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Smart Work Injury Management (SWIM) System: Artificial Intelligence in Work Disability Management

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Abstract

Purpose This paper aims to illustrate an example of how to set up a work injury database: the Smart Work Injury Management (SWIM) system. It is a secure and centralized cloud platform containing a set of management tools for data storage, data analytics, and machine learning. It employs artificial intelligence to perform in-depth analysis via text-mining techniques in order to extract both dynamic and static data from work injury case files. When it is fully developed, this system can provide a more accurate prediction model for cost of work injuries. It can also predict return-to-work (RTW) trajectory and provide advice on medical care and RTW interventions to all RTW stakeholders. The project will comprise three stages. Stage one: to identify human factors in terms of both facilitators and barriers RTW through face-to-face interviews and focus group discussions with different RTW stakeholders in order to collect opinions related to facilitators, barriers, and essential interventions for RTW of injured workers; Stage two: to develop a machine learning model which employs artificial intelligence to perform in-depth analysis. The technologies used will include: 1. Text-mining techniques including English and Chinese work segmentation as well as N-Gram to extract both dynamic and static data from free-style text as well as sociodemographic information from work injury case files; 2. Principle component/independent component analysis to identify features of significant relationships with RTW outcomes or combine raw features into new features; 3. A machine learning model that combines Variational Autoencoder, Long and Short Term Memory, and Neural Turning Machines. Stage two will also include the development of an interactive dashboard and website to query the trained machine learning model. Stage three: to field test the SWIM system.

Conclusion SWIM ia secure and centralized cloud platform containing a set of management tools for data storage, data analytics, and machine learning. When it is fully developed, SWIM can provide a more accurate prediction model for the cost of work injuries and advice on medical care and RTW interventions to all RTW stakeholders.

Ethics The project has been approved by the Ethics Committee for Human Subjects at the Hong Kong Polytechnic University and is funded by the Innovation and Technology Commission (Grant # ITS/249/18FX).

Keywords Artificial intelligence · Machine learning · Work disability management · Prediction · Return to work

Introduction

Work injuries represent a significant cost to the industry and productive capacity of both developed and developing countries. Absence due to sickness and work disability constitute a common and substantial public health problem with major economic consequences worldwide [1, 2]. When a person is injured at work, there are changes in all aspects of the person's functioning, whether the injury is short term or long term, permanent or temporary, serious or minor. The changes for the worker are complex. They may be physical, psychological, social, or financial in nature. These changes all interrelate and impact upon one another. The employer

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and the management of the workplace may also be affected by the work injury. There are both direct and indirect costs of work injuries, including medical expenses for the rehabilitation of the injured worker, loss of production due to the loss of the injured worker's skills, salary paid to the non-productive worker, and legal costs for litigation. Staff morale and the reputation of the company may also be affected [3].

Furthermore, returning to work after a work injury can be a complex process. The process is not purely physical; it also involves many psychological, social, and economic factors. In an ideal scenario, injured workers would follow a uniform return to work (RTW) trajectory consisting of a series of evolving phases, including seeking medical care, recovery, and sustained work re-entry. In many cases, however, the RTW process is not linear and a proportion of injured workers experience a variable and often undesirable RTW course, including extended (e.g. staying out of work for a longer period of time than expected) or intermittent work disability (e.g. alternating between being able and being unable to perform work tasks). It is influenced by the motivation, interests, and concerns of different stakeholders [4] in the so-called "Arena of work disability" [5]. An RTW stakeholder can be defined as any person, organization, or agency that stands to gain or lose based on the results of the RTW process [4]. Overall, there is a consensus among researchers in the field of work disability prevention that RTW stakeholders consist of workers and their families, labor representatives/trade unions, employers, healthcare providers, and insurance providers [6, 7]. Among these, employers, injured workers, and healthcare providers are three key stakeholders who play a significant role in the whole RTW process [8]. In other words, there are human factors from different RTW stakeholders that could act as facilitators or barriers in the RTW process.

Advanced analytic techniques have been used in the insurance industry worldwide to improve claims analysis and prediction. Basically, they use historical claim costs in the data set, after adjusting for inflation, to reflect the fair value of worker's compensation claims in today's economy.

