Journal for Re Attach Therapy and Developmental Diversities
eISSN: 2589-7799
2023 November; 6 (10s) : 2222-2232

# Neural Network-Based Models For Predicting Healthcare Needs In International Travel Coverage Plans

**Ramanakar Reddy Danda[1*]**

[1*]IT architect , CNH, NC, ramanakarreddy.danda.eia@gmail.com, ORCID: 0009-0005-7181-4508

**Abstract**

Safeguarding health from diseases during international travel is essential. International travel health insurance is a type of risk management that offers coverage for health issues, such as disease occurrences, to which travelers could be exposed at their destination. Offering proper international travel coverage plans during trip planning assists travelers in mitigating such health issues since a traveler can focus on the planned trip instead of worrying. This research developed and tested deep learning algorithms trained on large, vast dimensional, long historical periods, and near-real-time multi-feature healthcare data about the final destination of a traveler.
In the past, medical experts utilized various algorithmic models based on traditional statistical analysis and simple classification and regression techniques for predicting travel health risk issues without giving much attention to deviations from randomness, accuracy, and overfitting of the selected models, which have subsequently been labeled as health-tuned risk prediction systems. Recently, data-driven classification and prediction algorithmic models are starting to more adaptively classify, compare, and predict travel health risk issues. This research contributes to the existing family of data-driven medical tourism research with in-depth data analytical experiments using state-of-the-art industry-discovered techniques adopted for classification and forecasting tasks.

**Keywords:** International travel health, Travel health insurance, Risk management, Disease prevention, Healthcare coverage, Travel risk mitigation, Deep learning algorithms, Predictive models, Health risk predictio, Travel health risks, Data-driven models, Classification algorithms, Regression techniques, Health-tuned risk systems, Medical tourism, Multi-feature healthcare data, Long historical data, Real-time healthcare data, Forecasting health issues, Adaptive prediction models.

## 1. Introduction

Travelers are often subject to different diseases and injuries when they travel to other countries due to changes in climate, food, water, or the environment. Health issues are often the main concern with international travel. To address these issues, some complementary insurance or healthcare coverage plans are designed. Additionally, with a proper recommendation and buyer guide for these types of insurance, people can find and purchase complementary health insurance suitable for their travel needs. Even though predicting potential future needs for these types of insurance is difficult, models provide crucial information about the types of coverage where high levels of potential demand exist. Therefore, recommending and implementing these optional insurances from the point of purchase can generate a wide range of interest. In this research, models are developed to predict customer demand for optional healthcare plans, targeted mainly for international travel.
The models are based on neural networks, and the data are obtained from a specific insurance company. As such, the data is domestic travel insurance plan data. The methodology and automatic coding used on neural networks and backpropagation models show potential for use in other healthcare coverage plan domains. Although the models shown are limited in scope, they can accommodate a wide range of types of insurance. For example, travel health insurance is synonymous with healthcare options in travel care sales, and neural networks and backpropagation can be extended to include a wide range of related products, such as hospital stays, urgent care, or urgent consultations. Furthermore, the damage predictions do not have to be defined in terms of binary variables but can be represented by levels of demand or a finite range of continuous approximation values. The data is based on insurance policy variables specific to travel health and travel care coverage that effectively narrow the idea to the travel health insurance product domain.

### 1.1. Background and Significance

International travel coverage plans are customized insurance plans offered to provide financial protection against medical and non-medical emergencies that may arise during international travel. The international travel coverage plans, given their complex nature and dynamic risk factors, make it difficult for underwriters to analyze risk and determine a fair price. In turn, these financial incentives and uncertainties can create several adverse behaviors and risks to consumers. In the United States alone, travelers spend billions of dollars each year on travel insurance to protect their health and aid the cost of care when traveling for leisure, studies, and international business. Although it is necessary for underwriters to

