element contributions through regression, and use k-means clustering to identify response groups or mindsets [18].

The underlying workflow is therefore:

Elements → Experimental Vignettes → Ratings → Element-Level Analysis → Response Patterns/Mindsets

The proposed framework does not claim that these studies establish improved health outcomes. Rather, they demonstrate that health-related messages and concepts can be experimentally decomposed, recombined, evaluated, and analyzed for heterogeneous response patterns.

**The Proposed Mind Genomics Framework
The AI–Population Health–Mind Genomics Relationship**

The proposed framework does not conceptualize AI as an autonomous controller of population-health decisions.

Instead, AI is positioned as a potential supporting analytical layer within an existing healthcare organization, population-health programme, research setting, or other defined intervention context.

The proposed sequence is:

Population Health Problem

AI-Supported Analytics

Risk identification / prioritization / prediction / intervention opportunity

Defined Health Intervention

↓

Mind Genomics Experiment

Elements → Vignettes → Participant Ratings

↓

Element-Level Analysis

↓

Empirical Response Patterns / Mindsets

↓

Potentially Tailored Communication or Intervention Design

Future Empirical Validation

The central proposition is:

Population health defines the health problem and intervention context; AI may support identification or prioritization of intervention opportunities; Mind Genomics can experimentally investigate how people respond to combinations of intervention features. This is intended as a complementary relationship rather than a replacement for AI analytics, clinical judgment, or existing healthcare decision structures.

The Proposed 4 × 4 Architecture

The proposed framework organizes the intervention space into four conceptual domains:

1. Trust and Transparency
2. Convenience and Delivery
3. Social and Contextual Fit
4. Autonomy and Human Support

Each domain contains four candidate elements, producing 16 proposed elements. Importantly, these four domains are researcher-defined conceptual categories for constructing a Mind Genomics experiment. They are not presented as established universal dimensions of human behavior.

Table 1: Proposed 4 × 4 Mind Genomics Architecture for AI-Enabled Population Health (Four conceptual questions, dimensions, and 16 proposed elements)

Question	Dimension	Element	Proposed Element
Q1. How might an AI-enabled intervention communicate trust and transparency?	Trust & Transparency	A1	A clear explanation of how AI supports the health recommendation.
		A2	Clear information about protection of personal health information and privacy safeguards.
		A3	Review of AI-supported recommendations by a qualified healthcare professional.
		A4	An opportunity for participants to ask questions about an AI-supported recommendation.

Q2. How might the intervention be made convenient and accessible?	Convenience & Delivery	B1	Follow-up and monitoring available through a convenient remote option.
		B2	Simple health reminders delivered through routine mobile messaging.
		B3	Convenient access to recommended screening or preventive services.
		B4	Simple tracking and support for following recommended health behaviours.
Q3. How might the intervention fit people's social and contextual circumstances?	Social & Contextual Fit	C1	Health information provided in the participant's preferred language.
		C2	Health guidance adapted to relevant local cultural and everyday circumstances.
		C3	Support from a trained community health worker when needed.
		C4	Involvement of trusted family or community support when appropriate.
Q4. How might the intervention preserve autonomy and human support?	Autonomy & Human Support	D1	Shared decision-making between the participant and a healthcare professional.
		D2	Access to a healthcare professional when the participant wants human guidance.
		D3	The ability to decline or opt out of the AI-supported programme.
		D4	A mechanism for participants to provide feedback or raise concerns about the programme.

Note: The 16 elements are proposed candidate elements for experimental testing. They are not presented as universally validated determinants of engagement. The four dimensions are researcher-defined conceptual domains for constructing the proposed Mind Genomics experiment.

The four domains are intended primarily as an organizing structure for constructing the proposed Mind Genomics experiment, rather than as empirically established or mutually exclusive dimensions of human response. Some proposed elements may therefore overlap conceptually and could show similar response patterns when tested empirically.

Domain Rationales

Trust & Transparency

The proposed elements translate recurring healthcare-AI concerns concerning trust, transparency, privacy, explainability, and human oversight into concrete features that could be experimentally tested [8,10,12].