Nevertheless, it is inappropriate to directly adopt analytic techniques from other places without considering local contextual factors, since there are large cross-country differences in the management of work disability resulting from work injury. According to the Organization for Economic Cooperation and Development, there are two principal approaches: some countries emphasize a compensation policy approach, with broad access to disability benefits, combined with fewer reintegration efforts, and other countries emphasize a reintegration policy approach, stimulating primarily reintegration measures, with restricted access to disability benefits [9]. In some Western countries, there are jurisdictional-level workers' compensation policies for facilitating the implementation of an RTW program [10]. Moreover, use of traditional analytical methods will overlook up to 80% of the data, which we call "dynamic data". This information is found in unstructured textual formats such as medical notes from treating doctors, progress reports from therapists, worksite assessments, and dialogues between claim managers or case managers and different RTW stakeholders as well as injured workers. It has huge potential for identifying determining factors which could facilitate or impede the RTW process and thus could give more accurate predictions of claim costs and estimated RTW trajectories of injured workers.

Artificial Intelligence (AI) is a general term that implies the use of computers to model intelligent behavior with minimal human intervention [11]. The application of AI in the medical field has two main branches: physical and virtual. The physical branch is best exemplified by robots helping elderly patients to walk or helping surgeons to perform sophisticated neurosurgery. On the other hand, the virtual branch consists of machine learning (also called deep learning), which is essentially the use of mathematical algorithms to improve learning through "experience". There are three types of machine learning algorithms: (i) unsupervised (ability to find patterns), (ii) supervised (classification and prediction algorithms based on previous examples), and (iii) reinforcement learning (use of sequences of rewards and punishments to form a strategy for operation in a specific problem space) [11]. Previous study showed that a hybrid approach, combining unsupervised and supervised machine learning methods can accurately predict the outcome of interest using the discovered patterns [12]. The virtual branch of AI usually includes informatical approaches, from deep learning information management to control of health management systems, including electronic health records, and active guidance of physicians and therapists in making intervention decisions [13–15] and predicting intervention outcomes, including RTW after work injury [16, 17].

From the perspective of data management and analysis, each work injury claim has already created a substantial amount of information, including demographic data, injury management data, claim management data, return to work profile, and settlement information. In the broadest terms, there are three main types of data: numerical, categorical, and textual. The first is naturally the most easy to manipulate with machine learning. The second requires some processing, such as converting it into a multidimensional one-hot vector or a compressed representation (i.e. multidimensional vectors that can represent different classes in a continuous space). The third takes the most work, as it requires the use of recurrent neural networks such as lstm to project text into a latent space. When the data are represented as numbers or vectors, various machine learning techniques (e.g. neural networks) can be applied to them. The purpose of this paper is to illustrate an example of how to set up a work injury database: the Smart Work Injury Management

(SWIM) system. It is a secure and centralized cloud platform containing a set of management tools for data storage, data analytics, and machine learning. It employs AI to perform in-depth analysis via text-mining techniques to extract both dynamic and static data from work injury case files to perform unsupervised and supervised machine learning algorithms. When it is fully developed, this system can provide a more accurate prediction model for the cost of work injuries. Most importantly, it can also predict RTW trajectory and provide advice on medical care and RTW interventions to all RTW stakeholders. Figure 1 summarizes the conceptual framework of SWIM.

Methods and Analysis

Developmental Stages of SWIM

SWIM will be developed based on machine learning RTW outcomes of more than 50,000 work injury cases as well as local contextual human factors identified by different RTW stakeholders.

It comprises three distinct stages:

Stage 1: Identification of Human Factors Which Could Influence RTW of Injured Workers from Face-to-Face Interviews and Focus Group Discussions with Different RTW Stakeholders

In order to make SWIM able to learn different human factors that can facilitate and impede the RTW process of injured workers, in the beginning of the developmental stage of SWIM, face-to-face interviews with significant RTW stakeholders have been conducted. After these interviews, focus group discussions have been held to involve all RTW stakeholders (injured workers, trade unions, employers, healthcare providers, and insurers), so as to review the content validity of different opinions and, most importantly, to reach a consensus on the essential elements of an RTW intervention that will help injured workers to RTW. The end of this stage can help identity different indicators for predicting the RTW trajectory of injured workers as well as which interventions are effective in rectifying deviations from the expected RTW trajectory.