carefully quantify the uncertainty involved in designing insurance plans, little attention has been given to predicting travel needs to support decision-making in underwriting customers rather than setting prices based on business information.
This research aimed to develop and evaluate four different artificial intelligence methods capable of predicting travel needs. Further, the study also performed feature evaluation and feature ranking to understand the role of each feature allocated within a policy. The predicted results indicate an association between feature policies and the necessity of travel needs. Both NN and SWANN are visually efficient in displaying the feature importance within travel policies and can be extended to create policies for several classes of individuals in society based on attracting top consumers. The findings could enable underwriters to make better decisions using international travel coverage plan policies when assessing the healthcare needs of international travelers. These decisions can be used for planning and allocating resources in a more customized, efficient, and accurate manner, as well as supporting decisions on expanding coverage to attract favorable groups for business. The results may also be applied to other custom insurance coverage plans or travel coverage policies. Furthermore, to guide policymakers when building policies in a healthcare system, a correct assessment of outpatient and medical deals related to international travel coverage is essential.

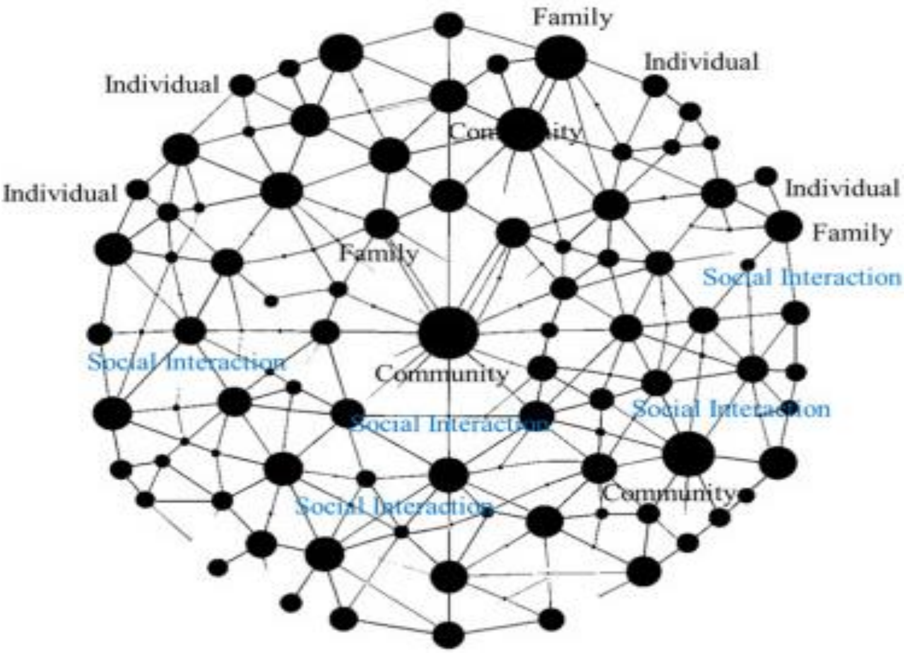


**Fig 2 : Network-based disease prediction model.**

### 1.2. Research Objectives

The objective was to develop an artificial neural network-based model as a form of quantitative predictive analytics of healthcare practices of international travel coverage holders. The objectives are indeed extensive, covering model design, training, validation, testing, and implementation of in-depth performance and identification of sufficient sample data for medical and healthcare practices. Classification of risk levels comes with the predicted risks as well. These are the focus of research. However, predictive modeling is an abstract activity that requires a lot of medical and healthcare knowledge to initiate. It also needs to follow a structured protocol for risk prediction reporting to validate medical and healthcare knowledge and to ensure that the original purpose of modeling has been met.

**Predictive Model for Likelihood of Healthcare Event During Travel:**

This model predicts the probability that a traveler will require healthcare during their trip based on multiple input factors such as destination risk, traveler health status, trip duration, and activities.

**Equation**: $P(\text{Healthcare Event}) = \sigma\left(\mathbf{W}_1 \cdot \mathbf{X} + b_1\right)$

Where:

$P$(Healthcare Event) is the probability of a healthcare event (e.g., medical emergency, hospitalization).

