Lifestyle Risk Factor Modelling and Adaptive Intervention Delivery: AI-Driven Platforms for Personalised Health Intervention in Preventive Care Settings

Dr. Olga Petrova, Professor of Information Technology, Mälardalen University, Sweden

1.1. Background and Significance

The existing strategies to promote health typically involve generic interventions and often reach only a relatively small portion of the population, mostly high-risk individuals, even though these individuals account for only a small percentage of the population's health problems. Allowing individuals to change their health behaviors can help lower the risks of many physical and mental disorders. Yet, health behavior change is difficult, and sustaining it until the effects become apparent requires affordable and scalable strategies. Personalized preventive care, that is, approaches tailored to individual patient needs, can increase the chances of positive health behavior change effects. The capability to personalize and target health promotion interventions, leveraging both detailed patient information and behavioral science models, can benefit from an AI-driven, data-driven approach. In most cases, the patients can only be in control, and full benefit can occur if the interventions are adapted to the evolving patients' needs.

AI makes it feasible for highly personalized interventions to be derived automatically by using large longitudinal cohorts of diverse populations to identify distinct patient subgroups who behave in similar ways. Personalized interventions are more effective and efficient for the participants and providers compared to what is currently feasible with one-size-fits-all methods. Natural language processing platforms and wearable devices could provide training data that could be used with reinforcement-based learning to adapt automatically to the physical and mental health responses of each patient. AI-driven personalization is data-driven and is not based on ledgers for a specific forecast. Such discovery-driven personalized care is enabled by the use of increasingly rich EHR and mHealth data and enables diagnostic-specific decision rules that are objective and personalized. Interventions that consider the unique patient context are more likely to succeed in improving health behaviors than standardized interventions. Customization, personalization, and the use of personalized recommendations and behavior models are several ways to facilitate adaptation of these models to the individual patients.

1.2. Objective of the Study

This paper investigates how deep learning algorithms can be incorporated into the preventive care process by developing an AI-driven platform that provides support to health practitioners in selecting, tailoring, and delivering interventions that aim to promote specific health behaviors in patient populations. This research question is studied in the context of a weight loss clinic where the practitioner decisions that could be supported with the AI-driven platform are associated with intervention selection and the personalization of the components of a weight loss intervention. The platform utilizes deep learning algorithms trained on clinical text data and a set of deep features defined from psycholinguistic and personality-based text analysis. To answer the primary research question, our study has the following specific research objectives: To identify the main decision-making support requirements of the health practitioner for personalizing interventions. To investigate machine learning research methodologies that support the achievement of the research objectives and develop a platform prototype that applies these methodologies. The prototype is built based on the weight loss clinic case study, which has the potential to be extended to other areas of preventive care. The developments include the assignment of predefined behavior change techniques into interventions, selection of interventions, and introspection of established interventions. The design guidelines and the decision-making methodology developed for the weight loss clinic are further validated in two additional cases of type 2 diabetes. To conduct an exploratory field study to evaluate the prototype with a group of practitioners and patients and gather insights for further research.

2. Machine Learning in Preventive Care

Machine learning has been shown to be highly effective in forecasting outcomes in preventive care that are associated with marked health care cost savings when catching diseases at an early stage, including cancer, chronic obstructive pulmonary disease, and congestive heart failure. Preventable hospital admissions and preventable emergency admissions can be driven by financial penalties and are indicative of serious, high-cost health episodes, thereby providing clear incentives for early intervention. Recent pharmacy-based tools have been deployed in practice to estimate patient risk of such events using machine learning and are shown to be effective at reducing preventable hospital admissions and preventable emergency admissions when triaging patients for more extensive care management programs. While these platforms demonstrate the significant potential of machine learning in preventive care, they do not personalize interventions to patients' health trajectories. Rather, they treat patient risk estimation as a stand-alone task, disconnected from the effectiveness, cost, and invasiveness of clinical interventions used to attempt to guide patients away from risky health transitions.

Current standards for machine learning applied to preventive care. These first-stage platforms train independent risk forecasting models optimized for the performance metric of a downstream public health goal, ignoring the intensive clinical interventions that are feasible for modifying predictions, which may be cost-effective for targeting to specific patient subgroups based on these intensive interventions. Preventing the most serious health episodes does not necessarily require the most costly interventions for all patients, as costs and health outcomes scale, offering reduced cost solutions designed around a variety of patient-specific behaviors, conditions, and personalized health incentives. For example, consider three patient subgroups in an intervention program, where resource constraints in the healthcare program prevent all three from being subjected to the most invasive and expensive interventions. One patient subgroup may stay well with a mobile health wearable, operating with greater personal autonomy as interventions are triggered by machine learning processes, another subgroup may require simple inexpensive follow-up patient scripts summarizing their historical care plan, while a third subgroup may require a complex new personalized clinical trial for guiding purposeful and ethical therapeutic exploration. Patients expressing a novel set or combination of characteristics can be guided through novel healthcare services sharing features, rotating genre services, or even expedited clinical trials with overlapping data-sharing agreements, affording a significant enhancement to patient care.