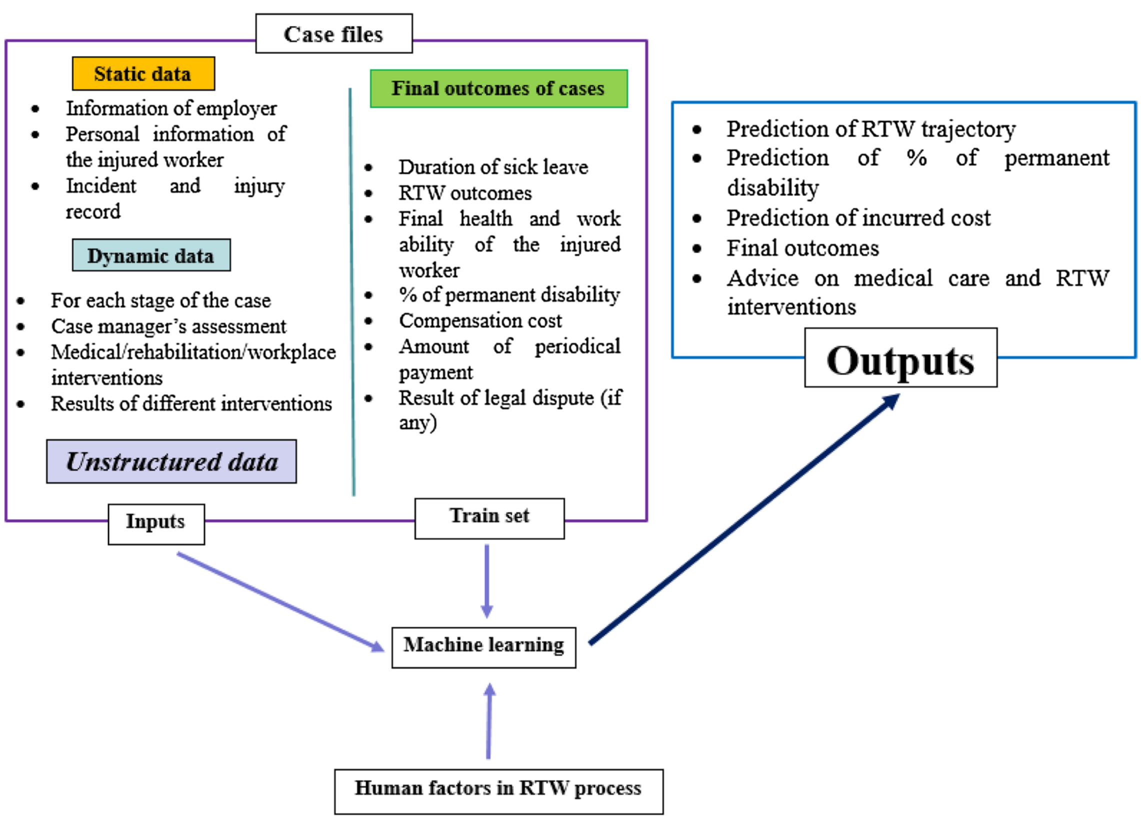

Fig. 1 Conceptual framework of SWIM

Stage 2: Blending the Human Factors with Machine Learning Algorithm to Develop a SWIM

The cloud platform of SWIM will then be built using Microsoft Azure's PaaS (Platform as a Service) due to its reliable performance. There are cloud platforms other than Microsoft Azure such as Amazon Web Services and Google Cloud. As far as budget is concerned, each platform can use its own price estimator to get an estimation of the cost. For example, a surface view of the pricing between the three platforms on image recognition tasks indicates that the prices are similar (Microsoft Azure: 1USD every 1000 images; Amazon Web Services: 1USD every 1000 images; Google Cloud: 0.75USD every 1000 images). Sometimes, it is very difficult to compare different cloud platforms as some functions may be solely available on only one platform. For example, the equivalent of Microsoft Azure's Cognitive Service on Amazon Web Service is Rekognition. Both can help predict predefined labels on an image. However, only the former allows custom training of a computer vision model (i.e. training a computer vision model to recognize novel objects), whereas the latter cannot.