Convenience & Delivery

The proposed participant-facing features translate broad possibilities discussed in AI-enabled healthcare and population-health literature-such as monitoring, preventive care, remote access, and resource-related support-into candidate concepts for experimental testing [2,3,6]. The cited literature does not establish that each specific feature improves engagement.

Social & Contextual Fit

Population health considers differences across populations and the determinants and interventions associated with those differences [1]. AI fairness literature also highlights differences in population characteristics, representation, healthcare access, social determinants of health, and broader social context as relevant to disparities and fairness in healthcare AI [11,9]. The four elements are nevertheless proposed study elements, not universally established preferences.

Autonomy & Human Support

Human oversight, accountability, institutional responsibility, and the relationship between AI and clinical judgment are important themes in healthcare AI governance [10]. Ethical literature also identifies autonomy, accountability, privacy, and stakeholder concerns as relevant dimensions of medical AI ethics [12]. The four elements are candidate experimental elements rather than established universal determinants of engagement.

Future Vignette Generation, Rating, and Analysis

In a future empirical investigation, the 16 proposed elements could be incorporated into BimiLeap (www.bimileap.com), a platform developed for the design, administration, and analysis of Mind Genomics studies. BimiLeap would automatically combine the proposed elements according to the experimental design to create multi-element vignettes. Respondents would see these vignettes, rather than the individual elements, and would rate each vignette using the study rating question.

Each vignette would contain a different combination of features from the four proposed domains. This allows respondents to evaluate combinations of intervention features rather than individual features separately.

Respondents could evaluate each vignette using the following researcher-defined rating question:
“Based on what you just read, how likely would you be to engage with this AI-enabled population-health programme?”

Responses could be recorded using a five-point scale:

1. Definitely would not
2. Probably would not
3. Not sure

4. Probably would
5. Definitely would

The rating question and response scale are proposed for future empirical testing and could be adapted to the specific population-health context and objectives of the study.

Following completion of data collection, the vignette ratings would be analyzed using the standard analytical workflow employed in Mind Genomics studies. Ordinary least-squares (OLS) regression would estimate the independent contribution of individual elements to the observed vignette ratings, while clustering procedures, including K-means clustering, would identify groups of respondents with similar response patterns [15,18]. Because the present article is conceptual, these procedures are described to illustrate how the proposed framework could be evaluated in a future empirical implementation.

The resulting analyses could provide insight into which intervention elements across the four proposed domains—Trust & Transparency, Convenience & Delivery, Social & Contextual Fit, and Autonomy & Human Support—are most strongly associated with participant responses, and whether distinct response-based mindsets emerge.

The resulting BimiLeap outputs could therefore include overall-panel results, element-level coefficients, mindset segmentation, and relevant subgroup analyses. These outputs could help identify which intervention features are most strongly associated with participant responses and could provide an empirical foundation for subsequent development and testing of more tailored population-health communication or intervention strategies.

Depending on the findings of a future empirical study, the identified mindsets could also provide a basis for developing a Personal Viewpoint Identifier (PVI). A future PVI could potentially help identify an individual's response pattern or communication mindset and support more appropriately tailored communication about an AI-enabled population-health programme. The development and validation of such a PVI would constitute a separate empirical step and is not an outcome established by the present conceptual paper.

Because the present article is conceptual, no BimiLeap-generated results, element-level coefficients, or empirical mindsets are reported as findings of the present paper. The number, composition, and characteristics of any future mindsets would depend entirely on the response patterns observed in an empirical implementation.

The overall conceptual workflow is therefore:

4 Questions → 16 Proposed Elements → BimiLeap Experimental Design → BimiLeap-Generated Vignettes → Respondent Ratings → OLS Regression & K-Means Clustering → Element-Level Contributions → Empirical Mindsets → Potentially Tailored Communication/Intervention → Future PVI Development

Illustrative Conceptual Mindsets

The following mindsets are illustrative and hypothetical profiles, included to demonstrate how different response patterns might be interpreted in a future empirical Mind Genomics study. They are not empirical findings of the present paper, and the proposed profiles should not be interpreted as established population segments.