2.1. Overview of Machine Learning

A machine learning model learns from input labeled data, called features, to give predictions on unseen inputs. Generalization translates to good predictions on data representing the same phenomenon but not seen by the model during training. In supervised learning, where the model makes predictions given some input, the evaluation is always on the ability to generalize, e.g., predicting unseen cases' classes or continuous labels. With good generalization, the model shows some ability to understand phenomena in the data. Discovering which features are important to the predictions the model makes is an added bonus. Unsupervised learning models learn probabilistic structures, also with the goal of good generalization. The structure can be clusters, representatives, order, manifold, density, or probability measures. Examples of such models include k-means, PCA, and GMM. Performance in unsupervised learning is also generalized to seen instances but is hard to define. There is much difficulty in selecting and designing evaluations. A related evaluation question asked about the utility of the learned structure in unsupervised learning. In reinforcement learning, called decision functions, output actions conditional on inputs and state, which subsume the historical data, one can view the set of input actions as the data, the value data.

2.2. Applications in Healthcare

Healthcare in the United States is widely recognized as inefficient, expensive, and difficult to access. High burden-of-illness conditions, such as heart disease, diabetes, obesity, and chronic obstructive pulmonary disease (COPD), have multiple enduring causes that pattern their onset and severity; these ingrained underpinnings challenge efforts at prevention and treatment by generating a continuously high and unequal demand for care services. Health policy experts now advocate for shifting attention and resources to prevention-oriented solutions interacting with multiple levels of influence and hundreds of entwined causes leading to adverse health events. Our key question is this – how can progress take place?

On the basis of recent scientific advances, it is now possible to identify individuals who have distinct, quantitative, and actionable risk for future adverse health events including, for example, heart attacks, strokes, and fractures. Among the direct tests we currently have available, researchers have demonstrated that selecting subsequent, individually graded health programs based on prospective genetic information increases the cost-effectiveness of preventive interventions; information gained from genetic testing can provide insight on how, when, or if preventive interventions should be implemented. While this is certainly a positive development, our central concern is with real-world care provided every day in numerous healthcare settings. This paper focuses specifically on one widely distributed setting—emerging AI-driven platforms employed by community and employer-based organizations partnering with large health systems. These platforms include data acquisition, AI-driven data interpretation with immediate personalization of health interventions, and automated delivery across large networks of healthcare agents working in near real time with individual patients at affordable cost. Which individuals should be tested, with which tests, at what intervals, and which direct-to-consumer tests and which platforms for collecting and interpreting the data most effectively inform preventive or treatment interventions provided by health systems or health organizations? The purpose of this paper is to inform policymakers and key stakeholders in the public and private sectors about the promise and challenge of this new technology.

The data needed to empower precision prevention and treatment encompasses single and combined measures of genetics, metabolite and enzyme levels, lipid fractions, urinary composition, tissue compositions, hormonally regulated peptide markers, behavioral and environmental information, medical records, and ongoing patient response to interventions. Taken together, these measures constitute a huge characteristic of the individual. A more efficient and cost-effective strategy than comprehensive direct observation of "all things health" is to engage in selective exploration. The choice of what to explore and build upon originally was thought to be well within the grasp of healthcare providers, who aimed directly at recognizing ill health and then directing individuals to necessary care interactions. Now, with the prospect of actually knowing a far greater array of specific, quantitative determinants of health and with increasing attention given to the generality of health interventions and goals, personal health platforms can, over time, gain the ability to disclose unprecedented individual health characterizations and extend this knowledge from single snapshots to real-time operation with the potential for inducing safe, meaningful, and lasting health changes.

3. Personalized Health Interventions

Artificial intelligence (AI) models are used to analyze large amounts of data to either learn what interventions are most effective for different types of individuals or use approaches to personalize interventions by incorporating the characteristics of individuals. For example, multi-arm or adaptive trials evaluate multiple interventions within a single study design to help more quickly identify effective interventions and enhance the efficient use of resources in trial settings. These studies randomize participants throughout the study to multiple intervention arms with the option to add or remove an intervention arm and equalize as more data on the effectiveness of the intervention are accrued. Challenges in identifying the most effective intervention include the uniqueness and variability of individual preferences and the multidimensional nature of interventions, which need to be simplified into a list of manageable options, and the pervasive individual variability.