The raw data for building the model will be stored in a hybrid database (DB) of Azure SQL service and Mongo DB in a Health Insurance Portability and Accountability Act (HIPAA) ready environment.

Mongo DB belongs to a different kind of DB, namely the document-oriented database, which, instead of storing data in tables with static attributes, stores it in documents with attributes able to be freely added or removed. This form of DB is more flexible compared to relational DBs. HIPAA ready environment is a function supported by some IT applications to deal with privacy and personal data. Azure's machine learning platform is then used to define the AI model of SWIM. Power BI is a Microsoft product that can be used in conjunction with Azure applications to view data interactively. It is used to create the interactive dashboard which allows us to access and interact with various data. For example, we can specify that we only want to view some data fields under specific conditions (e.g. we may only want to view injured workers who have received a particular intervention).

For security reasons, Azure AD (Azure Active Directory) and Azure Key Vault will be used for identity issues. The former is an Azure component that can be used to authenticate users (e.g. by providing a login page on the front-end and the related back-end architecture), whereas Azure Key Vault is a back-end component of Azure for securing "secrets" (e.g. user passwords) via encryption. Security Center, Azure Monitor, and Compliance Blueprint are also used for security. These are all components of the Azure architecture. Azure Security Center is a function of Azure that can be used to enhance security. It provides us with a "Secure Score" as well as security recommendations. Azure Monitor will be used in conjunction with Security Center to check whether there are any infrastructural issues. Azure Security and Compliance Blueprint comprise a set of commonly practiced configurations for securing applications on Azure. The platforms are displayed on the right hand side of the architectural diagram (Fig. 2), while the left hand side describes the role of data scientist, case manager, and system administrator. The work is started by the data scientist. First, the bulk data (50,000 documented work injury case files) will be converted into a HIPAA hybrid DB [a hybrid database here simply refers to a database that is a hybrid of a relational database (Azure SQL service) and a document-oriented database (Mongo DB)].

The AI, machine learning model, access mode, and display mode are defined by the data scientist in the cloud platform. The conceptual machine learning model is shown in Fig. 3. The raw data for building the model consist of the documented work injury case files and those human factors that could influence RTW collected from the Stage 1. Different machine learning techniques will be used to extract the unstructured data, dynamic data, and outcomes of work injury cases from the case files, and then build a HIPAA hybrid DB from the extracted data. There are three steps:

First, *Raw data preprocessing*. The raw data are from more than 50,000 documented work injury case files. A completed case file will include the following content: the basic information of the injured worker; the psycho-social status of the injured worker; the incident record; the medical treatment record; the interactions among the injured worker, case manager, and medical doctors; the assessment given by the case manager in every stage of the case, and the outcome of the case. All the information is recorded in free-style text and need to be extracted for further analysis. Take the medical treatment record as an example. First, important fields, such as symptom, diagnosis, treatment, and name of the doctor will be identified. Second, optical character recognition will be used to convert the hand writing to text data. Third, natural language processing techniques will be used to remove the stop words and extract the meaningful text. Text parsing and text categorization will then be used to turn the meaningful text into data models and structures, such as trees, graphs, and Word2Vec. Therefore, the raw data is divided into two parts: training input and output. Training input is then divided into static data (e.g. demographic data) and dynamic data (e.g. medical treatment record). The objective of this step is to process, combine, and store the data in a HIPAA hybrid DB.

Second, *Rule learning*. After identification of raw features from both dynamic and static data, which are numerical and textual, Principle component and or independent component analysis will be conducted to identify features significantly related to RTW outcomes or to combine raw features into

