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Decision-Making in Medicare Prescription Drug Plans: A Generative AI Approach to Consumer Behavior Analysis

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Abstract
This manuscript introduces the topic of consumer decision-making in the Medicare prescription drug market, where an annual enrollee decision process is the first stage of a two-stage sequential treatment that informs long-term insurance plan choice and actual utilization and claims. We examine the potential for generative AI to analyze decision-making in this context, which is of interest in consumer behavior more generally and in healthcare areas such as marketing, where both low-stakes and high-stakes purchase decisions are made by information-limited consumers. Knowledge potentially generated by this study could be of interest to all stakeholders in the Medicare Part D program. In summary, we present two broad contributions to this study. Methodologically, we demonstrate the use of generative deep learning models for inferring consumer preferences and heterogeneity from observational data in a specific consumer products market with implications for evaluation and public policy. Moreover, the approach presents a potential non interventionist method for determining individual or subpopulation-specific treatment effects from uncontrolled big data. At a more specific industry level, this study considers decision-making in the high-stakes healthcare market. We illustrate that low-income adults, who may have health complications in addition to age-related problems, can suffer disbenefits from consumer misinformation. We view this as an important and often overlooked area of policy and management research.

Keywords: Medicare, prescription drug plans, decision-making, behavior, consumer, generative AI, word embeddings, Gaussian processes, optimization.

1. Introduction

Senior citizens enrolled in Medicare are offered numerous prescription drug plans (PDPs) to choose from. In 2013, 2,103 stand-alone PDPs were offered in 34 Medicare regions, with or without deductibles for coverage gaps, the donut hole, and/or positive coverage during the donut hole. The list of covered drugs, or formulary, varies as well. These options make the choice of drug plans highly complex. Misunderstanding of these plan features leads to suboptimal decision-making. The patient might choose a plan that is inappropriate for the medicines they are actually taking. All these choices are confounded by serious health problems, such as cognitive impairment. Research has shown that people who are elderly, sick, and poor often make decisions at odds with their own self-interest. Our empirical analyses indicate that only one in 14 enrollees in stand-alone PDPs in 2013 chose the cost-minimizing plan. On average, suboptimal plans lead to 30 percent higher out-of-pocket payments, which amounts to $316 annually.

Generative AI is a novel approach that uses AI to model user behavior. This paper develops a generative AI approach that can be used to model senior citizens' decision-making behaviors in choosing stand-alone PDPs. The research is motivated by the following understanding: current decision support for analyzing seniors' behavior in choosing PDPs has limitations in features, either due to modeling errors or limited availability of records related to the choice process. Similarly, recent studies have significant importance for this paper. This study sheds light on using data envelopment analysis (DEA) to examine senior citizens' choice of prescription drug plans in the Medicare Part D program. Although the modeling framework is similar in terms of genetic programming, our research goals are different, as the focus in this paper is indeed to analyze human choice behaviors at the micro level. Genomics is an area of science in which the focus is on making choices, many of which require complex and difficult decision-making. By using AI, the researchers were able to better understand the consumers and help them engage and achieve better performance.

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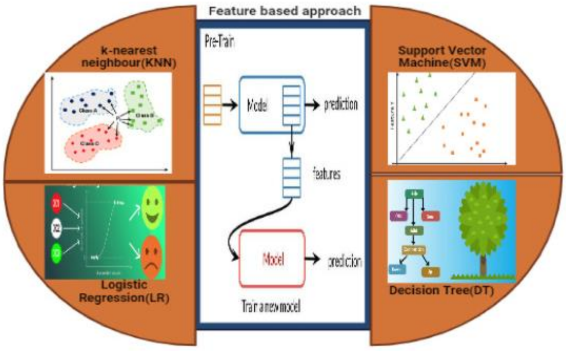

Fig 1: Revolutionizing drug discovery

1.1. Background and Significance

Medicare prescription drug plans (PDPs) were first offered in 2006 to beneficiaries enrolled in traditional fee-for-service Medicare. They were created to fill a gap in Medicare coverage left by the Medicare Modernization Act, which established the Part D program and required beneficiaries to directly pay for a substantial amount of their medications. A study found that "nearly seven in 10 (68%) Medicare beneficiaries are enrolled or will enroll in a stand-alone Medicare private drug plan or advantage plan with drug coverage," and that 45 million people were receiving prescription drug coverage through Medicare. This figure is approximately 16% of the U.S. population, and this number is expected to grow to 80 million or 22% of the population by 2030.