Recent targets for AI and machine learning-based personalization include the stage of presentation of decision aids, recommender systems for preventive activities, and therapy optimization as well as models that use free text to predict patient outcomes. More research is needed to establish the effectiveness of machine learning-based personalization of interventions, enhance transparency and interpretability of the AI models, and identify bias in the collection and use of the data to prevent unjust treatment and support wider utilization of machine learning-based AI in research and practice to ensure the generalizability and relevance of resources across populations. Improved data acquisition and quality based on signals such as mouse clicks, physician behavior, or single-arm trial data may help enhance usability and lead to better outcomes.

3.1. Definition and Importance

Humans are not identical in their response to the various environmental conditions and interventions to which they are exposed. This concept of heterogeneity in the way that individuals respond to different treatments is important in the healthcare field. As the risks and burden from many diseases can be reduced through health screenings and preventive care, healthcare providers and patients have numerous tools at their disposal to alter the risk profile. However, most of the tools currently used in preventive care are manually crafted and guided by generalized and averaged care guidelines. It has become increasingly clear that a system for predicting personalized disease risks and the effectiveness of health interventions—founded on measurements taken from patients early in the life course—is both feasible and essential.

A predictive model for personalized health interventions requires two ingredients: patient heterogeneity in health risks and health intervention heterogeneity in effectiveness. In reality, this second ingredient is faced with more skepticism than the first one. The skepticism regarding health intervention heterogeneity stems from the difficulty in manipulating an environmental condition or biological system and in having the manipulated condition interact with a given biomarker to produce disease prevention. However, when we consider the latest developments in this field, we believe it is both feasible and profitable to invest in this AI-empowered platform for preventive healthcare.

4. AI-Driven Platforms

With the increasing availability of large-scale, longitudinal datasets from diverse populations and advances in artificial intelligence driven technologies, the opportunities for developing tools for health interventions continue to expand. AI and machine learning algorithms embedded in digital health platforms can leverage diverse behavioral data to identify phenomena, infer relationships among the various health-related dimensions, and develop predictions with great precision, all contributing to a personalization potential for auto-generating therapies. These predictive tools allow for early identification of patterns and early intervention, whereas explainable AI systems associated with clinical interpretability can help to provide a better understanding of the circumstances to both patients and caregivers. These features, altogether, offer good potential for increasing adoption and adherence to auto-generated interventions. In the long term, we envision a future with fully automated, personalized health feedback and optimized therapies, guided by data-driven insights. In preventive care, AI-driven platforms have shown growing success in addressing multifactorial health and environmental risk predictive modeling and decision support for health care providers. For severe health risks, available guidelines and protocols support the identification of issues and the design of effective care plans. AI technologies in focus include data curation, predictive modeling on health risk factors including mortality, admissions, unplanned readmissions, care-efficient pathways identification, decision support for referral services across domains, and outreach engagement with high-risk and underserved populations to provide feedback and guide them towards best practices. AI-powered machine learning systems have enabled exploration of health data structure and affective representation learning for boosting predictive performance of multimodal data analysis toward forecast evaluations. Deep learning hypermodel frameworks project all application paradigms on disease heterogeneities, manifestation trajectories, and previously unexplainable data properties.

4.1. Features and Components

Relatively recently, businesses have started implementing machine learning and AI-driven approaches to personalizing health and recommendations of various preventive care products to consumers. Mobile platforms often distinguish between consumer apps and remotely supervised telehealth platforms, although the distinction is blurred as telehealth platforms become more like consumer apps. Nonetheless, advanced AI-driven platforms span two components: enabling preventive care interventions in different shapes and delivering a consumer app (or a seamlessly integrated app) running on user devices. The former builds on the power of artificial intelligence by providing AI-driven predictive and preventive algorithms. Platforms leverage biological data collected through point-of-care digital testing, behavior data obtained by analyzing personal alertness and activity patterns, and digital phenotyping data obtained by combining both biological and behavior data.

