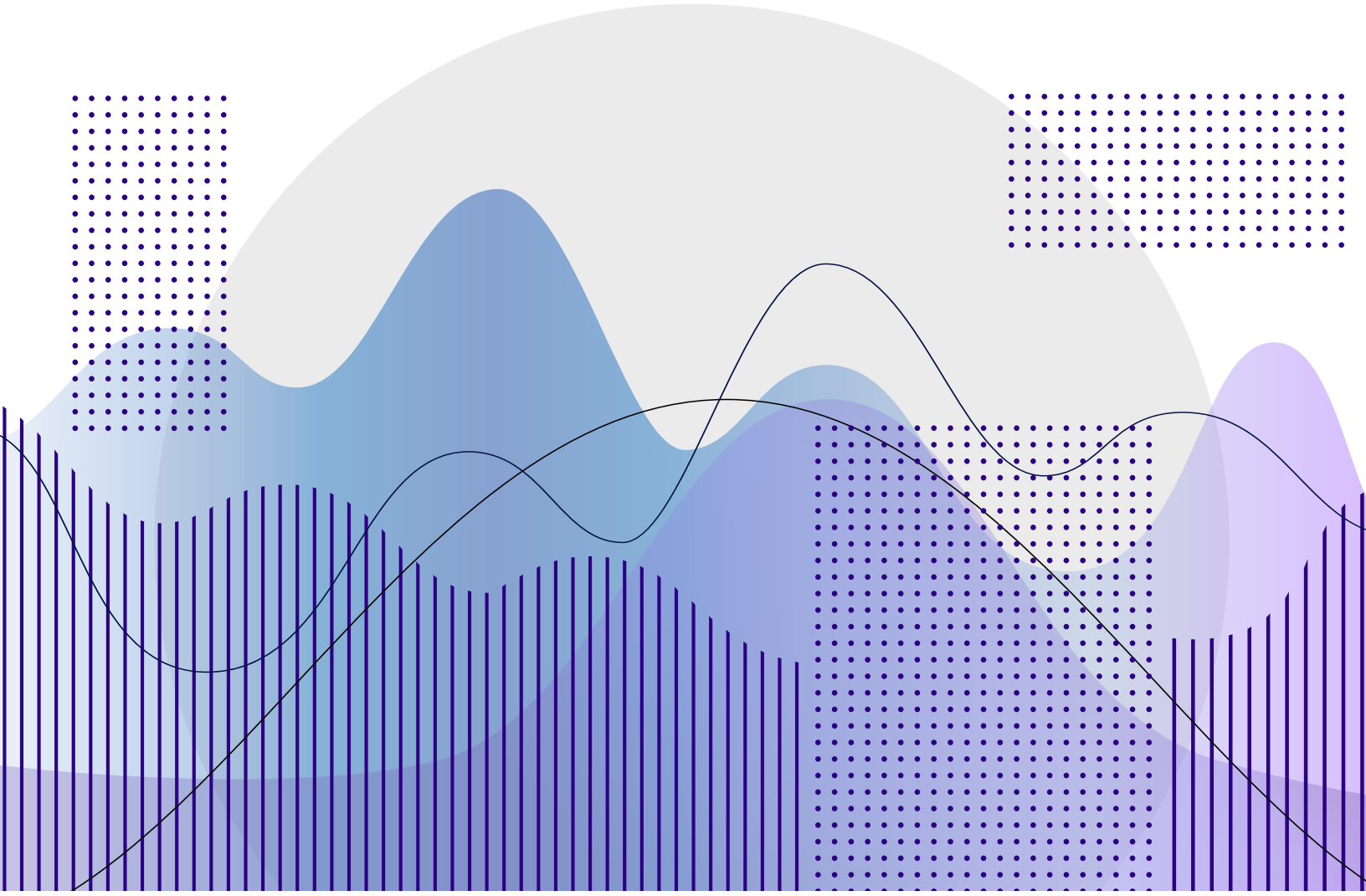
TIAA Institute

# Unit of Health™: The Currency of Longevity



Insights & Implications in Gerontology Series

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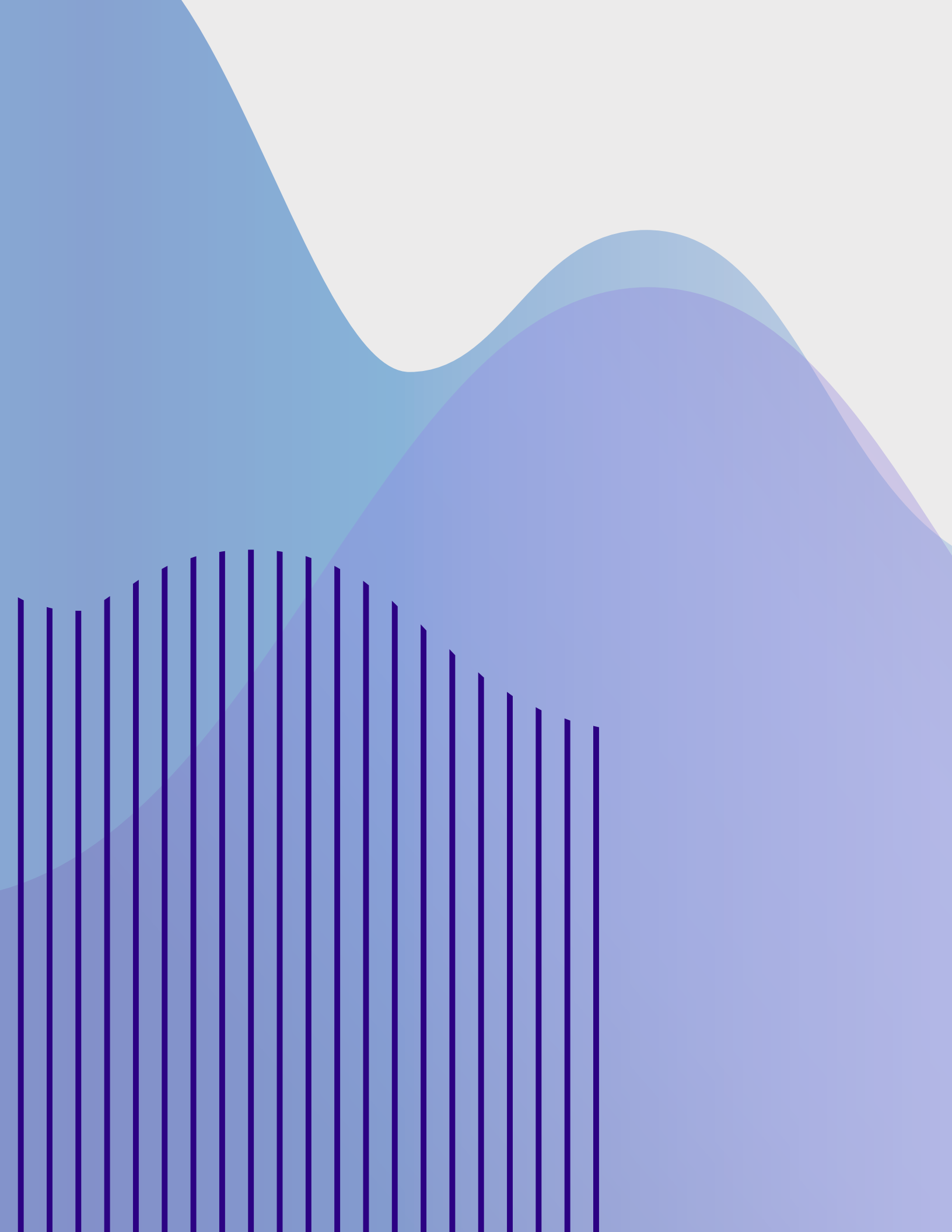
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## Executive Summary

Personalized health information (PHI), wearable devices, and other emerging tools for measuring a person's behaviors and clinical indicators could underpin a Unit of Health™ (Unit•H™)—conceptualized as one added day of healthy life. Using such a unit responsibly, however, requires careful attention to design, evidence, emotional impact, privacy, and equity.