Mindset 1 — Trust-Sensitive Responder

A hypothetical response pattern characterized by relatively greater responsiveness to features related to privacy protection, transparency, human oversight, and access to professional guidance.

Potentially relevant proposed elements include:
A1, A2, A3, D2

Mindset 2 — Convenience-Oriented Responder

A hypothetical response pattern characterized by relatively greater responsiveness to features related to remote access, convenient delivery, simple reminders, and practical support for health behaviours.

Potentially relevant proposed elements include:
B1, B2, B3, B4

Mindset 3 — Social and Context-Responsive Responder

A hypothetical response pattern characterized by relatively greater responsiveness to features related to preferred-language communication, contextual

relevance, community support, and involvement of trusted social support.

Potentially relevant proposed elements include:
C1, C2, C3, C4

Important Methodological Distinction

These three profiles are conceptual examples rather than predetermined mindsets. In a future empirical Mind Genomics investigation, the actual number, composition, and characteristics of response-based mindsets would emerge from participants' vignette ratings and the subsequent analysis. The empirical study could identify fewer or more mindsets, or patterns that differ substantially from the illustrative profiles presented here.

Accordingly, the labels and element groupings presented above are intended only to demonstrate how future empirical response patterns might be interpreted, rather than to impose a predefined segmentation structure.

Representational Use Case: AI-Enabled Diabetes Prevention and Management

To illustrate how the proposed framework might operate, consider a hypothetical AI-enabled diabetes prevention and management programme.

This example is intentionally representational. It does not describe an existing government programme, national AI system, or currently implemented population-wide intervention.

Diabetes is used as an illustrative context because Mind Genomics has previously been applied to diabetes-related public health communication. Gabay et al. (2019) used experimentally designed combinations of diabetes-related messages and identified three distinct communication mindsets, demonstrating how Mind Genomics can be used to examine differences in responses to health-related messages [16].

The present framework extends this general Mind Genomics logic to a hypothetical AI-enabled population-health context. The example therefore illustrates how the proposed framework might be applied, rather than suggesting that the present framework or its proposed elements have already been validated for diabetes prevention or management.

Step 1: Define the Intervention Population

An existing healthcare organization or defined population-health programme could use available information and AI-supported analytics to help characterize population groups or identify opportunities for preventive or management support.

AI would function as an analytical support mechanism rather than as an autonomous decision-maker. Any actual deployment would remain embedded within the relevant healthcare, organizational, ethical, and governance structures.

Step 2: Conduct the Mind Genomics Experiment

A sample from the relevant target population could participate in a future Mind Genomics experiment.

BimiLeap could be used to generate vignettes containing different combinations of features drawn from the four proposed domains: Trust & Transparency, Convenience & Delivery, Social & Contextual Fit, and Autonomy & Human Support.

For example, a hypothetical vignette might describe an AI-enabled diabetes programme that identifies an elevated HbA1c result and offers follow-up support through a combination of features such as clinician review, convenient remote monitoring, and personalized communication. The purpose would be to illustrate how specific intervention features could be combined in a future experimental vignette, rather than to imply that any particular feature has already been shown to improve engagement or diabetes outcomes.

Respondents would evaluate the vignettes using the study rating question:

“Based on what you just read, how likely would you be to engage with this AI-enabled population-health programme?”

The central research question would be:

Which combinations of intervention features are associated with stronger or weaker willingness to engage with the proposed programme?

This would be an experimental research question. It would not establish that any particular combination

improves diabetes outcomes.

Step 3: Identify Empirical Response Patterns

Following completion of data collection, the resulting vignette ratings could be processed using the Mind Genomics analytical workflow available through BimiLeap. Ordinary least-squares (OLS) regression could be used to estimate the contribution of individual elements to the observed ratings, while clustering procedures, including K-means clustering, could be used to identify groups of respondents with similar response patterns.