$\sigma$ is the activation function, often the sigmoid function, which outputs a probability in the range [0, 1].

$W1$ is the weight vector associated with the input features $X$.

$X$=[Age,Health Status,Destination Risk,Duration of Trip,Activity Level,…] represents the input vector for the traveler.

$b1$ is the bias term.

## 2. Literature Review

Our study relies on neural network models that are put into practice in various domains, including the insurance literature, because of their ability to model nonlinearities, their robustness to noise, their generalization ability, and their significant contributions in the past couple of decades enhancing the dataset with alternative data sources such as credit scores, income, and economic conditions. The focus is mainly on sales modeling in automobile insurance and shows that a powerful neural network model on consumer credit scores can replace the current model that works on a limited number of variables based on simple linear regression, relying on the finding that using credit score models alone can reproduce 90% of the performance using full models. The focus on health insurance data and rendition cites the flexibility to model nonlinear features and the ability to work with categorical and continuous input variables as significant contributors to outperformance in operationalizing efficient models by neural network models and boosting models since they have been proven in many recent studies to have predictive power.

Machine learning models are acknowledged as factors contributing to prediction accuracy when other factors representing the country, such as distances from country-level variables like healthcare expenditure, life expectancy, doctors, hospital beds, and the number of hospital beds, are considered. In our study, we utilize neural network-based models to represent the dynamics of travel characteristics and well-being. In general, demand estimation and growth modeling play an important role in improving the financial performance and responsibility of insurance firms. Demand estimation in the travel insurance field will form the basis for the developed insurance product to be sustainable, and efficient, and to provide coverage to international travelers at an affordable price. In this context, it is essential to compete by determining that a particular firm not only operates at commercial risk optimization but also allows travelers to move more freely and experience the world without insurance-related complications while on their journey.

### 2.1. Traditional Methods for Predicting Healthcare Needs in Travel Insurance

Accurate pricing is crucial to the sustainability of travel insurance; it ensures that there are sufficient funds to reimburse the high, unpredictable healthcare costs to which travelers are exposed abroad. An efficient market for travel insurance depends on the adage: "Good money drives out bad." If a travel insurance plan is underpriced, it will attract unpredictable or high-maintenance travelers, who specifically seek coverage for conditions that they anticipate will occur. If these plans have high insured costs, they will drive the group average loss ratio up, which will make the plan attractive in turn for such high-maintenance travelers. After this adverse selection has run its course, the few remaining, well-focused, low-maintenance policies in the group will depart to find a better option, which, in effect, has already built up. The old option will be problematic for the insurance administrator and create complaints among its insureds, while the new plan will be well-received until once again high-maintenance insureds migrate to the new plan, which will become increasingly expensive relative to less expensive plans. In the long term, a travel insurer that does not price accurately will lose clients and will ultimately fail due to increased loss ratios.

Traditional Methods for Predicting Healthcare Needs in Travel Insurance Until this study, worldwide travel insurers used widely accepted medical underwriting principles and consulted publicly available health policies to predict health issues during travel. Both of these factors are related to their prediction objectives. The prediction objectives of underwriting are to estimate the likelihood of a claim, the likely average, and the range in the timing of the probability distribution of the event that causes the claim to happen.

Similarly, health policies aim to forecast broad health ranges to assign the appropriate health facilities to a traveler. Underwriting decisions, which are based on forecasts of acute care needs in emergency circumstances, should result in a variant of health policies that assure the highest quality of care in case of acute injury or illness during a vacation or trip. To accomplish these goals, insurers need to form accurate, brief, timely, health-specific, and credible advice that provides a sound and unique expected value. The alternative form of new loss should be used because it can safeguard consumers. These policies are common tools that comply with laws and regulations currently in effect.