### Context and Core Concept

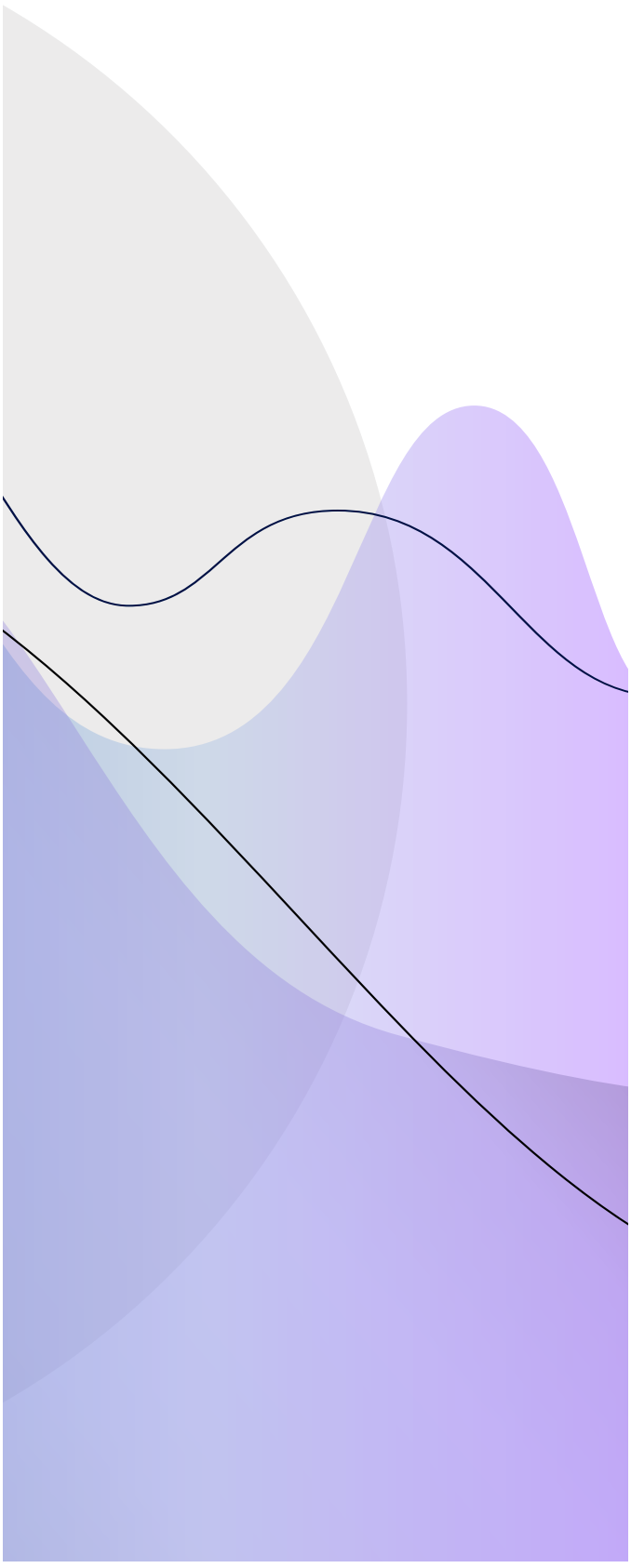
In contrast to financial planning—in which a clear unit of wealth (the dollar) exists—health planning lacks an equivalent, predictable unit. With the rise of wearables, electronic health records (EHRs), personalized medicine, and artificial intelligence (AI), individuals now generate continuous streams of PHI. With this information about activity, sleep, clinical biomarkers, genetics, and social activities, estimates of a person's health span—an average number of expected years of life remaining with healthy function—are possible.

Building on the TIAA Institute's definition, a Unit of Health™ is defined as a day of healthy life "earned" through beneficial behaviors such as exercise, sleep, social connection, and nutrition. Can this concept be operationalized in ways that genuinely inform decisions, rather than simply adding data anxiety or false precision?

### Domains and Technologies Shaping Health

Wearables and apps now routinely capture movement, sleep, cardiovascular metrics, glucose, mood, stress, and social engagement, while smart scales and home devices contribute weight and body composition to health apps that gather and summarize information. These streams integrate genomic and "multi-omics" data (e.g., epigenomics, proteomics, metabolomics, microbiome) with social determinants (such as neighborhood and income) to create a rich yet complex picture of health risk and resilience.

In addition to these common measures, advanced technologies are marketed for longevity: full-body magnetic resonance imaging (MRI) screening and other imaging technologies, epigenetic clocks and "bio-age" apps, genomic risk profiling and survivorship services, and composite indices used in health systems and consumer dashboards. Many of these tools offer intriguing insights at the population or research level but remain uncertain and unvalidated as individual decision aids, especially when their outputs are compressed into single numbers that appear more precise than the underlying science supports.



## The Vitalis Unit•H™ Dashboard

To explore how PHI might be made usable and motivating, the authors asked the Perplexity Computer to build a longevity-habit tracker focused on four pillars consistently linked to mortality risk: movement, sleep, nutrition, and social engagement. The resulting prototype, the Vitalis: Unit of Health™ Longevity Tracker, integrates evidence from large cohort studies and meta-analyses to model how behavior patterns over five years could narrow a "closable gap" between a person's current habits and adhering to recommended norms for these pillars.

Daily and weekly scores, four-week trend graphs, and a projected five-year impact visualization aim to help users see patterns and opportunities. Movement metrics draw on data showing substantial reductions in all-cause mortality with moderate leisure-time activity and strength training; sleep metrics model the optimal seven to eight hours of sleep; social metrics track both the number of daily connections and minutes of quality time, reflecting evidence that robust social ties can increase survival odds; and nutrition metrics translate research on fruit and vegetable intake and its association with lower mortality. The illustrator demonstrates how PHI might be displayed on a Unit•H™ dashboard.

## Emotional, Behavioral, and Unit•H™ Design Considerations

PHI is not just objective information; it is experienced emotionally. People can develop "data anxiety," becoming preoccupied with fluctuations in sleep or other metrics that may be hard to interpret and can worsen the very symptoms being tracked. Feedback is processed emotionally and cognitively as much as is the data displayed. To allow people to process health information, dashboards should highlight trends, context, and actionable next steps rather than moralize or present health as a binary verdict. Patterns and opportunity frames—showing trajectories and modifiable behaviors—are preferable to binary scores, which risk equating deviations from ideals with personal failure.

Dashboard and visualization research stresses the need for emotionally safe interfaces for health data: layered information, emphasis on manageable actions, reminders that health is probabilistic rather than fully controllable, and sensitivity to the greater emotional weight of negative health findings compared with financial or productivity metrics. Clinicians are urged to treat PHI as both technical input and relational material, helping patients interpret data without amplifying distress or implying unwarranted certainty.

## Clinical Care and Social/Companion Technologies

Patient-generated PHI should be integrated into electronic health records and clinical workflows to support more tailored care and reduce legal liability. However, clinicians are at risk of overload and burnout because of the sheer volume of largely unregulated and poorly studied consumer-generated information. Guidance from implementation studies suggests focusing on clearly defined clinical questions and workflows, selective use of monitoring (e.g., short-term continuous glucose monitoring tied to specific symptoms), and protocols for what data will be accepted, how it will be displayed, and how it will be acted upon.

Social and companion technologies—AI chatbots, social robots, and virtual reality platforms—are emerging sources and mediators of PHI. They can reduce loneliness, provide encouragement, and help organize data, but they also raise concerns about privacy, persuasion, and the blurring of lines between support and quasi-clinical advice. Their value in a Unit•H™ framework depends on whether they help users interpret PHI realistically and are in line with their goals, rather than nudging behavior based on oversimplified or commercially driven metrics.

## Limitations, Privacy, Equity, and Regulation

Fundamental limitations of health dashboards include models trained on narrow cohorts, wide confidence intervals around individual predictions, and incomplete evidence of links between dashboard scores and lifespan gains. Treating Unit•H™ outputs as hard guarantees of added days or years is therefore misleading. Privacy concerns also loom large, particularly for consumer-generated PHI that sits outside traditional health-privacy regulations.

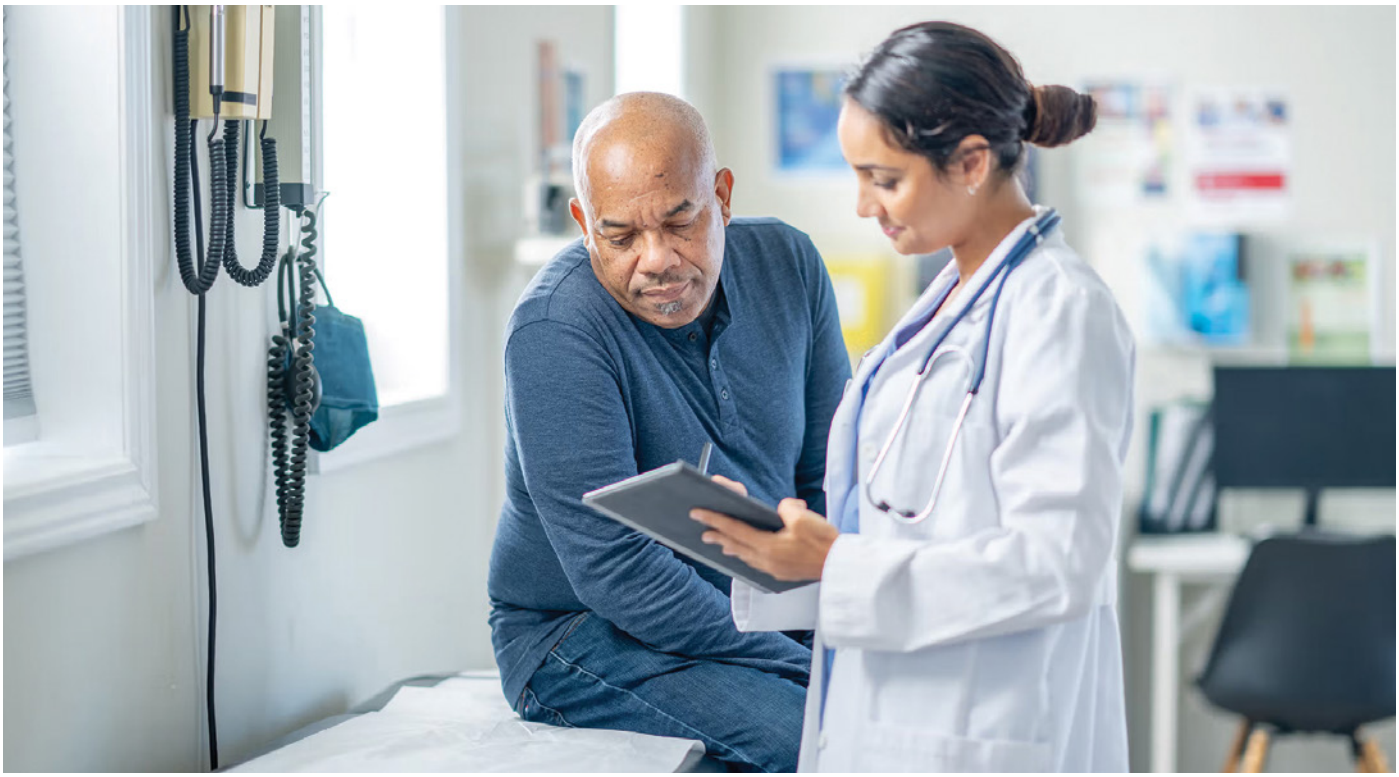
Equity issues are also pervasive. Adoption of and benefit from wearables, apps, and dashboards skew toward those with more income, education, and digital literacy, while health trajectories are heavily shaped by structural determinants such as wages, housing, and access to care. A Unit•H™ framework that relies on high-engagement technologies risks privileging already advantaged groups. Ethical and regulatory guardrails should be in place for research-stage tools entering consumer markets, with protocols for disclosure, follow-up, emotional impact, and accountability when these tools influence health decisions outside traditional clinical oversight.