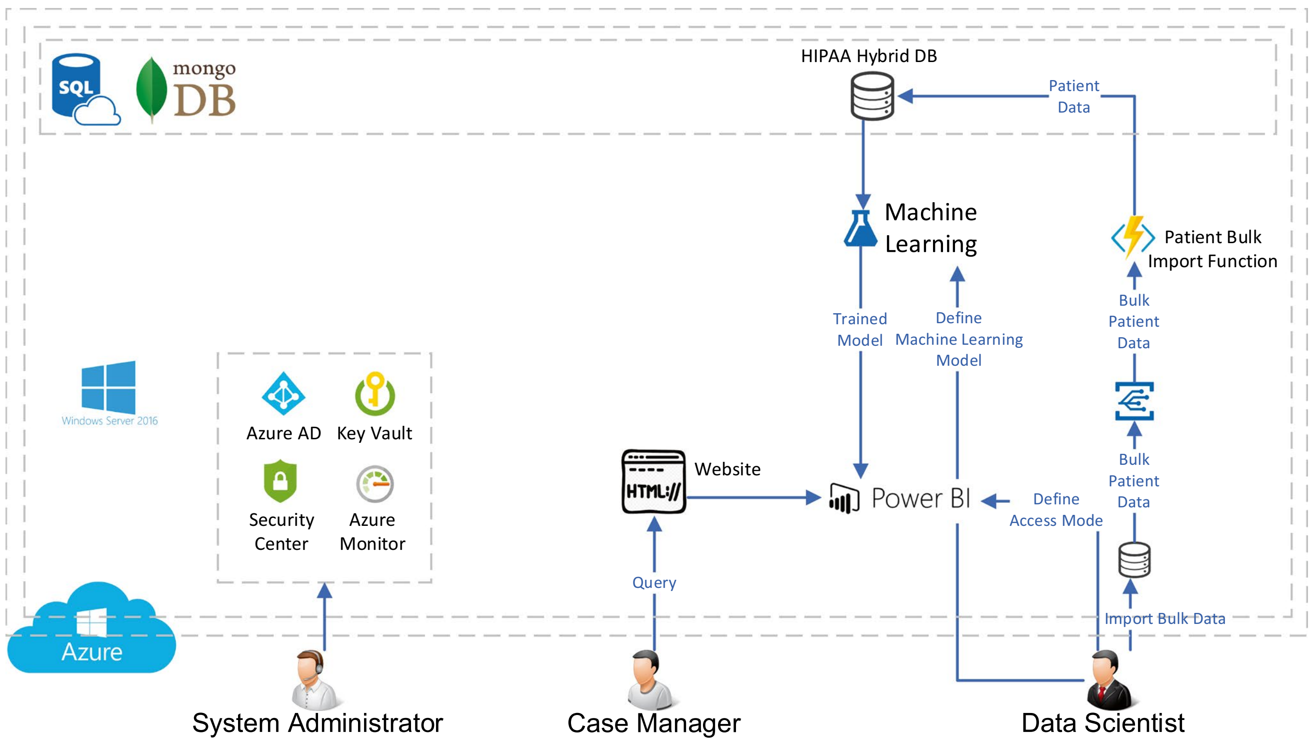

Fig. 2 Architectural diagram of SWIM

new features by using the data in the HIPAA hybrid DB. The training input in the DB and training output will be tested in the machine learning model. In this project, we will use the Hidden Markov Model and Variational Autoencoder for case similarly measurement, classification, clustering, feature, and probabilities compression. The Hidden Markov Model is useful in handling temporal data [18, 19], while the Variational Autoencoder is known to be able to produce interpretable latent space that can be used for clustering and more [20, 21]. Therefore, they are used to understand the dynamic temporal behavior of injured workers at different stages of recovery.

We will divide the dataset into two parts. The first part is called the training or validation set (typically around 70% of the dataset), on which we train the algorithm using a K-fold cross-validation where K is defined as 10. In machine learning, it is a common practice to divide the data into a "training set" and "testing set". The purpose of this division is to provide data to train a machine learning model while withholding some data to test if the model is generalizable (i.e. if it is able to learn the true distribution of the data). The former data comes from the training set while the latter comes from the testing set. Since the partition of data into training set and testing set is done with a random division, it is possible for the partition to randomly have a training set or testing set that has a significant difference with the true distribution such that it is not viable for training or testing. To ease out this randomness, we will consider partitioning the data in K different ways, such that for a dataset we can get K different training and testing set pairs. Then to test a machine learning model, we will use the aggregated result by training and testing with the K pairs.