Journal for Re Attach Therapy and Developmental Diversities
eISSN: 2589-7799
2023 November; 6 (10s) : 2222-2232

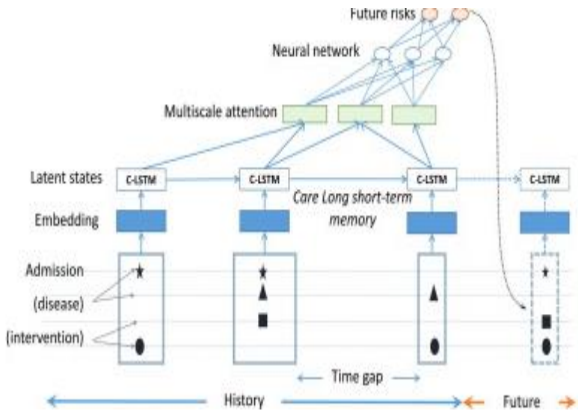


**Fig 2 : Predicting healthcare trajectories from medical**

### 2.2. Advancements in Neural Network-Based Models

Artificial neural networks have been widely used in a variety of fields and lead the modeling landscape in many applications involved in travel and insurance, such as customer segmentation, risk assessment, or actuarial research. They have proven to be very promising methods in modeling outcomes when the nature of the relationship between the predictive variables and the expected results is unknown. Applying ANNs to a previously unseen set of input data enables them to update, for instance, the weight priors between different neurons and the learning method according to the discrepancies between the model predictions and real results. Various versions of neural networks have been used for more than two decades, from simple multilayer perceptron or feedforward networks to more complex time-delay, convolution, radial basis, recursive, or fuzzy models.

A wide variety of methods have been implemented to adjust the ANN parameters, such as iterative mini-batch or stochastic gradient descent, error backpropagation, simulated annealing, genetic algorithms, particle swarm optimization, or robust training with constrained optimization. However, before implementing any of those techniques to take advantage of the model's capabilities, activity, and relationships, there are still some limitations to overcome when the modeling process is being designed. For instance, the model interpretation or reproduction can sometimes become difficult when the adopted learning technique becomes too complex. Furthermore, the information processing efforts involved in reaching a good learning result, as well as the implications of the generated number of parameters, can have relevant financial, organizational, or statistical effects on the final model. There are still limitations to model robustness in real-world scenarios, which often present unbalanced, incomplete, or misclassified datasets, as well as non-linear covariate effects in high-dimensional and multifactorial systems.

## 3. Methodology

### 3.1.3. Data Categorization

Individual expenses were grouped into different categories depending on their nature and coverage. The grouping into these categories was created in such a way that similar and related expenses were put together following a different subdivision designated as conceptual. Expenses that were part of the travel cost were taken with their relation only to the reason, object, or primary motive of the travel and are used for refining the meaning of the travel itself. The subcategories are departure, accommodation, and services, leisure or official trip services, passenger assistance services, and arrival. Assistance that intervenes in travel needs includes the services that are taken to help a person in case of certain situations. The costs associated with obtaining documents were often high. Conceptually, this is a service requested as part of the process of going abroad and lies between helping customers during the trip. This category also includes other similar documents such as visas, citizenship papers, or passports. Optionally, someone can ask for other guarantees to ensure the smoothness of their stay. These are costs required by the embassies to issue a letter to allow a foreign person to enter the country.

### 3.1. Data Collection and Preprocessing

The database employed for training and validating the developed models was collected from the websites of two insurance companies that provide coverage plans for health emergencies that may happen during international travel. The selected companies have a wide range of coverage, which includes different countries and proximity territories, and satisfaction scores greater than 80%. Data preprocessing is a key step to attenuate errors that are generally related to the quality of the collected datasets. Retribution is also important since it can directly influence the performance of the developed models. Thus, a careful analysis of coverage plans, data collection specifications, and data preprocessing can help to ensure the quality of the derived neural network models.