## Recommendations and Research Agenda

The Vitalis Unit•H™ illustrator is a conceptual device for structuring conversations about what the population at large hopes to preserve or gain in later life—longevity, function, quality of life, independence, and/or resilience. Future research should focus on these areas:

- **Baseline demographics and comorbidities—**Clarify which health dimensions are used to compare health states and ensure they align with people's goals at different ages.
- **Clarify what Unit•H™ models measure—**Treat Unit•H™ dashboards as aids to orientation to the concepts and decisions regarding longevity, with visualizations of data reflecting the uncertainty of longevity rather than precise conversions of points to years.
- **Design and implementation of personalized measurements—**Identify clinical scenarios in which Unit•H™ is most useful, align data and visualizations with users' goals, integrate them into supportive relationships, and establish ethical/regulatory guardrails and protocols for emotional impact and accountability.
- **Social and policy implications—**Examine how Unit•H™ interacts with socioeconomic inequality, aging, retirement, and long-term care financing, especially for the "forgotten middle" who have neither public assistance nor ample resources.

PHI-based tools and Unit•H™ framings can be helpful if they are selective, interpretable, and tied to realistic decisions—but only if designers, clinicians, policymakers, and industry resist the temptation to convert complex, uncertain health futures into overly authoritative numbers that risk becoming new metrics of personal worth.



## Introduction

Throughout life, people can reliably plan for the financial aspects of their later years. Money can be saved, invested, and grown at rates that are reasonably predictable over time. In middle age and older adulthood, a target retirement age can be set, and an income level during those years can be estimated. These calculations are reliable because people have a measure of wealth—in the United States, this unit of wealth is the dollar.

Health has not been like that. Someone whose parents and many aunts and uncles died of cancer or heart attacks might figure they will suffer a similar fate. But at what age? One aunt died in her 50s, his father in his late 70s, and his mother in her 80s. Without more information about lifestyle, genetics, diet, and sleep, those facts do not tell the person much more than population averages about their expected lifespan.

Until now. Through wearable devices, people can track activity, heart rate, sleep, exercise, and other health information as they go about their daily lives. Because of the advent of this personalized health information (abbreviated in this report as PHI, which should not be confused with "protected health information"), combined with an exponential growth in medical knowledge and the accessibility of electronic health records (EHRs), people and their health care providers have a plethora of valuable information that can be translated into predictions about their expected years of healthy life remaining (referred to as the health span). These estimates include the average number of years of life remaining with normal activity, free from chronic illnesses, severe cognitive decline, and disabilities. PHI can be supplemented in a number of ways beyond routine medical care and wearable-generated data, including comprehensive scans, predictive tests, health scores, epigenetic clocks, and longevity indices. Using artificial intelligence (AI), this vast amount of data about a single person can be analyzed to predict trends in their expected years of healthy life—their "health span."

This report examines the feasibility of using such data to develop a Unit of Health™, which is defined by TIAA as one day of added lifespan. As originally described by Kolluri (2025), "A Unit of Health is something we earn by doing something good for our future body and mind. Exercise earns a unit. Good sleep earns a unit. Social connection earns a unit. Meditation, clean eating, hydration, recovery, all of these are inputs. They are deposits just like wealth." By accruing these units, additional days can add up to months, and months to years. Soon, the health span is extended significantly. Surveys conducted by TIAA show that adults across all age groups would value a single

metric that shows the number of healthy living days they are gaining or losing through such daily behaviors. Yet how can we assess a measure like the Unit of Health™, also referred to as Unit•H™? If people had access to such a number, would they be reassured or more worried? Would people become so obsessed with tracking data that they forget to enjoy life? How would medical providers use these data to improve a person's care and encourage or support a healthier lifestyle?

## Domains and Contexts Shaping Health

The confluence of big data, cloud computing, supercomputers, wearable monitoring devices, EHRs, and AI is driving major and rapid change in health care. Numerous behaviors are tracked by wearable devices, including several that have been available for years. The types of wearable devices—such as Whoop Bands, Oura Rings, Apple Watches, Google Pixel Watches, and Fitbit Bands—are expanding to include earbuds and shoes that can record data such as heart sounds, sweat composition, environmental noise, and gait symmetry. Overall, spending on the wearable technology market is expected to top $100 billion in the United States in 2026 and double by 2033 (Grand View Research, 2026).

Today's wearable devices commonly track sleep, exercise, cardiovascular function, and other physiologic metrics. Emerging metrics tracked by these devices include stress, cognitive fitness (including brain exercises), and social connections. Smart scales track weight and body composition, delivering data to smartwatches and phones. These are key behavioral domains that may affect a Unit•H™.

Numerous apps have also been developed to support users' mental health, often in combination with data gathered by wearable devices and virtual appointments with mental health professionals. Mental health is an often-overlooked but important part of one's overall health and well-being. While typically related to personal challenges and interpersonal issues, mental health is important for all ages, and especially for young people whose formative years have been marked by disruptive external events, including school shootings, a global recession, and a global pandemic followed by social isolation and disrupted school attendance and activities (*The Lancet*, 2022; Geoffroy et al., 2022).

The personalized data gathered by wearable devices are just part of the movement toward personalized medicine—treatment based on each person's unique characteristics rather than a "one size fits all" approach to medicine. The availability of data from the Human Genome Project has led to the identification of genes and the determination of genetic links to normal and abnormal physiologic function. With greater availability of genetic testing, a person's genome provides a useful canvas onto which data from wearable devices, routine medical care, and emerging tests can be displayed with greater clarity.

A simultaneous "multi-omics" revolution is leading to the identification and analysis of a person's current genomic state (epigenomics), RNA transcriptions of DNA (transcriptome), protein expression (proteomics), overall metabolic state (metabolomics), and types of microorganisms present in the gastrointestinal tract and other body cavities (microbiome) (Ooka, 2025).

As researchers and clinicians analyze raw data on people's heartbeats, sleep, genetics, and multi-omics, they recognize that these data only go so far in predicting future health events or distinguishing between health and sickness. Socioeconomic risk factors and structural determinants are likely more important than the number



of steps a person takes each day. In fact, data on one's zip code—including whether there are sidewalks and parks where a person can walk safely—are associated with health, longevity, and the availability of healthy foods and quality health services (Chetty et al., 2016; Chen et al., 2012). For many reasons, people can have difficulty making ends meet for food, housing, and other basic necessities of life; they may not be able to prioritize health monitoring or predicting associations based on a Unit•H™.

A final factor in personalized medicine is the differing views people can have across the lifespan. Physical decline that an 85-year-old might view as inevitable could be perceived differently by someone at age 65 or younger. The death of a spouse or a "gray" divorce can reduce the positivity a person might have felt coming into older adulthood. Alternatively, people can be happy with early retirement, being able to volunteer in roles they truly enjoy, or traveling to bucket-list destinations they've always wanted to visit. These types of experiences and events can have a greater impact on a Unit•H™ than data from wearable devices—but they are much more difficult to quantify.

## Personalized Health Information in Everyday Life

Wearables and other smart devices can alert users to patterns, detect cardiac arrhythmias such as atrial fibrillation, and encourage people to increase their exercise and daily step counts. Blood pressure, weight, sleep patterns, and dietary intake can be shared with health professionals, providing valuable information that may be more accurate than in-office measurements and patient-completed surveys. Clinical information on conditions such as diabetes, heart failure, lung diseases, chronic pain, musculoskeletal disorders, and asthma can be gathered by wearable devices ordered by health professionals (Higgins & Wold, 2024; Agency for Healthcare Research and Quality, 2021; Office of the National Coordinator for Health Information Technology, n.d.; Tiase et al., 2020; Perez et al., 2019; Shcherbina et al., 2017; Gagnon et al., 2024).

Health care professionals can use data from patients' wearables to enhance care. They should incorporate the relevant information into therapeutic plans without questioning whether the patients are fixated on the data or using the devices excessively. Can wearables and other digital data be used to quantify change using the Unit•H™ (Khatiwada et al., 2024; Anders, 2021)?