As PDPs have become increasingly common, the underlying structure of the plans and their various components has evolved markedly, as has their impact on downstream consumer behavior. Research on consumer decision-making has lagged behind this rapid evolution, in part due to a dearth of empirical data on consumer behavior and choices. Even less research exists in the machine learning literature that addresses choices in Medicare prescription drug plans, presenting an opportunity to harness generative AI to bridge this divide. Consumers have substantial financial incentives to make the best possible enrollment decision. The average premium for PDPs in 2021 is estimated at $32.74 per month or $392.88 a year. Researchers estimate that the average savings per consumer who annually re-evaluates their plan and switches is $923 per year. Given this importance and the annual window during which people can either enroll in a PDP or switch from one to another, decision-making about which plan to select is a focused outcome of many studies. However, this decision cannot occur without first understanding how consumers learn about the potential choices. With such a densely packed choice set of PDPs, this first step is arguably just as important.

1.2. Research Objectives and Methodology

The research objectives of the experiment are threefold. First, we are interested in illustrating and investigating the underlying intrinsic reasons and heuristics of the decision datasets used previously. We present qualitative insights on how agents decide by identifying attributes and choice rules. Second, we explore a selection of methodological techniques that generate alternative decision datasets that are similar to those currently available. Our approach is to generate decision datasets that embody the behavior of simulated agents with varying levels of competitiveness. Third, we perform a detailed economic descriptive study of the simulated and actual datasets in order to display how the attributes and the advantage, enthusiasm, and neutrality scores behave.

To undertake the procedure, our methodology is multidisciplinary and is designed to investigate decision quality – we use both a qualitative and a quantitative research approach. Initially, we develop an explorative experimental design that moves away from traditional case studies to the incorporation of a generative AI model that simulates human-like agents. From a methodological perspective, our paper is unique in that it demonstrates a new approach that combines insights from several fields. We deploy a contracted version of generative AI to simulate possible decision-making scenarios and investigate hard-to-interpret data further. A straightforward economic description study is conducted to generate visibly engaging economic insights, which also explores if the new information could serve as a basis for future consumer decision support systems and policy-making. Our research draws together game theory, marketing, and political science. In these areas of research, generative AI has been less well published, but we customize a leading AI model to demonstrate our approach. Hosting high-fidelity consumer simulations using a trimmed decision dataset is extremely powerful.

2. Literature Review

Healthcare—the decision-making process, information search, and preferences—has been studied by researchers across the area. Specifically, Medicare prescription drug plans have been the subject of a significant amount of research, especially as Part D was launched in 2006 and the number of available plans exploded. Researchers, especially economists,

have been trying to estimate the cost-per-QALY values of AD treatments—that is, how many dollars it takes for a patient to gain one QALY in the real world. Part of that cost is in terms of Medicare. Systematic reviews of multiple studies on pharmacoeconomic outcomes take into account that many of the treatment effects reported by researchers have to do with a direct reduction in medical costs incurred by payers following the initiation of patients on treatment.
To remedy this, decision-making theories and consumer behavior-related research can provide additional insight into this dilemma. Decision-making theory argues that consumer preferences should be stable and that decision-makers will always favor better, higher utility outcomes. However, consumer behavior findings show that individuals often deal with preference-irrelevant information and often make decisions that do not reflect utility-maximizing principles. The phenomenon of decision quality declining or becoming "stupid" has been seen in many fields—some of this literature does specifically address choices related to healthcare. What makes consumer decisions more interesting in the context of healthcare? It is likely that, even if consumers are rational and carefully consider their options, the response to a disease is uncertain.Consumer decision-making in healthcare is uniquely complex because it involves navigating not only a vast array of treatment options, but also considerable uncertainty regarding the disease response and outcomes. Even when individuals attempt to make rational, utility-maximizing choices, the inherent unpredictability of medical treatments complicates the process. For example, patients may face uncertainty about how well a given medication or therapy will work for them, as responses can vary widely depending on individual factors such as genetics, comorbidities, and personal preferences. Additionally, the information available to consumers—whether through doctors, advertisements, or online resources—is often fragmented, and decision-makers may be swayed by irrelevant factors or cognitive biases. These complexities lead to suboptimal decisions, even among informed patients. In the context of Medicare prescription drug plans or Alzheimer’s disease (AD) treatments, for example, consumers may prioritize immediate relief or lower costs over long-term benefits, which can result in decisions that do not align with their overall health objectives. Thus, healthcare decisions are often not as straightforward as decision-making theory would predict, with emotional, informational, and psychological factors playing significant roles in shaping outcomes.

