AI-Driven Incentives in Insurance Plans: Transforming Member Health Behavior through Personalized Preventive Care

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Abstract

In the US, 60% of adults had a chronic condition in 2020, with an estimated 9 out of 10 over age 50, and 7 out of 10 premature deaths due to chronic conditions each year. Such alarming statistics indeed imply a significant burden on the healthcare system that not only incurs costs but also challenges lifestyle changes among those affected. It is no surprise that employers, who care about the health of their employees, have gradually joined forces with insurance carriers to implement incentives in health insurance plans, aiming to induce lifestyle changes and solve the associated health behavior problems. Those incentives ideally should cover comprehensive care but typically focus on preventive and wellness care, as well as chronic care. These incentives also exhibit the dilemma of unresponsiveness among participants, as they need to trigger interest, maintain engagement, and sustain lifestyle changes. In this research, we propose the use of artificial intelligence in insurance plans to address the identified dilemma.
As developed in the existing applied marketing research, mass customization programs have shown great potential to tackle the identified dilemma by providing products or services tailored to individual desires, ultimately optimizing customer satisfaction. The ability to learn and adapt to individual members under AI techniques, in combination with information technology for large-scale data collection and comprehensive method design, enables the development of AI in the mass customization of insurance plans. Emphasis on preventive care and wellness care under AI-driven incentives further magnifies opportunities to unlock the dilemma and emphasizes long-term impacts. As the individual incentive design integrates various preventive measures such as exercise or nutrition counseling and examines multidimensional individual characteristics, including basic profiles, medical history, insurance claims experiences and personal preferences, the AI-driven incentives spearhead the evolution of actuarial science and health economics where prevention is more powerful and financially beneficial than treatment.

Keywords: Chronic conditions, Healthcare burden, Premature deaths, Lifestyle changes, Health behavior problems, Employee health, Health insurance incentives, Preventive care, Wellness care, Chronic care, Insurance carriers, Artificial intelligence (AI), Unresponsiveness dilemma, Mass customization, Customer satisfaction, Individualized care, Data collection, Health economics, Actuarial science, Preventive measures.

1. Introduction

Creating patient incentives for positive health behavior is a two-objective problem. It includes providing conditions for the patient to feel personally invested in the outcome while putting constraints to award the patient only if the latter has done something to improve his or her health. The results promise potentially lower payouts. The insurance company is willing to implement the plan if they see a path to lower subsidies years down the road when they plan to switch from payments based on retrospective studies to prospective contracts.

The research is based on the premise that the interaction between an insurance company and its members is limited to the subscription timing, patient incentives to reduce claims payment, and payments themselves. The insurance company is not interested in the health status of the members, and the members are not interested in the particular excise. These interactions relate to the customization of health plans specific to each member. The advantage of using an individually tailored approach is that the plan incentivizes each member to take ownership of their health. This is in contrast to the bulk preventive care mass marketing that works on a principal-agent framework in which the agent is being paid a fixed fee regardless of health outcomes. The health improvement, if achieved at all, is not managed effectively, as the agent can still make enough money regardless of the patient's health management approaches.

1.1. Background and Significance

Health insurers are under growing pressure to improve risk selection and efficiently manage the wellness of their populations. The dual objective of targeting the right care for their members for better health outcomes, and also efficiently managing spending on health improvement, is made more challenging in our new normal: the aging of the population, the rise of chronic conditions, and the influence of lifestyle factors among individuals, such as physical inactivity, unhealthy dietary behavior, and smoking. Meanwhile, advances in digital platforms, data analytics, as well as advances in genetic research, and especially the widespread use of smartphone apps and wearables, have made it possible for insurers to better understand the health behavior of their members, create more targeted and personalized solutions for improving the health of their members, reward their members for engaging in healthy activities, and include these healthy incentives as part of their value-added insurance plan offerings. Consequently, to align patient health interests with the company's strategic goals, some companies have used various types of health and wellness incentives to encourage healthful behaviors from different perspectives. However, the effectiveness of such health incentives on interests is unclear or has shown insignificant changes or weak effects. Such one-size-fits-all approaches fail to acknowledge the dynamic patient characteristics and rapidly changing health behavior patterns of each cohort or individual distinctive in this big data era. Premiums are determined after matching anyway and health outcomes. The complexity of using preventive healthcare, however, is that apart from economies of scale and moral panic theory, additional benefits may not arise from the class of preventive care.