### Personalized Health Information: Categories and Accessibility

In the current health care environment, PHI refers to health-related data that is identifiable to a specific individual and organized or interpreted in relation to that person's biology, behaviors, environment, family and medical histories, and preferences. The goal of PHI, then, is to inform prevention, diagnosis, treatment, or self-management for that individual. Health data generated by the health care system during medical visits and interventions are stored in EHRs, which have been widely used for years. Wearable devices are now producing additional streams of data that can be useful to health professionals in monitoring patients' conditions and responses to treatment. When these data are shared with health professionals, the information needs to be incorporated into EHRs for the benefit of all health professionals using the record and for legal liability reasons should disputes occur (ten Klooster et al., 2024; Agarwal & Khuntia, 2009; ChartSpan, 2025; Anders, 2021).

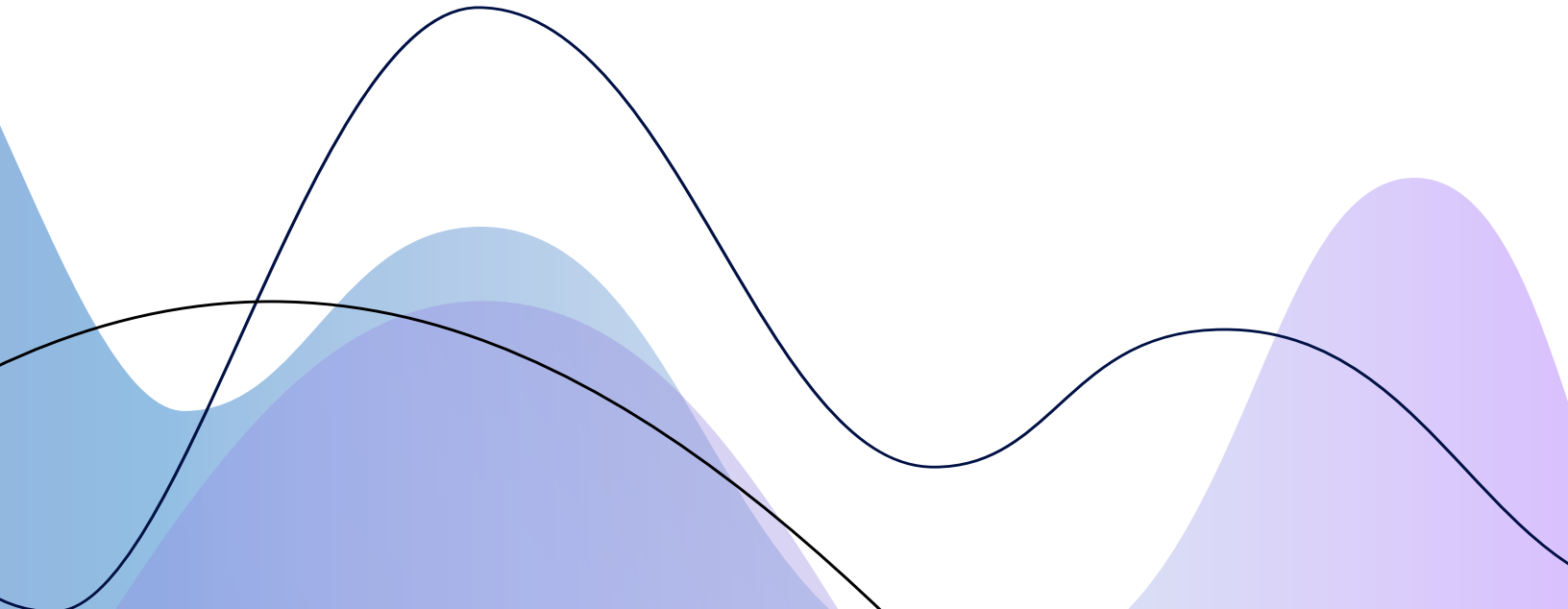
The advent of PHI represents a shift from population-based, algorithm-driven care to individualized clinical decisions for maintaining health and preventing disease. While this feels revolutionary, it is, in fact, an evolutionary step that follows innovations over many years, such as consideration of personal risk factors and comorbidities, age and family history, allergies, and monitoring of patients' drug levels (pharmacokinetics and pharmacogenomics) and responses to treatments. In health care, this type of individualized care can be summarized as the right treatment for the right patient at the right time. The difference today is the availability of large amounts of data that can be interpreted and applied through personalized medicine (Stefanicka-Wojtas & Kurpas, 2023; Agarwal & Khuntia, 2009).

Several types of PHI are available to clinicians and patients (Table 1). Together, these categories illustrate that PHI extends beyond traditional medical records to encompass behavioral, social, and financial data that shape an individual's health trajectory and their capacity to act on information.

**TABLE 1. TYPES AND CATEGORIES OF PERSONALIZED HEALTH INFORMATION**

| Categories | Examples |
|---|---|
| Identifiers and demographics | Name or coded identification plus age, sex, contact details, and other basic demographics |
| Clinical and biomedical data | Diagnoses, medical history, medications, allergies, laboratory results, imaging and its interpretation, vital signs, and genetic or other biomarker data |
| Mental and behavioral health information | Mental health diagnoses and treatment, as well as mood, stress, sleep, pain, substance use, and related self-reports collected during care or through apps |
| Lifestyle, activity, and physiological tracking | Data from wearables and apps on physical activity, steps, heart rate, blood pressure, glucose, sleep patterns, nutrition, and other day-to-day behaviors |
| Social and environmental context | Information on social connections, caregiving, work, housing, and other social determinants of health that influence risks and needs |
| Emergency, critical, and care-planning information | Key emergency data (e.g., allergies, implantable devices), advance directives, caregiving arrangements, and long-term care preferences |
| Insurance, financial, and utilization data | Coverage, claims, payments, and other financial or administrative information relevant to accessing and managing care |

Sources: Agarwal & Khuntia, 2009; ten Klooster et al., 2024; ChartSpan, 2025.



## Making Consumer-Generated Information Understandable and Motivating

Of the PHI listed in Table 1, four activities have been consistently associated with longevity and changes in mortality risk: nutrition, physical activity, sleep, and social engagement. To explore the development of positive ways that consumers can interact with these data from their wearable devices and other information sources (e.g., food and personal diaries), the Perplexity Computer system (an artificial intelligence system that can act as a digital worker) was given this instruction:

> "Build an interactive longevity-habit tracker dashboard that monitors these four core pillars: nutrition, physical activity (steps/strength), sleep (quality/duration), and social engagement. Include input fields for daily tracking, automated weekly summaries of progress against research-backed longevity markers, and alerts for gaps in activity or social frequency. Add a visualization showing the potential impact of these habits on healthspan markers over a 5-year period based on currently available longevity research."

In response, the Perplexity Computer produced the Vitalis: Units of Health™ Longevity Tracker (Figure 1). Perplexity drew the name from the Latin "vitalis," meaning "of life" or "life-giving" (the root of words such as "vital" and "vitality"), and combined it with the Units of Health™ focus of this report. Vitalis signals health, energy, and longevity in a single word, and reads cleanly as a product name.

The trends for each of the four pillars in this illustrator are modeled after available research data, as follows:

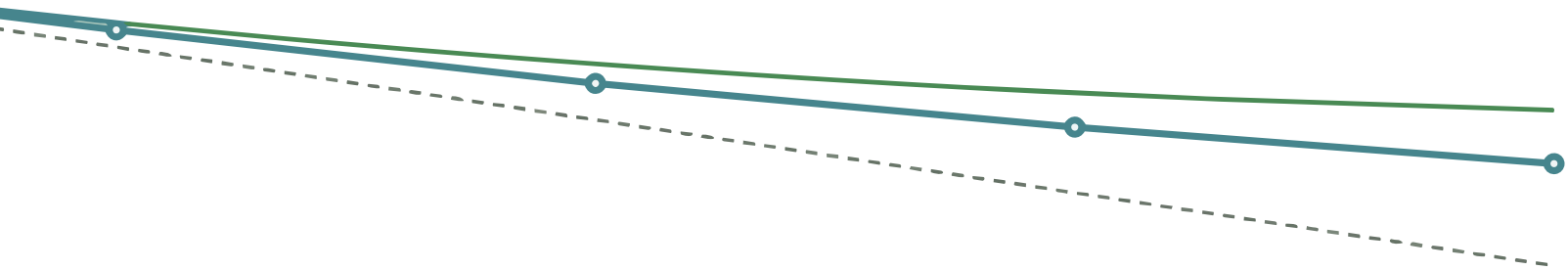
- Movement—data for aerobic activity came from Lee et al. (2022), who found a 19% to 25% decrease in all-cause mortality with moderate leisure-time physical activity among 116,221 adults over a 30-year period. Resistance exercise data came from a review article that focused on strength-training markers (Momma et al., 2022; O'Keefe et al., 2023).
- Sleep—Data were obtained from a 2025 meta-analysis of 79 cohort studies that showed a 14% increase in mortality with less than 7 hours' sleep per night and a 34% mortality increase with more than 9 hours' sleep. The U-shaped curve showed that 7 to 8 hours of sleep produced the lowest mortality risk; the supporting data came from an older systematic review and meta-analysis of nearly 1.4 million people (Ungvari et al., 2025; Cappuccio et al., 2010).
- Social—A review article provided the basis for this aspect of the Vitalis illustrator based on social connectedness data from 1972 to 2023. Information from the foundational analysis of this relationship was included in the Vitalis illustrator, which showed approximately 50% greater survival odds among people with strong social ties (Holt-Lundstad, 2024). Perplexity included two metrics for the social daily log: connections, a count of distinct social interactions, with a daily target of 3, and quality time, the total minutes of the interactions with a goal of 45 min/day. These metrics are weighted evenly in the social pillar score.
- Nutrition—In studies of nearly 2 million adults, individuals eating 5 servings/day of fruits and vegetables had 13% lower all-cause mortality than those consuming 2 servings daily. The risk reduction plateaued at about 5 servings/day, researchers reported, based on data from 66,719 women in the Nurses' Health Study (1984–2014), 42,016 men in the Health Professionals Follow-up Study (1986–2014), and 24 other prospective cohort studies (D. D. Wang et al., 2021; Sattar & Forouhi, 2021). This part of the tool could be adapted for specific diets known to be beneficial, such as the Mediterranean diet (Estruch et al., 2018).