The second part is called the test set (the remaining 30% of the dataset), on which we will evaluate the results of our algorithm and make sure that we do not overfit the data. It is important to remember that the goal of a machine learning model is to use some data samples to learn the true distribution of the population data. Overfitting refers to the failed scenario where the machine learning model has simply memorized the training data instead of using it to generalize. The result of overfitting is that the model is only able to perform well with the training data and performs poorly when given real world data (or testing data). Once the algorithm is trained, we can use it on new data to predict the RTW trajectory of injured workers.

Third, *Data visualization*. We will develop and train the algorithm on a labeled dataset, which contains over 50,000 past injured workers' RTW trajectories as well as findings from Stage 1, which are RTW facilitators and barriers identified by different RTW stakeholders, in order to predict the outcomes of work injury cases and provide guidance regarding intervention methods to case managers and related medical professionals. We will also use the rule learning technique to build a prototype system. The

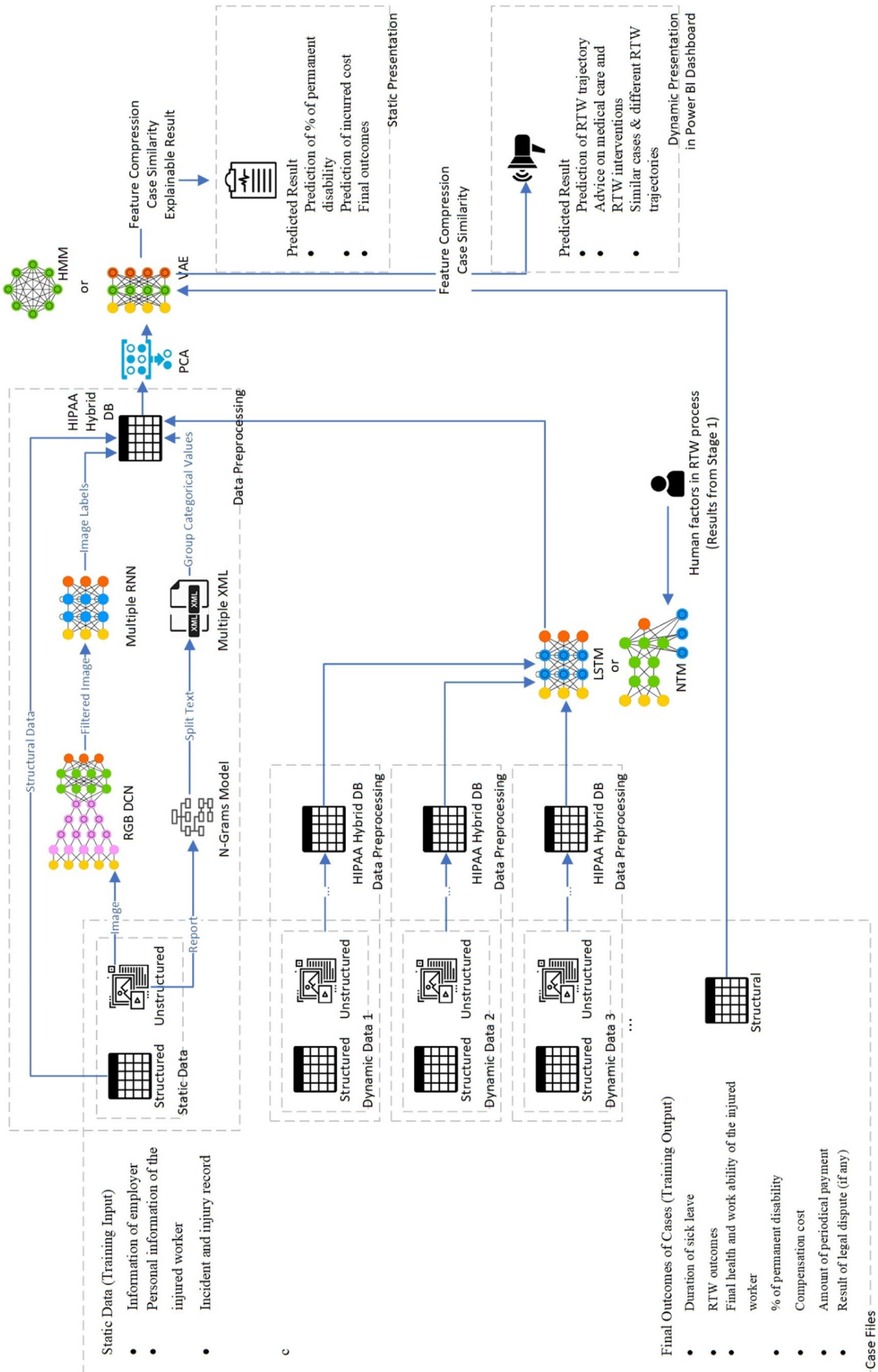

Fig. 3 Conceptual machine learning model of SWIM

rule-based machine learning technique is a technique for classifying records using a collection of "if…then…" rules and is generally used to produce descriptive models. With the class-based ordering approach, it can handle data sets with imbalanced class distributions. In this project, we will use the static and dynamic data as the rule antecedent and the outcomes of the cases as the rule consequent to generate the rules. The generated rule-based classifier can predict the outcome of a given case base on its static data or predict the stage outcome based on static data and stage dynamic data. The most effective intervention method could then be selected by choosing the intervention method that leads to the most desired RTW outcomes. Explainable machine learning results, including prediction of RTW trajectory and advice on medical care and RTW interventions, will be provided to the case manager in an interactive dashboard. Moreover, in the case of any deviation from our expected RTW trajectory, SWIM will send a signal to notify medical and allied health professionals, administrators, and/or case managers and, most important, SWIM will provide recommendations on how to bring the worker back to the normal RTW trajectory.

Stage 3: Field Testing of SWIM

Field testing of the SWIM prototype will be carried out at eight case management or insurance companies to test its prediction accuracy for new cases. In order to minimize possible bias in using data from the past to develop SWIM, a cluster randomized controlled trial will be conducted in which half of these companies will be randomly assigned to use SWIM for 6 months first. The other companies will serve as the control group to compare any difference in prediction accuracy for cost of work injuries. In addition, the duration of sick leave, compensation cost and percentage of permanent disability of the new cases after their case closure will be compared with a historical control of similar work nature, injury type and sociodemographic characteristics to assess its predictive validity for the cost of work injuries. Finally, User Acceptance Testing will be performed by the end users to verify and accept the system. Feedback and comments after the field testing will be used to fine-tune the machine learning model.