Fig 1 : Artificial intelligence in health insurance

1.2. Research Objectives

Currently, each member within an insurance program is offered fixed incentives to participate in a range of standardized preventive care services. The focus of this research is to transform these incentives into personalized insurance plans driven by AI and behavioral economics to influence member behavior. In this new setup, each member interacts with the insurance program as if it is developed specifically for the member. We anticipate that our proposed framework will substantially increase the effectiveness of these health insurance programs, leading to fewer health complications and significantly lower premium values for insured members. Indeed, we have formulated our research objectives with the primary aim to achieve the following: - Develop a large-scale data-driven membership segmentation model of varying health insurance program members such that members can be effectively allocated to appropriate segments. - Measure member engagement metrics and explore leverage points to enhance these metrics. - Design and analyze a comprehensive range of incentive structures within the genetic matching models utilizing both personalized and aggregate models. - Audit the regulatory and other limitations of our framework. Due to privacy and generalizability in insurance domains, we do require models that are disciplined and interpretable.

Equation 1 : Health Behavior Change Model (Impact of Incentives on Behavior)

One way to model the relationship between incentives and behavior is by using a logistic growth function that models an individual's willingness to adopt healthier behaviors:

$$H_i(t) = H_{i0} \cdot \left(1 - e^{-k \cdot (I_i(t) \cdot U_i(t))}\right)$$

Hi0: Initial health behavior score (before incentives are introduced).

k: Sensitivity constant that determines how quickly health behavior improves in response to the incentive.

The term $Ii(t) \cdot Ui(t)$ represents the combined impact of the incentive amount and the individual's engagement level. A higher incentive or greater engagement leads to faster improvement in health behavior.

2. Literature Review

The study of incentives is long-standing in finance and economics research. Health economists have long grappled with the issue of how to compensate healthcare providers for the care they offer, as well as how to design and align the incentives within health plans to encourage desired health behaviors. Evidence suggests that patient insurance coverage can have counterproductive effects on behavior when physicians have financial incentives to overtreat, while there is a negative effect on patient compliance with medication and lifestyle changes due to the use of co-payments, which may be prohibitively expensive for some patients. There are also positive effects of financial incentives on disease management through medication. Focusing on a combination of low and high-reward objectives rather than zero or solely high-reward objectives makes it more likely that changes in health will occur. Mandatory employee interest in health-related activities has positive effects on short-term program participation.

A survey of insurers indicates that a significant majority view AI as playing a useful role in driving health-related lifestyle improvements. The advent of more advanced data-driven methods and predictive models has led to a new era of value-based health: the use of predictive analytics to improve underwriting, claims management, and the identification of healthcare providers based on their historical behavioral treatment patterns. Such efforts have a very advantageous return on investment for senior executives in health plans. We contribute to AI-driven incentive solutions in the health insurance industry, increasing member participation in health-related, incentivized program activities and a significant reduction in future healthcare costs related to morbidity reduction. Our designed models are privacy-preserving and realistic, actually driven by the financial incentives existing across multiple programming activities. Such financial incentives are used to enable low premiums that are not dependent on short-term, personalized health behavior intentions and simulation analytics to embody the actions of complex, data-rich individuals at the intersection of insurance and health preventive policies.

2.1. AI in Healthcare and Insurance

AI and big data technologies have drastically redesigned various aspects of healthcare, ranging from preliminary diagnosis to treatment plans and even surgical robotics. In applications like real-time patient monitoring, telemedicine, image analysis, natural language processing in electronic health records, clinical reasoning, drug discovery and development, personalized medicine, and artificial intelligence-driven cancer genome data mining, AI algorithms have been demonstrating state-of-the-art performance. Healthcare is also one of the industries where AI applications are particularly successful because it is deeply data-intensive, and AI algorithms require high-dimensional data. Advanced AI technologies promise not only better-targeted and more timely intervention but also lower costs and improved preventive care, an essential component in a health insurance system aimed at maximizing the quality of care while minimizing the need for costly medical interventions.