Based on published data for these behavioral characteristics, the Vitalis illustrator presents scores for the current day and week, along with a graph tracking the four pillars (movement, sleep, nutrition, social) over the prior four weeks. To encourage the user to increase their healthy behaviors in these domains, the illustrator shows the "closable gap" over five years between continuing one's current habits and full adherence to the risk-reduction behaviors.

**FIGURE 1. SAMPLE REPORT FROM THE VITALIS UNIT OF HEALTH™ LONGEVITY TRACKER**




Source: Illustrator developed by Perplexity Computer using data from Cappuccio et al., 2010; Holt-Lundstad, 2024; Lee et al., 2022; Momma et al., 2022; O'Keefe et al., 2023; Sattar & Forouhi, 2021; Ungvari et al., 2025; and D. D. Wang et al., 2021. This is a conceptual illustration only. The Vitalis dashboard was built by an AI system to demonstrate how personalized health data could be visualized. It is not a validated clinical or diagnostic tool, has not been tested with real users or patients, and should not be used to estimate an individual's actual health span or lifespan. The research citations shown reflect population-level studies; they do not establish that this specific scoring method or visualization predicts individual outcomes.



> "Data anxiety is real—people get anxious just from tracking everything, especially sleep, which can end up worsening the very problem they're trying to monitor."
>
> ***—Martha Deevy, MBA***

### Emotional and Behavioral Responses to PHI

How people respond to Unit•H™ dashboards such as Vitalis depends in part on whether the information answers a concrete question or simply creates more uncertainty. For instance, short-term glucose monitoring to investigate unexplained symptoms illustrates a targeted use of PHI that can be clinically and personally meaningful because it is tied to a specific concern and a plausible decision pathway. By contrast, continuous tracking without a clear purpose may produce "data anxiety," in which people become preoccupied with fluctuations in metrics such as sleep or glucose that are difficult to interpret and may worsen the very condition being monitored. In this sense, more data does not necessarily translate into more understanding. Without context, more data may simply expand the range of things people feel responsible for managing (Ancker et al., 2015; Baron et al., 2017; Estupinian, 2025). In a study by Goel et al. (2026), about 30% of people using sleep trackers had orthosomnia, or anxiety associated with use of the app.

Important to remember is that people do not simply "use" PHI; they negotiate with it. Some integrate it into routines of self-experimentation, preventive care, or lifestyle modification, while others ignore, resist, or selectively attend to it because the burden of interpretation is too high or the relevance is unclear. The uptake of PHI is also shaped by trust: trust in the device, the app, the algorithm, the clinician, and the broader institutions that recommend or monetize these tools. Where that trust is fragile—or where the information conflicts with lived experience, quality-of-life priorities, or social constraints—people may disengage rather than deepen their use of data (Xie et al., 2022; Coiera et al., 2025).

### Design Principles for Personalized Health Dashboards

Behind the design of the Vitalis Unit•H™ dashboard is a wealth of research on optimal ways to display PHI that encourage people rather than scare or demoralize them. Its presentation matters as much as its content. One key notion to keep in mind is that the dashboard is not a neutral window into health; it is an interpretive device that can either orient people toward manageable action or leave them feeling concerned or even hopeless. Designing "emotionally safe" PHI dashboards, like the Vitalis Unit•H™ example, means recognizing that health information is received not only cognitively but also emotionally, and that fear, shame, discouragement, or overload can alter how users respond to the very information intended to help them (Snyder, Aaronson et al., 2012; Snyder, Blackford et al., 2022; Amagai et al., 2025).

One core principle is to present PHI and Unit•H™ information in patterns and opportunity frames rather than in binary pass/fail formats. When dashboards emphasize trajectories, ranges, and modifiable possibilities, they are more likely to convey that health is dynamic and partly improvable, rather than a fixed verdict on personal worth. Well-designed PHI scorecards, therefore, should highlight areas of success and gaps that can be addressed with specific actions (Robinson et al., 2019).

A health dashboard like the illustrative Vitalis differs in important ways from one displaying a person's financial status, though both can produce real and lasting distress. Financial setbacks such as job loss, inadequate retirement savings, the need to rely on Medicaid for long-term care, among others, can feel urgent, frightening, and in some

cases irreversible, particularly for people with little financial cushion. What distinguishes health dashboards is the direct association with mortality: an unfavorable signal can feel like evidence that one's remaining time, not just one's resources, is at risk. This added dimension means health dashboards require particular care in tone, pacing, and framing, even as financial dashboards deserve similar sensitivity to the real stress and limited options many people face. The Vitalis dashboard uses greater care in tone, pacing, and framing than analogous tools and models in other domains. Information is layered so that users can gradually move from overview to detail, rather than being confronted immediately with an undifferentiated picture of risk and deficiency (Ferreira et al., 2025; Lau et al., 2024).

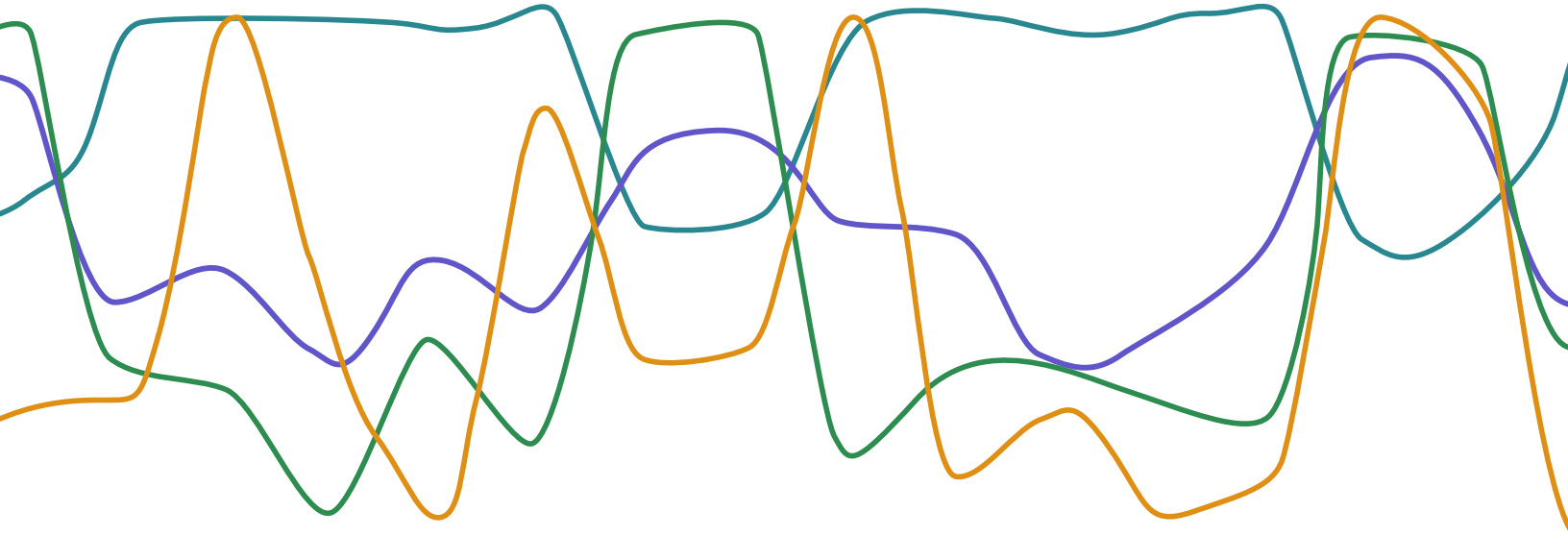
Some dashboards do combine the health, behavioral, and financial domains. Existing instruments, such as the Longevity Preparedness Index developed by the MIT AgeLab and John Hancock Financial, are useful examples of both the value and the risks of multidomain dashboards. On the one hand, such tools broaden the conversation beyond medical indicators alone by showing that readiness for later life depends on health, finances, care arrangements, social connections, home environment, and life transitions. However, by converting these varied domains into a single summary score or a set of domain scores, this approach can oversimplify what "preparedness" means and obscure the unequal resources people have for acting on the information they receive (Coughlin & the MIT AgeLab, 2025; John Hancock, 2025).

The challenge, then, is not to eliminate dashboards or composite indices, but to design them in ways that preserve nuance and protect dignity. Emotionally safe PHI should support interpretation, reflection, and practical decision-making without implying that every deviation from an ideal metric is a personal deficit or a forecast of decline. Especially in a Unit•H™ framework, where the temptation to reduce life to a single number is strong, good design requires humility about what metrics can capture and care for how people live with the information those metrics produce. The Unit•H™ is, therefore, inherently different from other dashboards (Ivers et al., 2022; Mohammed et al., 2022).