Ethics and Dissemination

The project has been approved by the Ethics Committee for Human Subjects at the Hong Kong Polytechnic University and is funded by the Innovation and Technology Commission (Grant # ITS/249/18FX).

Discussion

Injuries in the workplace constitute a common and substantial public health problem with major economic consequences worldwide. As time off work due to disabling injuries increases, injury-related costs, such as indemnity payments, medical and legal expenses, and employee substitution costs rise. However, the RTW process is usually not linear and a significant proportion of injured workers experience a delay in RTW. Hence, it is important to provide effective internvations from different RTW stakeholders to prevent work disability.

SWIM will be developed in order to provide a secure centralized electronic system for all RTW stakeholders so that all the information is protected and managed in one platform and the obtained information is accessible to all stakeholders with straightforward guidelines under the scope of the personal data ordinance. SWIM can perform an in-depth analysis of the claims database, including unstructured textual data, and help develop a prediction model for the identification of risk factors that may impede the RTW process of injured workers. Moreover, SWIM predict the RTW trajectory of injured workers. In the case of any deviation from the expected RTW trajectory, It will provide recommendations on what sort of services can be provided so as to bring the worker back to the normal RTW trajectory. Therefore, when a work injury is reported, SWIM will advise on the optimal way to manage the work injury at various stages of case development. In the end, this creates a win–win situation for all RTW stakeholders.

Conclusion

The purpose of this paper is to illustrate an example of how to set up a work injury database. It is a secure and centralized cloud platform containing a set of management tools for data storage, data analytics, and machine learning. It employs AI to perform in-depth analysis via text-mining techniques to extract both dynamic and static data from work injury case files to perform unsupervised and supervised machine learning algorithms. When it is fully developed, this system can provide a more accurate prediction model for the cost of work injuries.

Funding This project was funded by Innovation and Technology Commission (Grant Number ITS/249/18FX).

Compliance with Ethical Standards

Conflict of interest The authors have no conflict of interest to declare.

Ethical Approval All procedures performed in this project were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent Informed consent was obtained from all individual participants included in the project.

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