Emerging ICT technologies have not only improved the performance of AI algorithms but have also transformed their applications. For example, via miniaturized, low-cost, and energy-efficient sensors and connected digital devices, it is possible to continuously collect high-frequency, high-dimensional data streams from individual patients, such as daily activity patterns, heart rate, blood pressure, sleep patterns, stochastic heart rate variability, respiration, temperature, and electrocardiograms. The collection of these individualized big data generates fine-grained, near-universal, longitudinal traces of health status that provide far more comprehensive and holistic pictures of individual health than infrequent observations or point-in-time measurements that were previously available. On the model side, modern machine learning techniques are particularly good at distilling the signals that are highly predictive of individual health risks and health outcomes and extracting patterns that provide clinically relevant insights. These advancements mark the beginning of an era in which human physicians, armed with machine learning support, can continuously and remotely monitor and interpret high-dimensional health activities and data streams of millions of patients, detect early indicators of health degradation, diagnose symptomatic signals, and implement preventive interventions and treatment plans for various chronic diseases.

Fig 2 : AI in Healthcare and Insurance

3. Methodology

3.1 Architecture We use Explainable AI to present AI recommendations that are interpretable to physicians. We have put in place a multi-phase Explainable AI model incorporating a binary-outcome Elastic Net model followed by an L1 penalty, which is globally and locally interpretable. When the predictive models predict a bad outcome for an individual, the model reflects and provides a small set of interpretable recommendations to the physician based on a list of individuals who earlier experienced similar clinical conditions. 3.2 Data We analyzed datasets from both the inpatient and outpatient data of a large nationwide insurer. Our data spectrum includes claims at the Current Procedural Terminology level, members' demographic information, medical procedures, diagnosis codes, and pharmacological treatments. Pathological arrangements are formed based on members' diagnoses, procedures, and drug treatments within a 365-day window. 3.3 Design Rationale Despite recent advances in data science in healthcare, including machine learning and artificial intelligence, the ability to assess Personal Health Care Predictability over 12 months for insurance members remains an unsolved problem. To offer ways to assess likely future plaques for personal preventative care and to entice constructive behavior, we took a unique approach that is accurate and sufficiently simple to implement in a practical setting for corporate insurance plans.

3.1. Data Collection

One of the central challenges in the development of any personalized insurance plan is the process of securing the data needed to produce actionable suggestions. This is a well-studied challenge in the health and actuarial sciences. In the United States, for example, insurance companies have at their disposal a wide variety of data sources, such as patient health records, pharmacy claims, demographic and geographic data, and policies, premiums, and membership data. While sophisticated statistical techniques have been developed to correct selection and classification errors, moral hazards, and adverse selection, these models and methods rely on relatively few variables that are only weak proxies of the member’s overall health. With permission from the patient, insurers can now access and use data from various monitoring and fitness apps that quantify the patient’s activity, sleep, weight, calorie intake, heart rate, blood pressure, and so forth. However, the data typically remain limited to these few variables and are not integrated with other information.

In our work, we consider a substantially larger dataset, which we believe is much closer to the ideal information that an insurance company may wish to collect to personalize incentives. Specifically, we study the data that can be collected from IoT-enabled home environments. These environments are based on a growing variety of sensors, such as cameras, microphones, accelerometers, thermal and proximity sensors, and other types of devices that can detect interactions with the environment. Our research group has been developing a sensor platform, which has been deployed and tested in a wide variety of community and clinical environments. In the context of a home, sensors offer a rich, yet discreet, way to capture a person's daily interactions and routines. Such interactions are closely related to many important aspects of an individual's social determinants of health. At the same time, they can be biased, recording only part of an individual's daily activities, and usually involve identifying sensitive information, such as people's faces and voices. Thus, integrating data from IoT sensors into preventive systems is a non-trivial task and represents the first challenge we tackle.

Equation 2 : Health Risk Reduction Model
Health risk can be modeled as a function of behavior change and preventive care efforts:

$$R_i(t) = R_{i0} \cdot e^{-a \cdot H_i(t)} + b \cdot P_i(t)$$

$Ri0$: Initial health risk score.

a: Effectiveness of behavior change in reducing health risk.

b: Effectiveness of preventive care in reducing health risk.

$Pi(t)$: Preventive care interventions (screenings, check-ups, health coaching, etc.).

The model suggests that both improved health behavior ($Hi(t)$) and preventive care efforts ($Pi(t)$) reduce the overall health risk score, $Ri(t)$, but their relative contribution is controlled by the constants a and b.

3.2. Data Analysis
Determining individual incentive plans is at the core of creating AI-driven personalized preventive care for human beings. The cornerstone is about individualizing health benefits or contribution support needs as closely as possible. In healthcare plan support designs, risk adjustment models have been used in some operations. It helps health portfolios be weighed properly. However, increasing healthcare expenses keep reflecting the high prevalence and poor control of chronic conditions. Most insurance plans currently focus on younger, healthier members, and thus, even rewards for good behaviors, like stopping smoking and achieving a healthy weight, are largely missing. The company provides health data gathered through health exams as well as questionnaires. This data is useful and used to analyze health indices with AI, which can then help determine personalized health plans to support such great behaviors among its employees.