## Integrating PHI into Clinical Care

In addition to interacting with PHI through dashboards and devices, people also share their data with their care providers. Some information can be linked to and stored in formal medical records or accessed by providers via wearables and apps. However, at this time, data collected across different devices and systems generally must be accessed and evaluated separately. Patients also bring their own interpretations of what those data mean for their health and longevity. In principle, this broader pool





of information can help clinicians tailor prevention and treatment more precisely by adding longitudinal detail on symptoms, behaviors, and physiologic patterns that may not be visible in a brief office visit. For example, short-term use of a continuous glucose monitor to investigate unexplained lightheadedness or food-related glucose spikes illustrates how targeted, question-driven measurement can produce clinically useful information that shapes a care plan. In people diagnosed with diseases such as type 2 diabetes, long-term use of glucose monitors helps to control the disease, minimize complications, and reduce adverse effects of medications and other treatments (Tiase et al., 2020).

At the same time, integrating PHI into care is not straightforward. Health data are never neutral inputs into a model; they are filtered through human interpretation, and clinicians should respond not only to the numbers themselves but also to how patients experience and understand them. A patient who arrives with multiple streams of tracking data may be seeking validation, reassurance, explanation, or motivation, and the encounter can easily become as much about emotional processing as about risk-factor management (Ye, 2021; Tiase et al., 2020).

In practice, integrating consumer-generated PHI into clinical encounters should be understood as both a technical and a relational task. Clinicians and health systems will benefit from deciding which data to accept, how to display them, and how to incorporate them into documentation and decision-making. They must also help patients interpret those data without overstating certainty or worsening distress. The value of PHI lies not simply in giving providers more information, but in using the right information, in the right context, and with sufficient interpretive support to improve care rather than complicate it (Anders, 2021).

## Social and Companion Technologies

AI systems and robotic companions add another layer to the emerging PHI landscape and provide a unique source of PHI and other data that could be included in a Vitalis Unit•H™ dashboard, alongside its motivational data presentations. Their promise lies in availability and tone: unlike clinicians, they can provide frequent feedback, reminders, prompts, and conversational engagement within the flow of daily life. Such devices can also provide data on a person's social-emotional well-being and, more generally, on their lifestyle that may not be captured when looking at activities (e.g., exercise, sleep, nutrition) in isolation. In principle, they may help users organize large streams of PHI, recognize patterns over time, and cope with loneliness or low motivation by making health information feel more relational and less abstract. This may be particularly relevant for older adults, for whom managing health information might be intertwined with social isolation, caregiving needs, and questions of autonomy (Ho et al., 2018).

Emerging social and companion technologies illustrate both the promise and ambiguity of this role. ElliQ, for example, has been deployed as an AI companion for older adults living alone and has been reported in pilot and implementation studies to reduce loneliness and increase engagement, though the published evidence remains relatively early and not yet equivalent to long-term clinical validation. Robotic pets likewise appear to provide comfort, stimulate interaction, and, in some studies, reduce loneliness or agitation, especially in residential and dementia care settings, but systematic reviews note that positive qualitative reports are stronger than the current meta-analytic evidence. Virtual reality (VR) and related socialization tools show similar promise: some studies suggest improvements in social connection, affect, and perceived well-being, while reviews caution against treating

VR as a universal solution for loneliness (Abbott et al., 2019; Fogelson et al., 2022; Hung et al., 2023; Moyle et al., 2017; Lin et al., 2018; Yu et al. 2022).

For the purposes of PHI, people are sometimes less likely to collect and track data from a companion tool when the tracking process is tedious, or the novelty wears off, and they are less willing to have these data used or shared because of privacy or other concerns (Kang et al., 2026). Another key issue is not simply whether these tools reduce loneliness, but how their feedback style and "tone" shape the user's relationship to health data. A robotic or AI companion that presents PHI in a warm, encouraging, and socially responsive way may make information feel less punitive and more manageable. Yet these same systems can also blur the line between support and persuasion, especially when they frequently nudge behavior, simplify uncertain evidence, or present themselves as trusted interpreters without the accountability or expertise expected of clinicians. Their usefulness depends not only on engagement metrics but on whether they help people interpret PHI in ways that are realistic, proportionate, and aligned with their actual goals and constraints (Yu et al., 2022; Ho et al., 2018).

## Technologies and Metrics for Tracking the Unit of Health™

As discussed above, a wide range of consumer and clinical technologies now generate PHI that could be included in a dashboard based on the Vitalis Unit•H™ template. Wearable and other smart devices extend monitoring beyond the clinic into everyday life, offering continuous or near-continuous streams of data on physical activity, sleep, vital signs, symptoms, and nutrition. Robotic companions, apps, and wearable devices collect data and motivate people to improve their habits and behaviors, translating complex physiologic and behavioral states into scores, trends, or alerts that could be formatted on the Vitalis Unit•H™ or similar dashboards (Abbott et al., 2019; Margrett et al., 2022; Turchioe et al., 2019; Hung et al., 2023).

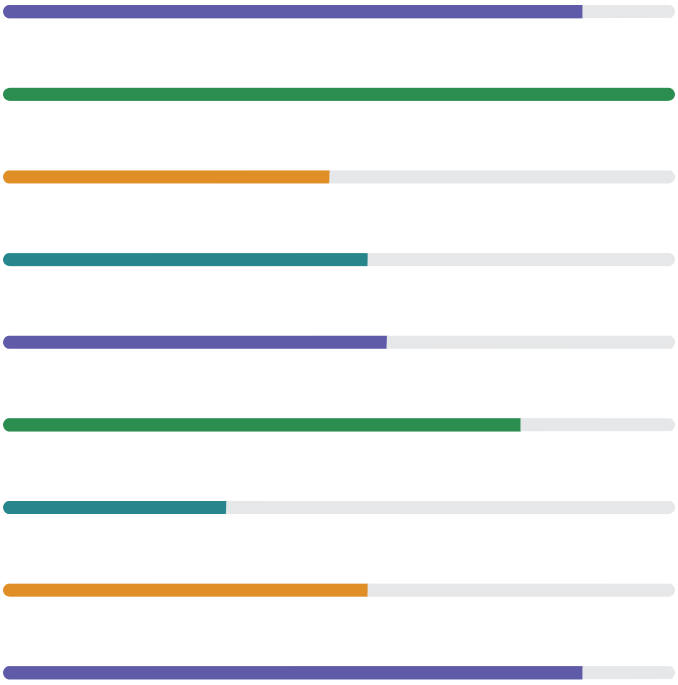
Beyond these technologies lie a wealth of more advanced technologies that may—or may not—extend people's health spans and lifespans. The research supporting these measures and interventions is not yet complete, but they are topics of presentations at longevity conferences and the basis for products and services offered by a wide range of companies.

### Full-Body Magnetic Resonance Imaging

Full-body magnetic resonance imaging (MRI) has emerged as a high-visibility example of advanced imaging marketed for early disease detection and "whole body" health assessment. Advocates argue that, when used judiciously, comprehensive MRI can reveal previously undetected tumors, aneurysms, or other structural abnormalities and provide detailed assessments of muscle, fat distribution, and bone health that might inform prevention or lifestyle choices. From the perspective of the Vitalis Unit•H™ framework, these capabilities are appealing because they promise to detect threats to the health span before symptoms appear, potentially enabling interventions that preserve or add to days of healthy life (Coiera et al., 2025).

At the same time, the radiology and health services literature underscores substantial risks and limitations. Full-body MRI has a high rate of incidental findings—abnormalities of uncertain significance—that can trigger cascades of follow-up imaging, invasive procedures, costs, and anxiety without clear evidence of net benefit in asymptomatic populations. Professional medical

> "It's not just about what the dashboard displays—it's about how that feedback gets emotionally and mentally processed on the user's side."
>
> ***—Chaiwoo Lee, PhD***



societies have generally not endorsed routine whole-body MRI screening for average-risk individuals, citing a lack of outcome data and concerns about overdiagnosis. In the Vitalis Unit•H™ framework, these issues raise the question of whether whole-body MRI meaningfully improves the expected number of healthy days for most people, or whether it primarily increases perceived risk and measurement noise that must still be interpreted and emotionally managed (Agency for Healthcare Research and Quality, 2021).

## Epigenetic Clocks, Bio-Age Apps, and Longevity Prediction

Epigenetic clocks and related biological age predictors enable quantifying health trajectories: rather than imaging organs directly, these approaches infer "biological age" or mortality risk from changes in the chemical structure of DNA (an increase in methylation of the base pairs that make up DNA) and clinical biomarkers present in blood samples. Research has identified measures that combine routine clinical variables (including age, blood biomarkers, and sometimes physical measures of the body) to estimate phenotypic age and mortality risk, as well as DNA methylation–based clocks that track how quickly individuals are aging biologically relative to their chronological age. Other models examine the interaction between life expectancy trends and population health, capturing differences in aging and health across socioeconomic groups and populations and offering powerful tools for demography and epidemiology rather than personalized prediction per se (Higgins-Chen et al., 2022; Yale School of Medicine, 2022; Crimmins, 2015, 2021, 2025).