Equ 1: Aggregate Cost Function

$$C_{\text{total}}(i) = P_i + \sum_{k=1}^{D_i}(C_i \cdot Q_k) - G_i$$

2.1. Decision-Making Theories in Healthcare

Health and health insurance plan choices are complex products that are plagued with uncertainty and differ from other markets. A successful decision-making model must integrate the unique challenges in healthcare, where many of the individual choices made involve decisions on health and medical treatment, with the state of being ill that is brought about. A review of this area has revealed that very little healthcare-related, individually-based decision-making theory either exists or has been applied. Decision-making approaches and individual choice behavior throughout this review have been based primarily on rational choice theory, where consumers are deemed to choose the most preferred alternative from within the set of available options, given the constraints and resources of the individual.
Traditional decision-making theories have long been criticized for their limitations in fully capturing the decision-making process. While rational choice theory assumes that consumers always make optimal choices, researchers have discovered that under some circumstances, individuals deviate systematically from the predictions of this theory. This is due to the fact that real individuals make decisions with limited cognitive capabilities, a condition named bounded rationality. In general, bounded rationality argues that individuals make successful decisions as opposed to optimal ones, given the constraints of time, perfect information, and surveys. As successful decision-making is paramount to understanding from a prescriptive viewpoint how individuals choose health plans, both the consumer rationalist and the psychologist must be considered. Balancing these two perspectives, a model of choice is presented in this paper.

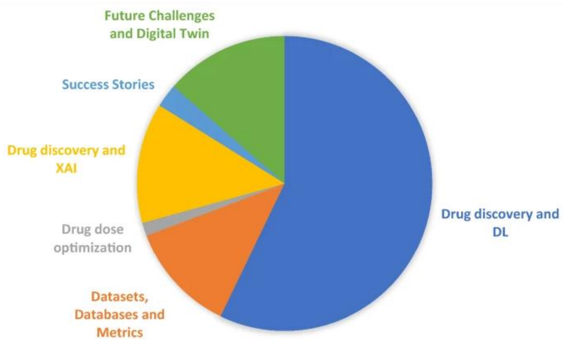

Fig : Deep learning in drug discovery

2.2. Consumer Behavior in Prescription Drug Plans

Consumer behavior in the health and health-related markets has received significant attention in economics and psychology for decades. This literature suggests that consumers are susceptible to numerous biases and affective influences and that heuristic decision-making processes are sensitive to environmental and individual context factors. The suboptimal behavior observed in choice experiments on health insurance is consistent with these results. This subsection briefly reviews consumer behavior dynamics, particularly regarding prescription drug insurance.

Consumer understanding and selection of prescription drug insurance plans in the United States is a complex process that merges personal health and financial decisions. For many, understanding insurance terminology and applying that knowledge to their own health needs is difficult. Lower socioeconomic status is associated with a lack of understanding of insurance terminology and emotional responses. Health literacy as a personality factor, particularly risk literacy, also shapes the decision-making process given its direct effect on the ability to understand insurance terminology and the environment in which these choices are made. Decision aids have been found to improve health insurance market choices, especially if the default settings are set at optimal levels. A successful intervention of such kind would counteract the passive choice problem exhibited in healthcare. Those living in areas with better access to electronic communication are more culturally and health literate. Thus, addressing the digital divide may also have positive implications for this kind of outreach. Given consumer confusion, the complexity of the insurance choice set, and the psychological literature informing each year's relative value, it is vital to tailor communication strategies for optimal consumer engagement.