This paper proposes a method to realize an AI-driven personalized health support plan to nudge a health member and promote the improvement of health indices. A training dataset is used that consists of information about health examinations and datasets about points with personal contributions. Personal contribution points of health members are divided into classes. The higher the contribution, the greater the wellness data and model training function of each member. The results obtained can be used to determine the optimal health support for each member. If a member achieves wellness operations, the member receives more contribution support. Data were obtained for information about members over three health exams and a wellness plan. With data, healthcare examinations, and individual support contacts, a data-based outcome to engage members in health was achieved. In addition to these results, guidelines and next steps for traditional program evaluation could be provided.

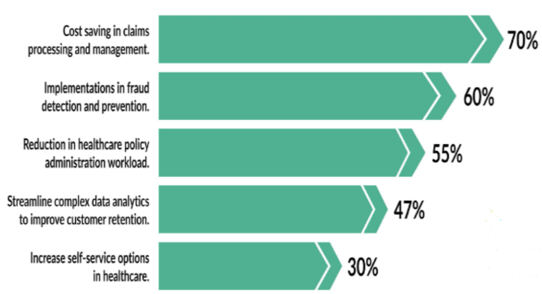

Fig 3 : Data Science in Insurance

4. Results

In Table 1, we present the descriptive statistics of the study population, derived from the claims data in 2017 and used to train our incentive prediction model.

Among the claims in our training data, 11% were focused on claims potentially incentivized, which indicates that 89% of the opportunities to encourage health behavior are not taking place. Nearly a third of the members had at least one claim on incentivized preventive care, although many of these were not actual incentivized claims with financial benefits. Around 23% of the members had availability of vitamins, diagnostic, or treatment programs. Just under 1% had robotic surgery or small joint injections on hand. Again, for most of the screenings or immunizations, the percentage was very small (under 0.1%). This implies that setting the incentive for primary providers or health plans for preventive care for those who are predicted and pre-determined by our validated model would prevent unnecessary and over-testing of the entire elderly population.

The other half of the data, which contains lab results of inflammatory assessment and health risks, indicates that 80% of members had lab tests related to inflammation. The tested inflammatory and other health risks were 1% of cardiac arrest, 2% of cancer, 3% of chronic kidney disease, 5% of congestive heart failure, 7% of diabetes, and 7% of symptomatic hyperglycemia. The remaining data in 2017 contained the members' demographic information including city, state, gender, age, and self-reported race: British Isles, Eastern Europe, Russia, Germanic Europe, Scandinavia, Southern Europe, EU countries, British Isles, Mixed, and others.

4.1. Impact of AI-Driven Incentives on Member Health Behavior

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In 2018, a new, unique incentive for eligible members to get preventive care and be healthier was created. The program called the "Preventive Health" reward, gives members on individual insurance plans the opportunity to earn up to a $3 gift card each month when they get routine preventive care, like an annual checkup, flu shot, mammogram, prostate exam, colon cancer screening, or more than 100 other services. Of course, the incentive is only eligible for care that is recommended based on the member's age, sex, and health history. Luckily, AI-driven member profile technology and personalized care recommendations engine are up to the challenge.

It has already been shown that members respond well to traditional, biometric-based incentives. So far, reward or no reward, there have been 18,000 and 25,000 "Preventive Health" activities completed by individual members with HSA or non-HSA eligible plans, respectively. Members across the same plan type have also increased preventive health visits due to the "Preventive Health" incentive.