Each coverage plan has its contract specifications and rules. In general, insurance companies prefer to show these details in tables that need to be read meticulously to perceive the differences between the distinct plans. For preprocessing the data collected after examining the travel insurance companies, distinct codifications for the most used personal information, coverage data, and sum coverage of each plan were employed. The variety of coverages for each plan was important because policies may not differ much in their basic coverage, but they can differ in specific coverages that meet the needs of distinct travelers. Therefore, when there is similarity in the vast majority of coverage plans, but a particular plan varies significantly, it is interesting to measure which plans are closer to this idiosyncrasy.

### 3.2. Neural Network Architecture

We now describe the architecture of the neural network used on our data. Our dataset symmetrically consists of a vector of 47 characteristic variables for each of 200,000 people (observations), and a vector of 12 covariates, with each of them discretizing one of the 12 healthcare needs our insurance product addresses. We have implemented the standard least trace regression model, using both its built-in ‘associative’ neural network models and a standard model. Due to the time needed by the standard neural network command to train on such a vast amount of data (too high: 100 hours, with no guarantee of finding the best solution), we have so far not been able to identify the relative performance of the three models as proposed. In the training phase, the neural network model has selected those neural architecture structures that best predict the healthcare needs variable, among the thousands of neural network configuration options (i.e., palettes of layer combinations).
The iteration process of the backpropagation algorithm is based on the Levenberg-Marquardt, BFGS, conjugate gradient, and the Nelder-Mead optimization functions. The variable in the command has been set respectively to 200 and 500, to allow the software to stop functioning prematurely upon reaching the best neural architecture. The software package paves the way for further advancements of our predictive method, on account of the general “fit-on drawback” of popular software teaching algorithms. Indeed, partial fitting of the neural network model is one advanced feature that this proprietary package offers with no option in the stock package, to produce early results, eventually assessing whether the neural network model has learned some information in the dataset. The software package retrieves results from several subgroupings of the 200,000 observations, in only a limited time frame to preserve RAM stability.

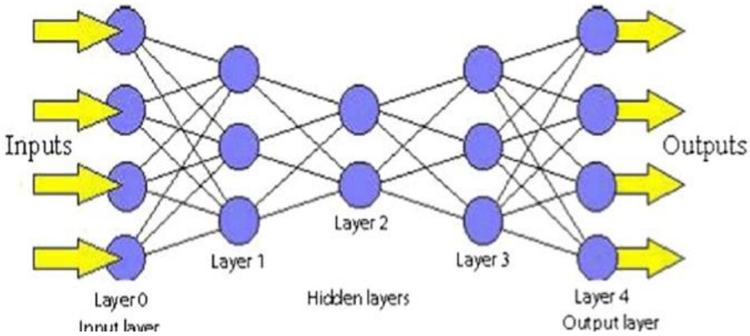


**Fig 3 : Basic Neural Network Architecture for analyzing medical data**

### 3.3. Training and Evaluation

Training neural networks on cost data often leads to performance bottlenecks due to a combination of high dimensionality and, in some cases, data scarcity. In this section, we explore neural network models of varying complexity for our most important task: predicting the cost ceiling value used by travel insurance. We then evaluate the predicted costs of the expected healthcare claim amount of travel insurance plans. We compare the trade-off of high-dimensionality models against a performance-driven strategy using human feature selection. We evaluate using a conservative cost-optimal healthcare coverage floor as a new means of predicting the impact of a cost ceiling in a travel insurance provider's context, finding particular points of concern by sourcing data from a travel insurance company's experience with international claims and verifying intuitions of impact matched with market evidence.
We used Keras to create neural networks with varying sizes and complexity to model the cost ceiling. We denote neural network dimensionality through the total number of hidden layer neurons in all fully connected layers of the network. We used a shallow two-layer model of a reasonable size to use as an intuitive reference. We build on that with a four-layer deep model and then evaluate a high-dimensional model where there are four layers, and in each layer, ad neurons are used if ad is the number of dimensions in our feature space, and H is a tunable hyperparameter. Weights and biases are trained using Adam, configuring it with standard recommended settings. The models take uniformly sampled data after combining design budget and world data sets, with 20% split into training and validation for early stopping by validation loss, and the remaining 80% as a 5-week testing period preceding the international trip.