Consumer-facing bioage apps and tests translate these scientific developments into products that promise to measure or even "reverse" biological age. These tools typically use proprietary combinations of laboratory tests, vital signs, and sometimes DNA methylation data to generate a single biological age number and an estimated remaining lifespan, sometimes accompanied by recommendations for diet, exercise, or supplements. Their appeal lies in offering an apparently objective health score that can be tracked over time. Yet they should be used cautiously, as the models are often trained in specific cohorts and may not be generalizable, confidence intervals around individual predictions are wide, and little prospective evidence indicates the inputs are linked to lifespan changes as predicted. For now, epigenetic clocks and bio-age metrics are best understood as research tools and population-level indicators that may inform a conceptual Unit•H™, rather than precise instruments for guiding individual medical decisions (Higgins-Chen et al., 2022; Yale School of Medicine, 2022).

## Genetics and Biomarkers in Human Longevity

The role of genetic factors in predicting longevity has long been downplayed. Today, the growing availability of genetic and genomic testing is reshaping research on lifespan and driving the development of survivorship services within health systems. These services provide a schedule of screenings for at-risk patients—including those in remission from cancer and others whose risk is elevated by genetic or other factors—as well as interventions for physical and emotional side effects and coordination of long-term wellness care (Denlinger et al., 2014).

Longevity is a complex, polygenic trait influenced by numerous loci (the physical locations of genes on chromosomes) that modulate susceptibility to age-related disease and the pace of biological aging. Early twin and family studies estimated that roughly 20% to 25% of variation in human lifespan was heritable, but newer analyses that distinguish intrinsic mortality (such as aging-related diseases and harmful gene mutations) from extrinsic mortality (e.g., accidents, infections, violence) suggest that about half of intrinsic lifespan may be genetically determined. This higher estimate strengthens the rationale for large-scale efforts to identify longevity-associated genetic variants and link them to specific cellular pathways involved in DNA repair, telomere maintenance, lipid metabolism, and immune

and inflammatory regulation (Shenhar et al., 2026; Caruso et al., 2022; Sebastiani et al., 2017; Smulders & Deelen, 2024; J. Wang et al., 2023).

At the gene level, common mutations in key genes have consistently been associated with exceptional longevity across multiple cohorts, largely by protecting against cardiovascular disease and neurodegeneration. Genome-wide association studies and sequencing analyses of centenarians and supercentenarians reveal that individuals with extreme longevity often carry both typical risk alleles for major diseases and a set of protective variants that appear to buffer against those risks (J. Wang et al., 2023; Govindaraju et al., 2015; Bin-Jumah et al., 2022).

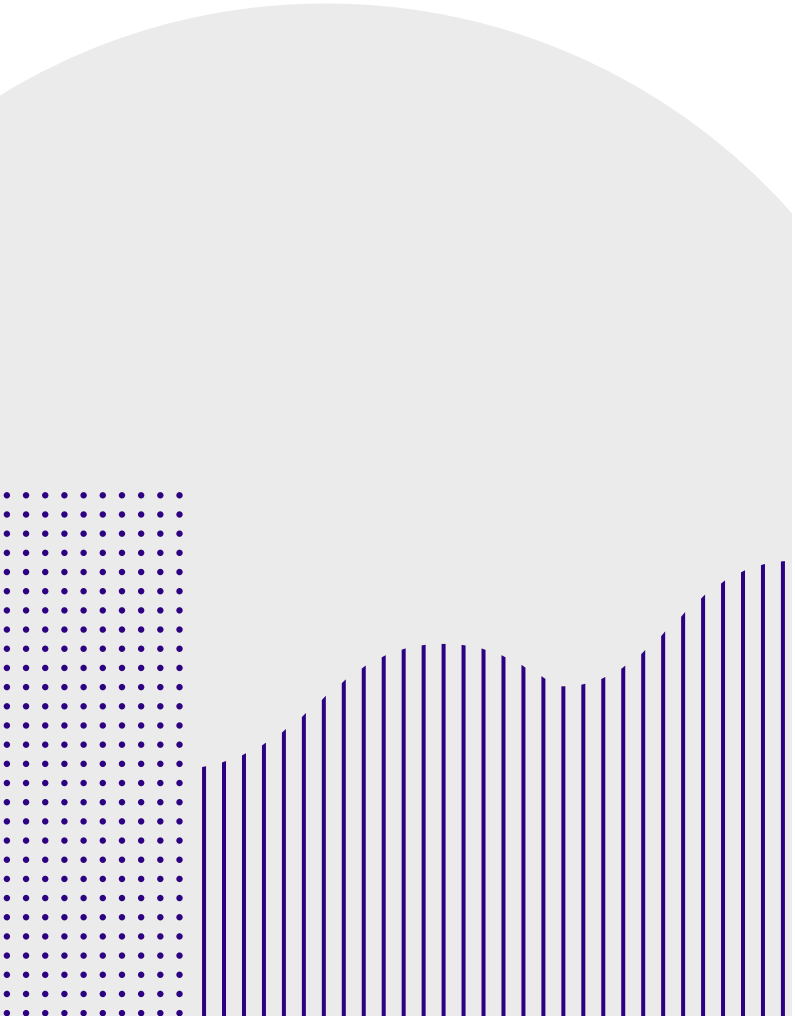
Crucially, human genetics and epidemiologic data converge on the conclusion that lifestyle remains a dominant determinant of survival through the first seven or eight decades of life, while genetic influences gain relative importance in very advanced age. A 20-year prospective cohort study of older Chinese adults integrated longevity gene scores with lifestyle metrics. Results demonstrated that healthy behaviors—such as smoking avoidance, regular physical activity, and prudent diet—can partly offset unfavorable genetic profiles, extending life expectancy even among those without "longevity genotypes." Conversely, individuals with favorable longevity variants still experience shortened lifespans when exposed to adverse environmental and behavioral conditions, underscoring the interplay between the genome and environmental factors, known collectively as "the exposome," across the life course (J. Wang et al., 2023).

In contrast to traditional clinical laboratory tests that flag discrete pathologies (e.g., diabetes or dyslipidemia), aging biomarkers aim to capture cumulative damage across molecular, cellular, and functional domains. Used longitudinally, such panels can show whether an individual's biological age is older or younger than their chronological age and whether specific interventions appear to slow or accelerate aging trajectories over time (Moqri et al., 2023).

Advances in human genetics and genomics have begun to translate these insights into clinical practice. High-throughput sequencing, polygenic risk scoring, and increasingly affordable whole-genome analysis enable more precise stratification of risk for cancer, cardiovascular disease, and other age-related conditions that drive mortality. In response, some health systems are redesigning survivorship services to integrate genetic information into long-term care pathways, particularly for cancer survivors. Structured survivorship programs now combine oncology, primary care, behavioral health, and pharmacy services to address late effects of treatment, hereditary cancer syndromes, and family risk communication, positioning survivorship care as a venue in which genetic findings inform monitoring, prevention of recurrent cancers, and counseling throughout the extended lifespan. As the genetic architecture of aging becomes clearer, such integrated models may evolve into broader "longevity clinics" that couple genomic risk assessment with personalized interventions designed to extend not only lifespan but health span (Rowett & McCullough-Squire, 2025; Yoon & Gim, 2026).

"Epigenetic clocks deepen our scientific understanding of aging, but they're not ready to be individual decision tools that guide someone's personal health behavior."

*—Pinchas Cohen, MD*



### Composite Scores and Dashboards in Clinical and Consumer Settings

Health-system dashboards are those used by physicians and other health care professionals to track the wealth of data in patients' EHRs on an aggregate level. By looking at data on their own patients and seeing how their clinical decisions might differ from those of other practitioners in their health system, physicians can consider their tendencies as reflected in multiple indicators of clinical quality, safety, utilization, and operations. These patterns are sometimes aggregated into composite performance scores tied to incentives or public reporting.

Systematic reviews show that dashboards are widely used in inpatient and outpatient settings to monitor measures such as readmissions, infection rates, wait times, and guideline adherence. They often serve as audit-and-feedback or decision-support tools for clinicians and managers. Composite scores, such as facility-level quality indices that aggregate several process and outcome measures, can summarize performance and reduce cognitive load, but they also obscure which specific components are driving change and may mask variation across patient groups. In this sense, they resemble potential health-currency metrics—useful for high-level benchmarking but limited in their capacity to capture individual experience or equity concerns (Amagai et al., 2025; Xie et al., 2022; Helminski et al., 2024).

Consumer dashboards, including those offered by insurers, employers, and financial services firms, extend this composite logic into everyday life. Tools such as health scores, wellness indices, and longevity preparedness scores combine data on behaviors, clinical risk factors, and financial or care-planning variables to provide single-number assessments of readiness for the challenges people may face in their later years or at the end of life. These dashboards illustrate how Unit•H™ framing might be operationalized in practice, but they also demonstrate how easily complex, unequally distributed determinants of health and longevity can be compressed into a single score, thereby risking the obscuring of underlying structural differences and uncertainties.

### Limitations, Privacy, and Equity Concerns

Across these technologies, predictive models and lifespan estimators face fundamental limitations that constrain their usefulness as individual-level Unit•H™ gauges. Models trained on specific cohorts may not generalize well to populations with different sociodemographic characteristics, comorbidities, or residential or health care environments. Even when aggregate risk prediction for populations of people is accurate, year-by-year lifespan



predictions for individuals remain unvalidated, with wide confidence intervals and high sensitivity to small changes in inputs. Treating such outputs as precise promises of added years can therefore mislead users and policymakers about both the certainty and fairness of the underlying science (Xie et al., 2022; Coiera et al., 2025).

