B-Track: A model for assisting in non-communicable diseases through human behavior analysis

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Abstract. *Chronic diseases are among 7 out of the 10 leading causes of death worldwide. The main chronic diseases are heart disease, cancer, chronic respiratory diseases, and diabetes. Heart disease alone causes 9 million deaths a year. Lifestyle changes can prevent many chronic diseases' deaths and their risk factors. In addition, machine learning and wearable devices have been used for behavior analysis. Therefore, this research proposes B-Track, a computational model for assistance in chronic disease care through analyzing behaviors that attenuate or worsen the risk factors associated with chronic diseases, working with user behavior profiles and recommendations for healthier behaviors. Besides, an ontology was created to be used as a knowledge model for the B-Track model to track behaviors associated with risk factors for chronic diseases. The B-Track collects data from different data sources for current and future human behavior analysis through the usage of data fusion and machine learning models. These data comprise the patients' context histories, which include sensor data and data from self-management surveys. Based on the ontology inferences, the B-Track acts in a personalized manner, sending recommendations for habit changes to patients and allowing user accompaniment by health professionals. The scientific contribution of B-Track model is the analysis of human behaviors directly associated with risk factors and their susceptibility to the development of chronic diseases. The model was evaluated through a prototype, which was used by 10 patients during their treatment. Patients participating in the experiment had habits associated with risk factors with susceptibility to developing coronary heart disease, diabetes, and dementia. Some of these patients already had heart disease, hypertension, or diabetes. Patients P4, P5, P6, P7, and P8 showed positive changes in their behaviors in the long term, where P4 increased their consumption of healthy foods, P5 started exercising with highest frequency, and P6, P7, and P8 also made positive changes to their exercise habits. Patient P1 showed no changes, and the others had only shorter-term improvements. Overall, the TAM evaluation showed that B-Track model was useful to 83% of patients, and 80% of the patients found the model easy to use.*

1. Introduction

Noncommunicable diseases (NCDs), also known as chronic diseases, are defined by the World Health Organization [WHO 2022] as long term duration diseases resulting from a combination of genetic, physiological, environmental, and behavioral factors. Cardiovascular diseases, cancers, chronic respiratory diseases, and diabetes are the NCDs with the most number of world deaths, accounting for 41 million people each year, equivalent to 71% of all global deaths [WHO 2020].

Controlling unhealthy lifestyle choices that lead to NCDs development and acting primarily in the risk factors can reduce the prevalence of such diseases. For example, tobacco use is associated for over 7.2 million deaths every year and salt (sodium) excess is responsible for 4.1 million annual deaths [Kyada and Baria 2019]. Furthermore, according to El-Gayar et al. [El-Gayar et al. 2020] unhealthy lifestyles cause 1.6 million deaths annually, while alcohol usage accounted for more than 1.7 million annual deaths [Monteiro et al. 2018]. Early changes to a healthy lifestyle can prevent NCDs and thus reduce the number of deaths. These changes may include reducing tobacco and alcohol usage, practicing physical exercises, and having a healthy diet. Moreover, the promotion of activities towards a better lifestyle is a low-cost way for countries to save lives and provide an economic boost [WHO 2022]. In that way, understanding the human behavior associated with the way of living is relevant to promote improvements in lifestyle [Griffiths et al. 2020, Rehackova et al. 2020].

Technology may be used to explain and predict health behavior and the key events that promote outcomes for a better lifestyle and health behavior changes [Milne-Ives et al. 2020]. In this way, the increasing access to digital technology worldwide allowed health care to be literally in the back of the hand. With more than 8 billion mobile phones worldwide, digital health data-driven strategies can assist the understanding of human behavior across the population [Milne-Ives et al. 2020]. In this scenario, smartphones play a major role, collecting high amount of data from the context of user due to their varied range of sensors [dos Santos Paula et al. 2022]. This context data can help systems to understand user behavior, such as activity, mobility, or sleeping habits [Grimaldi-Puyana et al. 2020].