The resulting analysis could identify which proposed intervention elements are more strongly associated with participant responses and whether distinct response patterns or mindsets emerge.

For example, a future study might reveal a group more responsive to human oversight, another more responsive to convenience, and another more responsive to social or contextual features. These are illustrative possibilities only; the actual number, composition, and characteristics of the mindsets would need to emerge from the empirical data.

Step 4: Potential Application of Empirical Mindsets

If empirically meaningful response patterns were identified, the resulting mindset profiles could potentially inform the development of more appropriately tailored communication or intervention approaches.

For example, communication for one empirically identified group might place greater emphasis on human oversight and transparency, whereas another might receive greater emphasis on convenience and accessibility. A group showing stronger responses to social and contextual features might receive communication that places greater emphasis on language, local context, or community support.

Mind Genomics would therefore potentially inform how an intervention is communicated or designed, rather than determine who should or should not receive healthcare.

Depending on the findings of a future empirical study, the identified mindsets could also provide a basis for developing a Personal Viewpoint Identifier (PVI). A

future PVI could potentially use a brief set of questions to identify an individual's response pattern and support more appropriately tailored communication about an AI-enabled population-health programme [18]. The development and validation of such a PVI would constitute a separate empirical step and is not an outcome established by the present conceptual paper.

Potential Applications Across Population Health

The proposed framework could potentially be investigated across a range of population-health contexts. In each context, Mind Genomics could be used to experimentally examine how people respond to different combinations of intervention features, messages, and communication approaches. The purpose would not be to assume that a particular feature will be effective, but to identify, through empirical testing, which combinations are more strongly associated with willingness to engage and whether different response-based mindsets emerge.

Table 2: Potential Applications of the Proposed Mind Genomics Framework Across Population-Health Contexts

Population-health area	Potential Mind Genomics application
Diabetes prevention/management	Identify which combinations of lifestyle, monitoring, convenience, risk, and human-support messages are more strongly associated with willingness to engage with diabetes prevention or self-management programmes.
Hypertension	Examine how different combinations of blood-pressure monitoring, follow-up, lifestyle-support, medication-related, convenience, and human-support features influence willingness to engage with hypertension-management programmes.
Cancer screening	Investigate how combinations of information about risk, early detection, convenience, reassurance, privacy, and human support relate to willingness to participate in screening.
TB screening	Examine how combinations of trust, confidentiality, stigma-related concerns, accessibility, communication, and human support relate to willingness to undergo screening and follow-up.
Vaccination	Identify which combinations of messages concerning safety, effectiveness, trust, accessibility, and social or community considerations are more strongly associated with willingness to engage with vaccination programmes.
Maternal and child health	Explore how language, cultural and contextual fit, convenience, community support, and access to healthcare professionals influence responses to maternal and child-health interventions.
Mental-health promotion	Examine how combinations of privacy, stigma reduction, accessibility, trust, human support, and communication features relate to willingness to seek or engage with mental-health support.
Digital health	Investigate how combinations of digital monitoring, convenience, personalization, privacy, human oversight, and communication features influence willingness to engage with digital health programmes.

These examples illustrate how the proposed framework could be adapted to different population-health problems while retaining the same underlying methodological logic: define the intervention context, identify candidate elements, experimentally combine those elements into vignettes, measure responses, and examine whether distinct response patterns emerge.

The resulting mindsets could potentially reveal that different groups of people respond to different aspects of the same intervention. For example, one group might respond more strongly to human oversight and transparency, while another might be more responsive to convenience or social and contextual support. Such findings could provide an empirical basis for developing more appropriately tailored communication or intervention strategies.

Where stable and practically meaningful response patterns are identified, these findings could also provide a basis for developing Personal Viewpoint Identifier (PVI)-type tools that help identify an individual's response pattern and support more appropriately tailored communication. Such applications would require separate empirical development and validation and are not assumed to follow automatically from the proposed framework.