Privacy and data governance pose additional challenges, particularly for PHI generated outside traditional health care settings. While EHRs are subject to health privacy regulations, data from consumer apps, wearables, social robots, virtual reality platforms, and commercial bio-age services often fall into less-regulated categories, making them vulnerable to extensive tracking, secondary use, targeted advertising, and breaches. Legal scholars and policy reports note that many health and wellness apps share data with third parties, sometimes without clear user understanding, and that security practices vary widely across vendors. These gaps complicate any attempt to use consumer-generated data as the basis for a Unit•H™ system, because they raise the risk that sensitive health and financial information will be exploited in ways that undermine trust and exacerbate existing inequalities (Troiano, 2017).

Finally, there are significant issues of burden and equity regarding who can and does engage in continuous tracking. Studies on digital health tools emphasize that adoption is patterned by age, income, education, digital literacy, and health status, with more advantaged groups more likely to use and benefit from wearables, apps, and online dashboards. Moreover, the time and attention required to track multiple metrics can itself be a form of labor, one that not everyone is able or willing to perform and that may detract from activities that directly contribute to one's quality of life. In this sense, a Unit•H™ framing built primarily on high-engagement technologies risks systematically privileging those with resources, stability, and digital fluency, while leaving behind those whose health trajectories are already most shaped by structural disadvantage (Margrett et al., 2022; Turchioe et al., 2019).

Similar concerns apply to loosely regulated industries related to longevity and functional medicine ecosystems. In these spaces, unproven supplements, peptides, stem-cell procedures, and off-label drug combinations are often paired with advanced measurement tools and dashboards, implying they can control aging despite limited or conflicting data from human subjects. From an ethical and regulatory standpoint, a responsible Unit•H™ framework would prioritize interventions with robust evidence of benefit, insist on transparent communication about uncertainty, and guard against using profit-driven, poorly validated claims about extending life (Xie et al., 2022; Coiera et al., 2025).

## Toward Responsible Use of the Unit of Health™: Recommendations and Research Agendas

Before any future Unit•H™ can be used responsibly, many conceptual refinements and substantial research are needed to incorporate patient-specific information, such as baseline demographics and comorbidities, and to clarify exactly what the model measures. Another need is practical guidance on design and implementation to clarify when and how personalized measurement is most useful. A final priority is to place any Unit•H™ framework within the broader social and policy structures that shape health and longevity (Table 2).

### *Existing Factors Related to a Unit of Health™*

Further work is needed on how uncertainty, heterogeneity, and distributional information are communicated. Much of the appeal of Unit•H™ language lies in the promise that a complex future can be distilled into a simple, motivating metric. Yet such simplification risks obscuring the uncertainty surrounding forecasts of health, disability, or survival. Instead of presenting deterministic claims such as "*X* points equal *Y* years," future methods should make visible the range of possible outcomes, the population distributions underlying predictions, and the fact that intervention effects often vary substantially across subgroups.

Developers and clinicians should avoid promising guaranteed additional years or simple formulas that translate composite scores into lifespan gains. Unit•H™ tools should be presented as aids to orientation and decision-making, not as devices that can guarantee that moving a score in one direction will add a known number of years to life. Visualization research in this area should focus on formats that preserve nuance while remaining interpretable to nonexperts, especially when predictions are derived from AI, composite indices, or biological-age models (Turchioe et al., 2019; Shenvi et al., 2023; Brazier et al., 2007).

## Design and Implementation Guidance

To make the Unit•H™ most useful, researchers and designers will need to figure out whether to tie guidance to a clear question, a plausible decision pathway, an elevated risk state, or other scenarios. The step in the developmental process is consistent with patient-generated health data implementation guidance, which emphasizes defining the purpose, intended action, and workflow relevance of patient-generated health data before collecting these data at scale.

The targeted, short-term use of tools may be more clinically and psychologically appropriate than indiscriminate "overmeasurement" for everyone, particularly when the marginal information gained is small relative to the cognitive and emotional burden imposed (Khatiwada et al., 2024).

Personal health data and patient-facing visualizations of this information must also be aligned with people's goals and not left standing alone as a judgment. This is especially important in health, where an adverse or clinical finding or identification of a mass as cancerous carries greater emotional weight than that of parallel dashboards for money, productivity, or household consumption. Any Unit•H™ dashboards and scores should be designed to support understanding, behavioral change, and shared decision-making, and not as moral report cards. As with the Vitalis dashboard, data should be used to highlight trends and context, and to identify one or two actionable next steps to support an individual's decision-making and choices among alternatives (Turchioe et al., 2019; Shenvi et al., 2023).

A further need is the creation of ethical and regulatory guardrails for research-stage technologies entering consumer and clinical settings. Future research should include protocols not only for technical performance, but also for disclosure, follow-up, potential emotional impact, and accountability when consumer-facing tools shape health decisions in the absence of traditional clinical oversight.

## Equity, Aging, and Policy

Research on life expectancy gaps and "deaths of despair" from suicide and drug overdoses makes clear that unequal health trajectories are not simply the result of different choices by differently informed individuals; they are deeply shaped by genetics, education, wages, labor markets, health care access, addiction, and other structural determinants. Any attempt to quantify health as a personal asset or currency must therefore examine how such framings intersect. This is especially important if Unit•H™ measures are ever used to guide incentives, consumer products, or public policy (Rehkopf et al., 2022; Case and Deaton, 2015, 2021).

Research is also needed on how Unit•H™ ideas interact with older adulthood, retirement, and long-term care financing. A useful research agenda would examine whether Unit•H™ tools can help people plan for shifts during retirement without reducing aging to a narrow optimization problem, one with the "best" combination of behaviors, treatments, and financial decisions to maximize outcomes such as years lived, functional status scores, or money saved. Another research question would be how such tools are best used by people who earn too much to qualify for public assistance yet too little to self-finance extended care needs (the "forgotten middle"). In this domain, the goal should not merely be to predict longevity but to connect health expectations with realistic planning for function, housing, caregiving, and financial vulnerability across the life course. This connection points toward a broader set of questions for the financial services sector. If people could reasonably anticipate a longer or healthier retirement, how might that change savings behavior during working years, the timing of retirement itself, or decisions about when and how to draw down assets?

Finally, policy research should examine whether and how changes in healthy behaviors can be incorporated into interventions and payment models while preserving equity and evidentiary rigor. Large-scale dietary and activity programs in institutions, quality metrics in value-based care, and prevention-oriented health technologies may all benefit from clearer ways of expressing gains in function, quality of life, or time in healthy states. However, such metrics must not become substitutes for robust evidence of outcomes or excuses to ignore unequal starting points. The challenge is to design policies that use Unit•H™ concepts as organizing heuristics—helping patients, providers, and policymakers think more concretely about preserving healthy life—without allowing a speculative metric to harden into new metrics of personal worth.

**TABLE 2. AREAS OF RESEARCH TO SUPPORT FURTHER DEVELOPMENT OF THE UNIT OF HEALTH™**

### Baseline Demographics and Comorbidities

- Identify and examine dimensions of health that can be used to compare health states.
- Examine whether these dimensions of health align with people's goals across different life stages, including measures of mortality and morbidity.

### Clarifying What Unit•H™ Tools Measure

- Identify, examine, and refine Unit•H™ tools as aids to orientation and decision-making.
- Continue visualization research into ways Unit•H™ data can be presented to and used by everyone, not just experts in longevity and related fields.

### Design and Implementation of Personalized Measurements

- Identify the most useful clinical scenarios for use of the Unit•H™ tool, with emphasis on the purpose, intended action, and workflow relevance of patient-generated health data.
- Align personal health data and visualizations with users' goals and integrate these into supportive clinical and social relationships.
- Create ethical and regulatory guardrails for research-stage technologies as they enter consumer and clinical settings.
- Develop and examine protocols for technical performance, disclosure, follow-up, emotional impact, and accountability.

### Social and Policy Implications of the Unit•H™ Framework

- Research the intersection of the Unit•H™ framework and tools with socioeconomic inequalities such as life expectancy gaps and "deaths of despair."
- Examine how Unit•H™ concepts and tools interact with aging, retirement, and long-term care financing.

## Conclusion

The idea of a Unit•H™ is appealing because it offers a way to crystallize questions about health, aging, prevention, and trade-offs. Used carefully, it has the potential to help structure conversations about what people are trying to preserve or gain over time, whether that is longevity, function, quality of life, independence, or resilience in the face of decline. In that sense, the Unit•H™ framing may be valuable less as a literal currency than as a conceptual device for linking everyday choices, clinical decisions, and broader planning for later life. But its usefulness depends on resisting the temptation to treat it as a precise forecast of added years or as a fully validated summary of a person's future.

The PHI that will inform the Unit•H™ is most helpful when it is selective, interpretable, and tied to decisions people can realistically make. PHI and related dashboards, clocks, scores, and predictive tools may improve understanding and motivate action, but they can also create anxiety, imply unwarranted certainty, and obscure the fact that health remains heterogeneous, probabilistic, and only partly measurable. The responsible deployment of such tools therefore requires attention not only to technical performance but also to emotional impact, social context, and the quality of evidence supporting any technology or intervention.

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