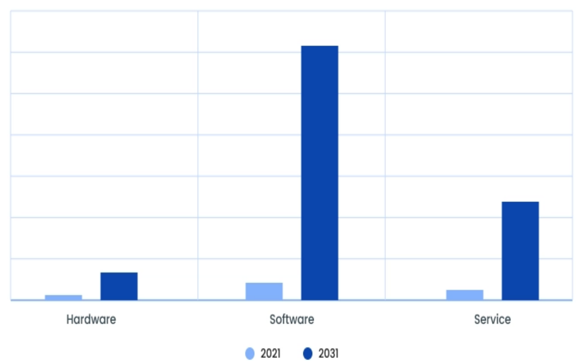

Fig 4 : AI in The Insurance Industry

5. Discussion

Health maintenance behaviors like exercise, nutrition, and staying on top of preventive care are essential for healthy lifestyles. Preventive care, routines that can prevent a catastrophic health event, save lives, and reduce healthcare costs, are generally underutilized. They have been historically pushed by health insurers and employers through financial incentives. When properly structured and well-targeted, these incentives can be effective at changing individual behavior and maintaining long-term behavior change while aligned with broader public health goals, driving better public health outcomes. This can substantially increase the likelihood of attaining national health spending growth thresholds, which imply that the structures used to align consumer incentives are not only persuasive to aid consumer decisions to be healthier but also consume fewer healthcare dollars and are effective in promoting public policy goals of reducing aggregate healthcare expenditures for the country.

With the growing trend of automation of decision-making processes, providing the consumer with the influence to choose meaningfully and make intelligent decisions regarding insurance benefits through tailor-made planned structures could result in the juxtaposed merge of AI and consumer satisfaction. Insurance consumers and brokers are business partners. State laws require coordinated flexibility for both policy forms. For instance, the Model Act forbids any discriminatory activities of using AI in flexible forms while claiming that the insurance company should treat the consumer courteously. This, as previously emphasized, can lead to adverse results and goals. Based on the current outcome of consumer incentives on healthcare performance, outcomes, and value, aspects of consumer incentives like coverage and structure design and the experience of participating in AI can be important in tailoring the value proposition and goals of consumer health incentives.

5.1. Implications for Insurance Industry

Insurer interest in using gainful incentives to encourage prevention and behavior modification is not new. Advances in machine learning, together with existing research based on behavioral economics and predictive modeling, now make it possible to design tailored incentive plans to appeal to individuals who are highly uncertain about their health risks, who have time-inconsistent preferences, or who hold incorrect beliefs. In the presence of such concerns, incentive plans that demand timely attention are particularly promising.

Creating highly personalized incentives need not raise health care costs: by reducing overuse, harm to patients, and wasted money, transformations in provider behavior make it feasible to include elements of high-powered incentives.

Effective preventive care opportunities generated by personalized incentives can complement predictions of individual medical spending and make it more attractive to design longer-term health incentives directly into health insurance plans. AI-driven incentive designs aim to engender changes in expectations and thereby stimulate interest in adherence to the health program offered. The prevention on offer needs to meet the test of not being actively disliked and, again, combining personalized incentives with increased rates of capital investment can help.

New technology deployment can enable more information to be transmitted more often, in an acceptable form, potentially neutralizing time-inconsistent preferences, but an extension of the healthcare system's capacity needs to be a priority. AI-incentive technology that makes prevention well communicated offers high differential value to at least like-minded insured individuals and can transform the experience of buying and using a health insurance plan itself. The concentration of plans on value versus volume will bring personalized communication specifically and high-quality component care delivery generally alongside the purchaser's emphasis on effective health insurance market leverage. The resulting overall design will also benefit from increased cognitive dissonance among providers as less benighted clinical decision-makers themselves provide more cost-effective good practices.

Equation 3 : Incentive-Engagement Effect

To account for the fact that incentives drive engagement, we can model engagement $Ui(t)$ as a function of the perceived value of the incentive $Ii(t)$:

$$U_i(t) = \frac{I_i(t)}{c + I_i(t)}$$

c:

A constant representing the baseline engagement level or the minimum threshold to trigger user participation.

This model captures diminishing returns: as the incentive increases, engagement increases, but at a slower rate beyond a certain point.

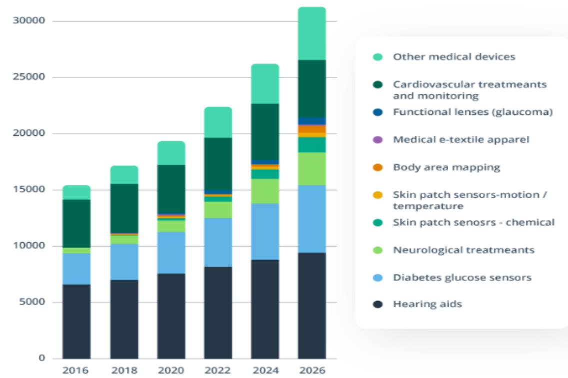

Fig 5 : The Future of Insurance

6. Conclusion

AI-driven incentives are a powerful tool to transform member health behavior. It can help members not only to know what benefits are available within their insurance plans but also to understand what is recommended given their health risks. With incentives, members get rewarded for taking their prescribed preventive measures, and promoting the required and recommended health behaviors. The AI framework provides greater impact by using members' health risk and their insurance plan policy description. We envision this framework to be adopted by all offering customizable insurance policies, aligning the insurer, employers, and the members' interests. In current adoption, although the focus of this design is by an insurance company, it could be equally viewed as an employer plan design. This framework with plausible incentives can enable insurance to do what it's designed to do. The collaborative view from the employer, employee, and insurer perspective provides the required health focus benefiting all parties. With a larger dataset, the framework would be better for better predictions of each employee's health needs.