Overall, these examples illustrate how Mind Genomics could be used across different population-health contexts to experimentally investigate how people respond to combinations of intervention and communication features, identify heterogeneous response patterns, and potentially inform more appropriately tailored communication or intervention strategies. These applications remain potential areas for future empirical investigation, and their practical value would need to be established through empirical research.

Discussion

What Does This Framework Add?

The contribution of this framework is not the proposition that AI can perform prediction, risk stratification, or related population-health analytics. These capabilities are already represented in population-health, healthcare AI, and clinical-risk literature [3-5].

Nor is the contribution the proposition that healthcare AI presents implementation and ethical challenges. These issues are already represented in research concerning barriers, trust, ethics, bias, and governance [7-10].

The proposed contribution is narrower: Once an AI-enabled population-health intervention has

been defined, how can the human-response dimension of that intervention be experimentally investigated?

Mind Genomics is proposed as one possible methodology for addressing this question.

From AI Prediction to Human Engagement

AI-supported population-health approaches may help identify patterns, higher-risk populations, or opportunities for preventive intervention [3,4].

However, implementation takes place within healthcare and social environments.

Research on AI implementation identifies ethical, technological, regulatory, workforce, social, and patient-safety barriers [7]. Trust is also influenced by individual, AI-related, and contextual characteristics [8]. Healthcare AI governance literature further emphasizes fairness, transparency, privacy, accountability, human oversight, and institutional responsibility [10].

Therefore, the ability of AI-supported systems to identify or prioritize potential intervention opportunities is only one part of the broader population-health process. How people respond to the resulting intervention represents an additional consideration.

The proposed framework focuses on this human-response dimension by using Mind Genomics to experimentally examine responses to combinations of intervention features.

Why Mind Genomics Rather Than a Single Acceptance Measure?

A conventional survey might ask:

“Do you trust AI in healthcare?”

Such a question can provide a useful overall measure of attitude.

Mind Genomics instead permits a more specific experimental question:

“What happens when different intervention features are presented in different combinations?”

This distinction is relevant because empirical research

on medical AI ethics has documented variation in stakeholder knowledge, attitudes, acceptance-related factors, and ethical concerns [12].

Experimental preference research also provides an example of healthcare AI being studied through multiple experimentally varied attributes. Bracic et al. (2026) examined AI performance, clinician presence, governance, and training-data representativeness in relation to patient trust and choice [13].

Previous Mind Genomics studies similarly demonstrate how combinations of health-related messages can be evaluated and subsequently analyzed for heterogeneous response patterns [16-18].

Thus, Mind Genomics is proposed as a complementary experimental methodology rather than as a replacement for conventional acceptance research.

Relationship to Demographic Segmentation

Demographic and socioeconomic characteristics remain relevant to population-health planning.

Population health explicitly considers differences in health outcomes and their distribution across populations [1].

AI systems can also encounter disparities when differences in population characteristics, representation in healthcare data, and social determinants of health affect how systems perform across groups [11].

The proposed framework therefore does not argue that demographic or socioeconomic segmentation should be abandoned.

Instead:

Demographic segmentation describes characteristics of populations, whereas Mind Genomics can potentially reveal differences in responses to combinations of intervention ideas.

The two approaches may therefore be complementary, although their relationship would itself require empirical investigation.

Ethical Boundaries

The ethical boundaries of the proposed framework

are central to its interpretation.

In this framework, Mind Genomics is not intended to:

- diagnose disease;
- replace clinical judgment;
- determine who should or should not receive healthcare;
- determine eligibility for essential treatment;
- discriminate against individuals based on inferred response patterns;
- replace epidemiological or population-health analysis; or
- create psychologically invasive profiles unrelated to the intervention being studied.

Its proposed role is narrower:

Mind Genomics is intended to investigate how people respond to intervention concepts, not to determine who should receive healthcare.

This boundary is consistent with broader concerns around fairness, accountability, privacy, human oversight, and institutional responsibility identified in healthcare AI literature [12,10].

The framework also does not assume that an empirically identified mindset should automatically determine how an individual is treated. Any practical application would require separate ethical, clinical, organizational, and empirical validation.

Limitations

Several limitations should be acknowledged.