2. Problem

Due to chronic diseases are linked to more than 70% of deaths in the world population, reaching high proportions [WHO 2022], research has been carried out to bring improvements in the prevention, diagnosis and treatment of chronic diseases. For treatment to be more effective, recommendations to change to a healthier lifestyle must be effective, and patient compliance is paramount. As a result, human behavior analysis research focuses on determining its associations with risk factors [Jones et al. 2021, Dias et al. 2022]. Understand the right moment to make a recommendation to the user, thus bringing greater effectiveness in acceptance. This analysis of user behavioral data can enable systems to offer a lifestyle change. Thus, with a history of user behavior, a system can analyze whether the recommendations made to change a healthier lifestyle are being accepted by the user and thus the effectiveness of NCD management.

3. Objective and Contribution

The objective of this work is to create B-Track, a model to assist patients through the analysis of human behavior associated with NCD risk factors. The model relies on user accompanying to obtain information on user daily habits, including diet, physical activity, emotional well-being, and mobile device usage. The recommendations for user activities are aimed at promoting healthier habits, improving quality of life, and reducing the risk factors associated with NCDs.

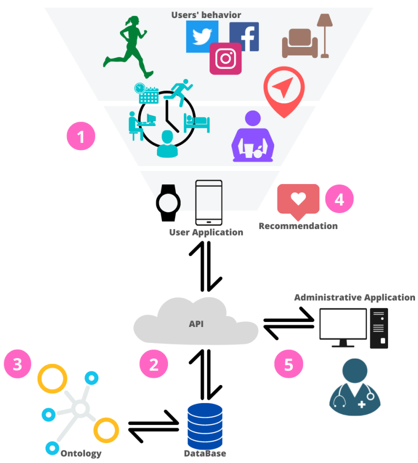
The creation of the B-Track is the main contribution of this work. B-Track is a computational model that uses data analysis to recommend healthier habits based on the relationships between human behavior and NCDs. This approach to analyzing behaviors was not explored in any of the related works. In this way, the model dynamics rely on certain activities which are: collecting data from users, generating healthy lifestyle recommendations, inferring users' profiles, and training models for detecting and computing human behaviors associated with NCD risk factors [Dias and Barbosa 2024]. By accomplishing these activities, a model could recommend preventive behaviors for health improvement and make people aware of the influence of their behaviors on their health.

Additionally, this model proposed an ontology called B-Track Onto to infer how patients' behaviors can impact NCD risk factors. The ontology is another contribution, whereas B-Track Onto was the first ontology that correlates human behavior and risk factors of chronic diseases and its potential as a tool for classifying preventive and non-preventive behaviors [Pfeiffer Salomão Dias et al. 2023, Dias et al. 2024]. A specialist can configure these classification results as part of an information system in a decision support platform.

4. Model Overview

Figure 1 illustrates the B-Track model overview, presenting the five macro phases of workflow. Each phase represents one stage performed by the model. The complete workflow exhibits a macro view of the whole process, from collecting data to analyzing human behaviors, inferring the risk factors associated with non-preventive behaviors, recommending healthier activities, and reporting concerns to the assisted individual.

Figure 1. B-Track Model Overview



The first stage (1) is the user context data collection. The data source does not restrict this model, and the data is related to user behavior such as physical activities, diet habits, location, daily activities, sedentary activities, social interaction, and others. Thus, the user data could come from: a) sensor data from mobile, environment or wearable devices; b) self-management questionnaires; and c) data from social networking platforms, such as Facebook©, Twitter©, and Instagram©. After the data collection, in the second stage (2) the B-Track stores all information about user context data into a database. The model organizes this set of data into Context Histories, following the structure of the

Human Behavior and Risk Factor Ontology (3). The model uses all gathered data for identifying non-preventive behaviors associated with NCD risk factors and assisting the users. Ontology and machine learning models analyze the data stored to identify human behaviors to reinforce or praise the practice, learn about behaviors, or promote change to healthy behaviors.