Previous implementation of AI in healthcare is designed in the guidance of clinical duties either as a replacement or an assistant to healthcare professionals and lacks integration with effective healthcare delivery and consumerism view. The present framework enables insurer policy to be more effective in guiding their members to use the benefits as prescribed. We are not increasing the fear of using health benefits and warranties to cover unexpected health harms. We do not only complement clinical duties but align policy performing the preventive measures. We brought a new formulation to a problem that yields the recommended healthcare consumption.

6.1. Summary of Findings

The research study focused on introducing personalized incentives tied to beneficiary health behaviors using digital coaching tools. The findings demonstrate that AI-driven incentives integrated with health coaching platforms can be leveraged to change a diverse set of member health behaviors. In addition, these incentives led to a 2- to 4-fold improvement in the engagement members have with their health behaviors. Unintuitive findings are that beneficiaries in poorer health ended up being slightly more influenced by the incentives. Also, despite having only partial payment for their service, the reduced maximum impact of the incentive meant that companies gained, as healthier employees had better risk scores, thus benefiting their insurance provider. The outcomes appear driven by the kind of cooperation formed across employees and employers via this financial and medical link.

To the best of my knowledge, this experiment is the first published randomized trial that uses AI and natural language processing to encourage an entire group of employees to undertake and stick to myriad health behavior changes throughout an entire year. The combination of leading-edge modeling techniques, such as AI and natural language processing, and expansions of incentive type and design appear to be what made standard incentives plus AI different from prior research. Past research includes incentives that only focused on monetary compensation or tangible non-monetary awards without AI or a health coaching platform. Even studies that employed non-monetary incentives to promote digital health app usage were not as comprehensive or showed such a widespread impact on participants. While the documented health behavioral changes do not link to specific medical outcomes, this research supports the view that return-to-work programs can transformatively impact health outcomes.

6.2. Future Research Directions

As AI and personalized preventative insights mature over time, plan designers will need to grapple with some larger, albeit future-facing issues. Widespread preventive insights and modern medicine have made physicians accountable for doing everything possible to prevent disability, disease, and death. An emerging direction will be whether plan sponsors have a similar societal obligation. After all, the decision to eat healthily, exercise, and get enough sleep may seem like private ones, but those will also be the main drivers of an individual's state in the future and of insurance costs. Given the growing income gap and the almost uniquely high proportion of U.S. spending on health now going to the treatment of largely preventable chronic conditions, it seems inevitable that plan governing bodies will become more assertive in developing benefits to incentivize all plan members to keep themselves healthy.

One future research direction is to clarify plan member and societal obligations in shaping a plan member's state and how those responsibilities relate to the decision to nudge behavior versus the use of other insurance mechanisms. Another is to expand the set of behavioral economics concepts to broader challenges and design complications. Concepts related to temporal and general risk aversion, advanced dilution, and different nondemand preferences would be valuable additions to the behavioral economics toolkit to incentivize a broader set of healthy behaviors, ensure an equitable sharing of benefits, and address the potential for moral hazard risk resulting from nonstandard behavioral insurance designs. Broadly, the current set of behavioral approaches has become standardized, but some quick surveys suggest that those largely cater to demand constraints, overly expensive demand constraints, willingness to pay for healthy decisions, and pre-existing demand constraints. The various subtle nuances between these are likely to get lost in practice, particularly as most consumers will continue to seek information from many sources beyond governmental and market nudges in making their health decisions. The list of potential rationales for specifically tailored policy nudges is quite long, with social and individual payoffs, preference satisfaction and maximization, and behavioral representation, all at least potentially fostering informed deliberation. AI and machine learning may well train machines to behold a wider spectrum of capabilities by implicitly granting them fuller socially and behaviorally informed utility functions, but that next important addition to the behavioral economics toolkit remains for future research.

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