Qualitatively, regarding initial product sorting, retirees enter feeling overwhelmed by information and decision complexity, often for more than one type of product. They perceive a great many external forces behind this, making selection decisions. These things range from emotions—confusion, and mistrust among the informational materials they are provided—to a more general belief that the healthcare marketplace is incomprehensibly complex. A few admit to an initial refusal to fully engage with the material. They characterize themselves as "super simple" and therefore believe they can receive an appropriate product by simply choosing low premiums. Many also exhibit some degree of overconfidence that rests on their general feelings of competence. This overconfidence seems to decrease as beneficiaries gain more concrete information. In sum, many beneficiaries are in need of intervention to steer their decision processes. Research should be dedicated to understanding the best way to reach this priority group in terms of market intervention. Generative AI models have the potential to help us engage with this kind of evidence, create powerful illustrative tools, and help us design interventions to support positive consumer behavior.

3. Generative AI in Healthcare

Generative Artificial Intelligence is a category of AI technology that can synthesize something new: a text, an audio, an image, or even an animation. For example, a generative AI can not only understand how to play chess but can generate new chess games. Since generative AI can perform new operations on inputs and thus simulate scenarios, it can be used to understand aspects of consumer behavior that can be completely new. Here, we introduce a generative AI behavior that can mimic consumer preferences for health insurance products.

AI solutions, in particular, can find patterns in very large amounts of data. Using large datasets with millions of users, generative models can tell us how decision-making changes for different input characteristics, for example, for different prices and plan designs.

AI solutions to date are well positioned to analyze consumer behavior in several healthcare practices. Some of the intriguing applications generative AI can do with healthcare planning include:

1. Improving the average consumer’s decision-making. AI systems can understand if health insurance customers make consistently good or bad choices.

2. Expanding the scope of consumer options. AI systems can help identify new, demanded services and help design insurance or care system services, a much larger set of potential services that could be tested in a traditional randomized control trial.
Such techniques do involve specific ethical concerns, particularly those of data misuse, consent, and equity. For example, if insurers design plans that minutely reflect the average preferences of consumers, then those with traits that may make them more likely to trigger those preferences (and thus more costly to insurers) could be charged a higher premium. Overall, it is important to ensure that the deployment of artificial intelligence technology is clinically responsible. Administrative systems, by trialing constantly improving AI, may help increase the uptake of healing pathways.

Equ 2: Stochastic Choice Model

$$P(\text{Choose Plan } i) = \frac{e^{EU_i}}{\sum_{j=1}^{N} e^{EU_j}}$$

3.1. Overview of Generative AI
Generative models in artificial intelligence (AI) are capable of learning the structure of a domain, e.g., voices, images, and music, as well as generating new data or data points from it that are notably realistic. AI researchers are known to get excited about generative models and to use applications to build a fundamentally novel view of the world based on a training set and to draw from it. The first GAN was based on the 'simplified game' where neural networks compete—in which a generator creates 'realistic' data and a discriminator tries to figure out whether it's fake data or real. It doesn't just generate nice pictures, though. Generative AI can be used for simulating complex systems, weather patterns, and patient characteristics. Indeed, the ethos of generative modeling as it has emerged in deep learning seems quite tailored towards helping us simulate and generate noisy data points. From climate simulation to synthetic data for machine learning, its utility lies in providing proxies for understanding in temporal and cross-temporal contexts. Millions of noisy data points can be referred to as big data when they have a dynamic representation of multipulse systems.
This capacity to simulate and create casts generative AI as an innovative tool for decision-making using such permuted inputs and their vastness, including predictive analytics and personalized medicine. That said, while the techniques show great promise, we also raise ethical and legal questions relating to the generated data. Generative modeling, or artificial intelligence's ability to generate data, images, and simulations that have 'never' been, is becoming increasingly prevalent across the domains of health care, finance, and the legal fields. Deep learning has shown particular success in developing sophisticated generative models, largely through the use of neural networks. AI researchers are able to create a generative model that can simulate realistic healthcare data about patients—exploring both real patients and those who are non-real—in ways that can assist with predictive analytics, personalized medicine, and joint parameter and model learning. In each application, the operating principle is the same: a neural network learns a system of interest and is equipped to generate novel data points in this system.