The fourth stage (4) shows recommendations made to users to practice preventive behavior. The analysis of user recommendation adherence is made by an analysis comparing whether the newly collected data from user behaviors changed when compared with the older data. Thus, the model can check if the non-preventive behavior has stopped and if the preventive behaviors have been instituted. Finally, the fifth stage (5) allows users and their health professionals to analyze their state and evaluate the user progress. The model provides an interface for health professionals to customize recommendations based on the user profile, increasing the assertiveness of recommendation adoption. Also, the B-Track provides visualizations regarding the users' data, allowing the monitoring of trends.

5. Results

The experiment involved 10 patients with NCDs, who used B-Track in their daily activities for more than two weeks, between July 2023 and April 2024. This study was approved by the ethics committee of Unisinos under the code (CAAE 67413623.3.0000.5344), which is accessible on Plataforma Brasil[1]. The experiments indicate that 80% of patients agree on the utility of using B-Track to assist in their NCD treatment. However, the experiment had limitations and requires evaluation with a larger patient group, including a control group, and over a longer period for a more detailed analysis.

The analysis of patients' behaviors worked with two macro groups, namely eating behaviors and physical activities. Of these groups of behaviors, eating habits are those that stood out most in terms of both preventive and non-preventive behaviors, showing a tendency towards a sedentary lifestyle. 80% of the patients had non-preventive behaviors majority related to physical activities, whereas 60% of the patients had preventive behaviors mostly related to physical activities. Incentives for physical exercise, drinking water, and eating vegetables and grains are among the main points of attention for the patients observed. Patients participating in the experiment exhibited habits linked to risk factors for developing NCDs such as coronary heart disease, diabetes, and dementia. Some patients already had conditions like heart disease, hypertension, and diabetes, and their habits could potentially worsen these existing conditions.

Analysis of patients' behavior led to recommendations for healthy habits through educational material. Users could access a screen in the prototype to track their healthy and unhealthy behaviors during the experiment. Patients P4, P5, P6, P7, and P8 achieved changes in behaviors for a longer period. Patient P1 showed no changes, while other patients experienced behavioral changes for only short periods. Patient P4 improved the consumption of grains, nuts, seeds, vegetables, and soy-based foods from rare to normal. For P5, the frequency of aerobic practice increased from rare to excessive. P6 also improved the frequency of aerobic practice, changing from rare to excessive, while P7

[1] $http://plataformabrasil.saude.gov.br$

changed their aerobic practice from rare to both normal and excessive. Finally, P8 increased the frequency of aerobic exercise from rare to normal, frequent, and excessive.

After two weeks of using the prototype, the users answered the Technology Acceptance Model (TAM) questionnaire. The TAM evaluation highlighted areas for improvement in B-Track, particularly in the educational materials, which P5 found unhelpful. P2 and P5 experienced difficulties identifying risk factors associated with their habits. Additionally, P2 and P8 reported challenges with the food options, while P5 struggled with the activity options. Lastly, P1 and P5 felt that the number of notifications requesting updates on their habits was excessive.

6. Conclusion

This study aimed to distinguish how human behavior data analysis has been applied to support the treatment and prevention of NCDs, what technologies are currently used, and what gaps are still left unexplored. In this sense, the work proposed a computational model called B-Track, which aims to assist in the management of non-communicable diseases (NCDs) by analyzing behaviors that either alleviate or exacerbate the risk factors associated with chronic diseases. The objective of B-Track is to raise individuals' awareness of their behaviors linked to NCDs risk factors and encourage them to adopt a healthier lifestyle. Another goal of B-Track is to recommend preventive behaviors to help improve overall user health. The model was evaluated through an experiment involving 10 patients with NCDs, who used B-Track in their daily activities for at least two weeks. The TAM evaluation showed that B-Track was useful to 83% of patients, and 80% of them considered the model easy to use.

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