AI algorithms can play multiple important roles in real-time decision making. First, AI algorithms identify and rank users needing preventive care based on health state, stress, and social context, already at unperceivable levels of stress they should be considered for a personal intervention. Second, real-time decision-making algorithms recommend the most effective intervention, ranked socially, ecologically, or personalized considering biological phenotyping, a decision more difficult than just ranking its biological effects. Potential interventions could combat health issues caused by exposure to stress, by emotional state, by incorrect circadian distribution of energy, by hypertension, or other chemical signals. Third, personalized preventive algorithms provide users with optimal personalization strategies, considering energy, sensitivity, and living habits, including psychologically important events. The personalization algorithms manage to adapt individual pharmacokinetics for interventions as a function of phenotype, momentary energy, stress, phenotype excursions, and other exposure to variable stress. Due to increasing variability, preventive platforms and intelligent wearable and point-of-care devices monitor personal health and stress states in free-living conditions. Such platforms enable interventions with higher immediate, longer-term compliance and lower exposure levels compared to regularly scheduled interventions.

5. Case Studies and Results

In this section, we present two case studies, including the planning of the studies, types of experiments, methods for data collection, and the most relevant results. A first analysis of the partnership to develop an app that empowers university students to take care of their health is presented. The second study refers to the development of a mobile application for a project that seeks to help families take care of their health by reducing the consumption of ultra-processed foods and guiding the selection of healthier alternatives for food products.

In the platform's intelligence model, which uses data from multiple sources to provide care and information tailored to individual needs, three transformations are made in sequence with user data to compute a health risk score. The first transformation takes demographic information and activity data to create activity summaries, making it possible to calculate activity frequency distributions, clustering with engagement types, and labeling with activity descriptors. The second applies semantic labeling to natural textual documents from other sources. Finally, the third transformation calculates the user's health score from two-dimensional scores: variety of activities, healthy diet, regular sleep, range of circadian rhythms, and energy utilization. In each of these transformations, categorical labels are determined by applying machine learning techniques to probabilities or results from user stream data. Overall, the data comes from a study to monitor and engage the health of university students.

6. Future Direction

Potential Future Developments In addition to the advancements proposed above for the future direction of digital health intervention personalization research, we propose here the ways in which the current AI-driven platforms for personalizing health interventions framework can be advanced towards providing preventive, personalized health interventions. These advancements are inspired by the platforms identified in the survey as well as the feedback and insights provided by the researchers and domain experts in their respective scientific and industry areas of research and implementation. Inference over Multiple Health States for Developing Multi-fidelity Health Stereotypes The data acquired from a patient is highly context-dependent, yielding a spatio-temporal-based view of physical and behavioral characteristics. Here, each health state is a snapshot of the patient on the system's block that captures their behavioral health. Traditional health care data-driven research studies treat the health state as an atomic, single-point representation of the patient, although a patient's health continuously evolves. However, by considering the patient as consisting of a continuous evolution of behavior, we can consider the patient's characteristic health states as forming health stereotypes in multi-dimensional behavioral health at multiple fidelities. In addition to discovering simpler-to-diagnose characteristic population subgroups, each fidelity of health stereotype can also describe clinical course and progression, which informs the design of interventions across different conditions. We expect that going beyond function engineering towards developing multi-fidelity health stereotypes will improve health risk assessment, unclear outcomes understanding, health recovery, and response monitoring—key capabilities in personalized digital health systems.

7. Conclusion

Health management is a battle between treatment and prevention. Since the 1980s, the wearable health landscape has been rapidly evolving to take the battle from the health care providers directly to the consumers. The vast majority of these wearables emphasize providing self-tracking data to help the consumers with self-motivate healthy behavior change. Motivation still works in relatively small groups and people will just stop using the devices. The trend is changing, however, as there is an increased focus from the scientific community to use the tracking data as a feedback loop for health management, in a form of personalized behavior change interventions. Despite decades of work, the design of such interventions is still a labor-intensive iterative process that relies on the knowledge of experts in both health behavior change and machine learning.

In this work, we propose a 3D-driven AI platform for designing AI-driven interventions at scale that combines three levels of AI models: a stress model, a health behavior model that focuses on personalized modeling of long-term behavior progression, and a usage model that models behavior within the app. Our novel AI component learns a new stress model that predicts stress level for a long-term period. The end-to-end feedback loop learns AI-driven interventions that enforce the users to move the predictions on the best stress path. The intervention shows promise in having immediate stress reduction effects and improved usage of heart rate monitor meditation feature.

Even though we are the first to design such an end-to-end platform, the design of the AI components is designed for the general setup and, in principle, is ready to be generally applicable to other health tracking problems, after a retraining of the models. It is also a test bed to evaluate the AI-driven designs due to the multi-resolution control it can exert on the AI-driven platforms. The more ambitious goal for similar future research is on live experiments that follows the design-based, test-based engineering paradigm. The effectiveness of such AI-driven platforms will eventually be testified by the delayed outcomes of the targeted health improvement, and we hope to continue our work and contribute a new computational approach on the future family of such health behavior change problems.