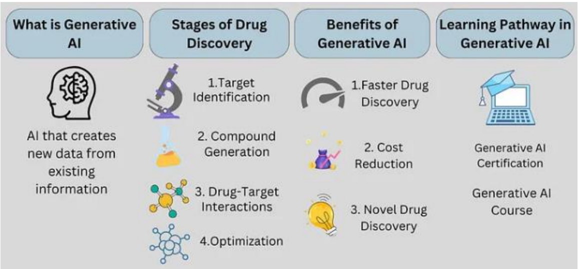

Fig 2: Generative AI in Drug Discovery

3.2. Applications in Healthcare
Discussion of the potential of advanced AI in the domain of healthcare often emphasizes the transformative role these generative models can play. Numerous high-value use cases emerge, including drug discovery and medical research, personalized medicine, education, diagnosis, and assistive technologies. Key to these opportunities is the models' ability to use data to synthesize information that can be used for decision-making, facilitating many aspects of healthcare and consumer behavior touched on in our generative AI approach: minimizing risk, ensuring safety, and educating and involving patients.
A system that enables patients to consult with high-quality healthcare professionals and learn about their medical conditions in a personalized way, providing relevant information or explanations. Generative models could also be applied to generate consumer-relevant information and advice on medication used to manage these conditions, such as medication side effects or interactions. The information generated by such models could be used to facilitate separate activities where

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AI is generating personalized healthcare solutions based on patient data, for example, through synthetic user studies. Advances in technologies, such as virtual human systems to enable natural conversations around complex and sensitive health-related topics, are already beginning to provide such support. This approach requires vast amounts of data on health and personal information, which has to be treated sensitively.
In this setting, AI can amplify the expertise and educate more consumers and patients by providing another source of information in addition to comments from professionals. As with a conversational agent aiding diagnosis for patients, there are implications for the skills of both the professional and the patient in the use of resources containing AI, relevant to their understanding, confidence, and the use of their initiative and critical thinking. Information provision can further enhance the patient's education about the condition, diagnosis process, and potential treatments and is invaluable to a condition, such as a mental health condition, where patients voice that they felt they were not being told about the potential side effects of the prescribed medications. Short of actually possessing years of clinical experience and knowledge, there is no other way to provide such effective engagement of the patient in their care and education around the medications and treatments that are being provided to them.

4. Methodology

Generative AI is positioned to provide new insights into decision-making in Medicare prescription drug plans. Existing analytical methods focus on observing consumers' decisions and outcomes using stated preference surveys, revealed preference data, or interviews with expert stakeholders. Although data-driven, these methods almost exclusively use qualitative or quantitative data. All research subjects except interviewees lack the requisite information to perform a generative analysis. Moreover, it generates dynamic insights into decision-making processes from a large volume of qualitative interview data that would be infeasible with traditional analysis. However, no existing literature or method exists to perform a generative analysis of policy changes directly from stated preference surveys or interviews. To produce this analysis, we first held qualitative interviews with beneficiaries, caregivers, and professionals. Based on the results, we designed and conducted a structured choice experiment, which we used to obtain our empirical data.
We employ a mixed-methods approach using disclosed preference experiments and one-on-one interviews to explore beneficiaries' decision-making in stand-alone Medicare Part D. For the choice experiment, a random sample of beneficiaries was administered a survey instrument that simulated an enrollment decision in the current Medicare Part D program. This discrete choice exercise was developed with input from the design team based on the results of the qualitative interviews. Preferences and priorities expressed by beneficiaries in this choice experiment were then described and discussed in qualitative interviews during a follow-up structured interview. We use churn in Part D plans to illustrate the unique insights that can be generated using generative AI techniques. The results indicate that without subsequent enrollment in another plan, approximately all beneficiaries would drop out of the Part D program, higher than those who currently have the opportunity to switch plans. In the year the interviews were conducted, beneficiaries dropped out of Part D plans between January and May. However, the challenges of this methodology include recruiting interview participants, resolving the trade-off between computational costs and training set performance, and clustering interview data.
Partly because of the large number of unique expressions of these consumer decisions, we first processed the raw transcripts and then coded the content with a question that the model would consider in the process of generating appropriate responses. For example, we have a code that specifies the decision elements that Medicare beneficiaries consider important, as well as the features of the varying number of different prescription drug plans that they prefer. Because interview participants were provided with many resources and documentation related to their Medicare enrollment, these may have been important influences on their subsequent responses when it came time to choose and enroll.