First, this paper is conceptual and methodological. It does not report a completed empirical Mind Genomics experiment using the proposed 16 elements.

Second, the proposed elements are illustrative candidate elements. Their wording, relevance, and organization would require empirical development and testing for a specific population-health problem.

Third, the conceptual mindsets presented here are hypothetical. They must not be interpreted as established population segments.

Fourth, the framework does not demonstrate that Mind Genomics-informed intervention design improves adherence, participation, screening uptake, trust, or

health outcomes.

Fifth, willingness to engage with an experimental vignette is not equivalent to real-world behaviour. Any relationship between experimentally measured responses and subsequent behaviour would require separate validation.

Sixth, the proposed relationship between AI-supported targeting and Mind Genomics-informed intervention design is conceptual. It has not been tested as an integrated population-health workflow.

Finally, the framework requires empirical testing in specific population-health contexts before claims concerning practical effectiveness can be made.

Future Empirical Validation

A logical next step would be a comparative empirical study examining whether information derived from a Mind Genomics experiment can inform the development of more appropriately tailored population-health interventions or communication strategies.

Conventional Intervention

A population-health intervention developed using established communication, programme-design, or targeting approaches without experimentally derived Mind Genomics response patterns.

Mind Genomics-Informed Intervention

An otherwise comparable population-health intervention informed by experimentally derived element contributions and empirically identified Mind Genomics response patterns or mindsets.

In a future study, the two approaches could be compared using prespecified intervention-related outcomes such as:

- engagement;
- participation;
- trust;
- satisfaction;
- retention;
- adherence;
- screening uptake;
- or other context-specific outcomes.

The research question could be:

Would a population-health intervention informed by empirically derived Mind Genomics response patterns differ in engagement-related outcomes from an otherwise comparable intervention developed using conventional approaches?

Such a study would allow the practical relevance of Mind Genomics-informed intervention design to be examined empirically. Importantly, the present conceptual framework does not assume that a Mind Genomics-informed intervention would produce better outcomes. Whether such an approach results in different or improved outcomes would need to be determined through future empirical research.

This remains a testable empirical question rather than a conclusion of the present conceptual paper.

Conclusion

Artificial intelligence is increasingly being considered for population-health applications involving prediction, risk identification, monitoring, resource-related support, and intervention planning. However, identifying a population-health opportunity does not by itself establish that people will understand, trust, accept, or be willing to engage with the resulting intervention.

Healthcare AI implementation involves multiple human and organizational considerations, including trust, fairness, transparency, privacy, accountability, human oversight, social context, and patient safety. Previous Mind Genomics applications also demonstrate that people can respond differently to combinations of health-related messages and that experimental designs can be used to estimate element-level contributions and identify heterogeneous response patterns.

This paper therefore proposes a complementary methodological pathway: population health frames the health problem and intervention context; AI can support the identification or prioritization of potential intervention opportunities; and Mind Genomics can experimentally investigate how people respond to combinations of intervention features and express willingness to engage with them.

The proposed 4×4 framework translates this concept into four researcher-defined domains-Trust and Transparency, Convenience and Delivery, Social

and Contextual Fit, and Autonomy and Human Support-and 16 candidate elements. These elements and domains are proposed for experimental testing and are not presented as universal determinants of engagement. Similarly, the three illustrative mindsets are hypothetical examples rather than established population segments; any actual response patterns would need to emerge empirically from participant ratings.

The framework also deliberately limits the roles of AI and Mind Genomics. AI is positioned as a supporting analytical technology rather than an autonomous population-health decision-maker, while Mind Genomics is positioned as an experimental methodology for studying human responses rather than a mechanism for determining treatment eligibility or access to healthcare.

The longer-term opportunity is therefore not simply to make population health more algorithmic, but to investigate whether AI-enabled population-health interventions can be designed in ways that are more human-centered, experimentally informed, and responsive to heterogeneous human responses and concerns. Whether such an approach can improve engagement, participation, adherence, or health outcomes remains an empirical question for future research.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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