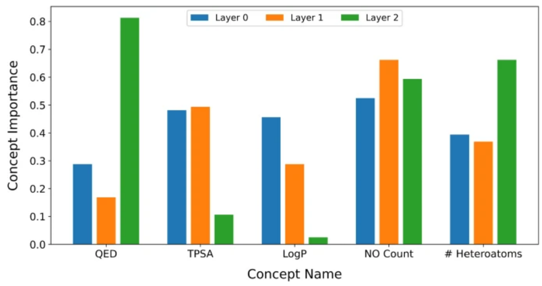

Fig : Explainable AI in drug discovery

4.1. Data Collection and Preprocessing

Based on the objectives of our project, a number of qualitative and quantitative data collection instruments were used, namely an online survey and online interviews. The online survey data was followed by interviews intended to provide a more in-depth understanding. Given the different levels of understanding of the background of PDPs in society and the diversity of information comprehension methods, we attempted to make the characteristics of contacts as diverse as possible. In particular, the surveys were published on different portals, quantitatively and qualitatively, to attract various potential participants. Regarding interviews, we tried to recruit participants with diverse backgrounds that represented the collective. The interviews were conducted online to minimize the potential spread of COVID-19. Before each interview started, we informed the participants about the nature of the study as well as the data collection and analysis process. We made interview guidelines with open-ended questions and sub-questions before the participants filled in the survey to use them as a reference during the interviews. The online interviews were guided by the interview guidelines, which enabled the interviewers to conduct the interviews in a structured manner and to cover the entire content of the study. The intent of the preprocessing step is to prepare the collected data for further analysis. As part of the preprocessing step, sorting data into groups, handling missing values, and categorical variables, and checking the distribution of continuous variables are done. Each data point is identified with a unique primary key, but no primary keys are repeated between the two datasets. The necessary data is somewhat distinguished in that the first concept survey (qualitative data) contains 49 samples, and the second concept survey only received 28 data points. The age ranged between 36–60 and 61–75 years for both surveys. It was detailed in more specific ages since there was a statistical term that we had to use in the model. Additionally, there were only 18 responses on the second survey that had only one data entry related to a movie. Initially, data from qualitative data that initially contained 49 data points had missing values of 8 data points. Then, the remaining 41 data points were sorted based on categorical data. It was found that there were no missing values in the data. The data was categorized into 8 categories. Typically, the frequencies of the categorical data are nearly an even number. The lowest frequency is for the category of books, which is 7. As for preprocessed data for qualitative survey #1, it is a kind of minimal/clean data, with 8 categories for numerical values and 41 samples.

4.2. Generative AI Model Implementation

Implementing generative AI models was a key component of our research framework. We employed recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) units to analyze consumer behavior data. In particular, we used a Gated Recurrent Unit (GRU) with a Conditional Variational Autoencoder (CVAE) to analyze consumer behavior data, model sharing artifacts, and generate consumer choices. The CVAE model was trained to examine the variation in decisions based on the specific individual's characteristics, plan details, and local choices in comparative plans.

The models were trained and tuned to create the best character-to-character fit possible within each framework. Each of the different training processes was allowed to run for 100 epochs with early stopping enabled after 10 epochs from the optimal results, as validation errors did not improve. The datasets used to train both generative models utilized the consumer observation dataset that was aggregated by the number of plan options. LSTM-based context-rich generative AI models were implemented to approximate consumers' decision-making processes using the rich consumer behavior data in Medicare Prescription Drug Plans. These models could simulate sequences of consumer Plan IDs as their decisions at the end of the interaction with the plans. The nature of the data, along with our model, presents a way to uncover the patterns and preferences of how consumers investigate and accumulate information to make decisions.

The implementation of generative AI faced several challenges that could affect the validity of the analysis. First, there are technical challenges, including the setting of various parameters, including the disruptive behavior of the model, such as vanishing gradient during the process attributed to factors like large vocabularies with relatively small available data to train on at each epoch. Setting the batch size, learning and decay rates, and early stopping were paramount in the training process to avoid large computational costs. Second, there are ethical challenges, including the fairness of utilizing large aggregated data to train a model, and how to ensure the trained generative model produces a fair representative output. General concerns should include immediate validation of the generated sequences to ensure that they make sense within the familiar standards of the Medicare Part D domain.

To mitigate the technical and ethical challenges, the two trained generative models were validated and tested on a unique, independent dataset that was not utilized during the training process, which was a randomly chosen validation set for both the LSTM and GRU CVAE models. Furthermore, the outputs were examined directly between the two randomized subsets and for the synthesized and actually gathered Plan choices. The scripts that train such models include data aggregation between training and testing to ensure they are impervious to overreach.

Equ 3: Expected Benefit Function

$$B_i = \mathbb{E}\left[\sum_{t=1}^{T} \frac{\text{HealthBenefit}_{i,t}}{(1+r)^t}\right]$$

5. Results and Discussion

This method has been illustrated using a case in the context of the Medicare Part D program. We find that the 109,115 decision-making patterns generated from the trained generative models show the main patterns we have reported for the model and the data in previous reports. Furthermore, we found that 5% of the generated decision-making patterns had a unique feature that violated the "separability conditions," which rational choice models such as random utility and expected utility models rely on, and nine decisions with "followed by none" (for the priorities of three drug fill types). In modern society, people are facing complex decision tasks in various fields. However, "the most serious problem with a good number of theoretical models related to decisions is that their empirical validations sometimes are either weak, nonexistent, or odd."

The standard way to address this criticism is to imply empirical studies or experimental reports. In contrast, it is not common for people to try to evaluate the (descriptive) validity of decisions by examining a huge number of decisions. In this report, we provide results of a descriptive kind showing that certain "bizarre" aspects of human decision processes, such as many observed violations of assertability, or the zero probabilities that represent risky prioritized decisions that were previously discussed, can be replicated in generated decisions produced by generative models trained using big data and generative AI. The decision-making generation approach discussed in this draft launches a route of research that aims to facilitate and steer the possibility of discovery and explain people's choice behavior on the basis of "how" they make decisions rather than "what" kind of economic preferences should be used for decision-making generation. In a word, this draft suggests that rather than manually imposing economic normality upon the generated data, some merely trained outputs unmasked by empirical data can be analyzed to determine the extent to which they comply with typical models of consumer choice.

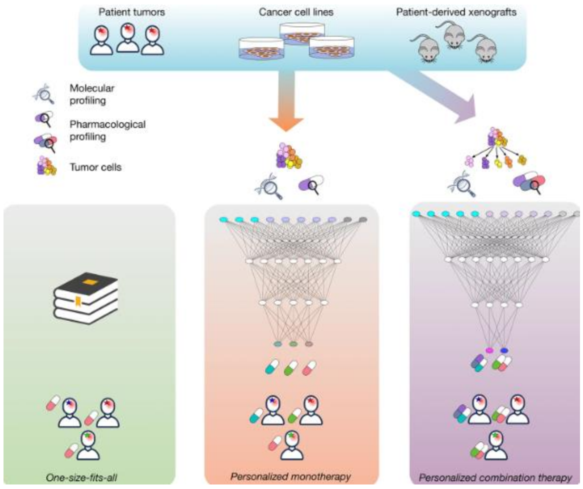

Fig 3: Prescription decision making

5.1. Analysis of Consumer Behavior Patterns

This is an analysis of the patterns of behavior of the Medicare Part D and C consumer training tools. We identified a number of covariate effects of the interaction of certain demographic factors with decision-making. We produce detailed outreach literature that can form the basis of a set of interventions to assist consumers. We conducted groundbreaking experiments that adopt the generative probing method to illuminate large data landscapes of user choice. We provide insight into the tools in addition to presenting a detailed analysis of who uses them and when, and visualizing usage and behavior of these users. Tools offered to assist consumers in purchasing modern drug insurance turn out to be used by those with very high medication expenses. Yet, high- and low-users share common concerns with drug pricing. Our results are meant to inform the policy debate over how to design and implement such tools.

Responses to outreach are stretched in supplements of insurance coverage by race, age, gender, and consumption. A detailed analysis of gender pairs shows significant differences in who would benefit from decision-making training. The intervention literature is put in the context of a review of the literature on health literacy and decision-making, and policy simulations test the effects of selected interventions. We present a new analysis of many large-demand surveys of Medicare prescription drug plans. We offer findings that can form the basis of possible policy interventions and, at the same time inform the design of future research.

5.2. Comparison with Traditional Methods

This subsection discusses how modeling the decision-making process by generative AI methodologies enhances, refines, or argues against traditional decision-making models in health economics. It is crucial to reduce different alternatives so that practicing healthcare managers can choose better options during planning or forecasting. Comparison with traditional methodologies focuses on the studies related to the comparison of healthcare decisions with generative AI methodologies to conduct healthcare decisions.

The strength and computational efficiency of generative AI methodologies, to identify patterns and make predictions in complex data, greatly benefit the ability to understand consumer decision-making. In the healthcare literature, Experiential Rationality Dilemma (ERD) refers to situations where traditional economic theories, behavioral rules, models, principles, and patterns fall short of capturing the differential nuances or complexity of consumer choice behavior empirically. It is the doctoral or dissertation part of ERD. Traditional methodologies such as machine learning, big data, and artificial intelligence in healthcare or other contexts may exhibit different patterns and behaviors of consumers. It is called systemic empirical comparison among the mentioned methodologies explicated in the preceding paragraphs. The result of such comparisons is whether these new generative AI methodologies can improve our ability to understand consumer choice behavior in healthcare or other sectors compared to traditional AI methods.

The review of healthcare operations and management literature indicates that the partnership among VAE, GAN, and traditional machine learning methods has not been conducted in healthcare, presenting an emerging area of academia in healthcare management. Justifications for the above must be provided through an empirical comparison of VAE/GAN with traditional methodologies, called a ‘conclusive study.’ There is a lack of multiple qualitative studies on the properties of GAN compared to traditional AI methods in healthcare and in other fields. Further, less attention was devoted to the investigations of system variations of the two approaches. Empirical findings on ERD are limited in healthcare and other areas so far. It represents the potential usefulness of these generative AI methodologies in the healthcare marketplace, providing a structural paradigm shift in laboratory management in a hospital, consumer captive buying, predictive and planning behavior, consumer information, and any consumer behavior on the provider side. The proved null for behavior in IO/ERD indicates several implications concerning the behavior of the generated winner and the generated loser in this market.

6. Conclusion

Our analyses provide insights and measurements of decision-making in the Medicare prescription drug plan market. Our study addresses a key challenge in traditional approaches to policy and measurement—both often assume, as a first approximation, observed data on the underlying latent decision-making. Generative AI gives an alternative approach, estimating decisions conditional on everything else observed, and has the potential to improve decision-making both within health plan options, via secure and personalized choice tools, and in markets, through the process of bringing offline choices to the online margin.

Our results show how generative AI can be used with computing, frustration, and longitudinal/personal measurement. Comparison with alternative generative algorithms highlights how generative adversarial networks can effectively leverage additional types of data within the Medicare prescription drug plan market. Our analyses are consistent with growing evidence that primary concerns for health plan choice involve uncertainty as to future medical needs, uncertainty about plan structures, and perceived effort and stress of making decisions. Our work is new to our knowledge in the modeling of Part D decision-making using generative AI, but it shares implications consistent with prior randomized controlled trials conducted in the Medicaid market.

Our work is of interest to multiple audiences and fields. First, it is of interest to health policymakers and practitioners, serving as a complement building off of the basic facts. Recent calls support the utilization of cutting-edge tools, such as generative AI, to improve consumer engagement in health plan choice. To date, no work has examined the potential information leakage that results from applications such as these.

6.1. Future Trends

AI is anticipated to gain importance in identifying consumer behavior. Data quality can be further improved by integrating payor-level data with social intake data from health centers. Decentralized systems, AI decision support, and federated learning models can be developed to ensure consumer privacy and security. The increasing capability of AI tools to generate realistic images, videos, and documents drives the need for increased attention to data provenance and copyrights in healthcare systems. An intersection of personalized medicine, heterogeneity of consumer beliefs, personalized pricing, and personalized AI decision-makers is anticipated in the future. AI tools can be developed to assist patients by suggesting numerous options and addressing individual patient willingness to pay, side effect trade-offs, rivalry between drug sellers, and other factors in an integrated framework. Research making use of the multiplicity of human subject strengths and expertise can be further improved to predict choice behavior using advanced studies. Consumer behavior analysis in decision-making is augmented by allowing interdisciplinary and inter-organization team research, including primary care, specialized health centers, industrial organizations, and relevant stakeholders. Research in AI, specifically generative cognitive architectures, data processing, and interdisciplinary collaboration, will be critical to improving our decision-making, tools, and research. AI big data tools, survey results, and the popularity of plans will change over time. The evolution of healthcare with drugs and data systems, and the development of therapies, vaccines, insurers, and consumers will require continuous research and accreditation. Emerging models for digital health and descriptive pricing are important services and merit such investigation over time.

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