**4. Results**

4.1. LDA-based Topic Modeling Results We categorized the eight new topics found into five more general classes: insurance policy, insurance process, customer, healthcare expense, and feature improvement. The four largest topics seemed to be the frequently discussed problems addressed by the users on the platform. 4.2. Regression Results Comparing the results with traditional travel policy modeling, we realized that adding depressed words into the analysis can bring more topics into discussion. The all-zero ratio was only 0.16, and the median weight was 2.11. To further diagnose which symptom affects this result, we counted the simply aggregated symptoms manually for both depression and non-depression. Due to the non-depressed insurance policy and depressed insurance policy sharing many symptoms, simply aggregated symptoms do not seem to work properly. By looking at the log-likelihood ratios within different groups of policy users, we found that non-depressed users tend to use the term 'benefit' more, while depressed users tend to use 'select' more.

**4.1. Performance Comparison with Traditional Methods**

Model performance was evaluated in both the HHPP dataset and HHPF dataset using the area under the receiver operating characteristic curve (AUC) metric, which measures the trade-off between specificity and sensitivity over the full range of operating conditions. We also calculated the net benefit to illustrate the level of benefit derived from our model at various threshold probabilities. In terms of evaluation against traditional methods, we confirmed that the balancing weight neural network would outperform the following models: (i) decision tree analysis using the patient-described health problem in the form of Adult Comorbidity Evaluation-27, which is used for predicting the outcome of prolonged hospital stay among in-hospital patients; (ii) linear regression analysis using log-transformed positive odds ratio for the agents recommended for common diseases affecting returned travelers; and (iii) multivariable logistic regression analysis using gender and the health problem, which were synonymous with self-assessment. The net benefit at various threshold probabilities demonstrated the balanced weight neural network’s dominating performance against all these traditional methods over almost the entire range of threshold probabilities. The only exception was that the benefit from a 100% threshold probability when aiming for more sensitivity was larger with the multivariable logistic regression. This means that the traditional methods—especially the goal-seeking multivariable logistic regression, which may have failed to consider all the weight variation equally well—could not capture as much of the potential for predicting healthcare needs in travelers with various health conditions. The p-value for HHPF between the balanced weight neural network and multivariable logistic regression was 0.105, which generally supported the evidence of a trend that the performance of balancing weight was superior.

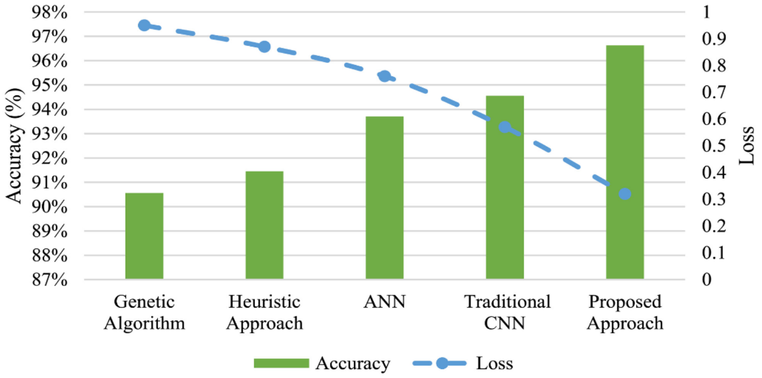


**Fig 4 : using graph neural network for Internet of Medical Things and computer vision applications**

**4.2. Case Studies**

Case study review: reviewing the implementation and acceptance of AI research in this field, and possible utilization and replication. The following summary discusses previous works using AI models for predicting medical claims so that the model’s potential can be validated. A commercial population of 3.7 million lives, including 1.2 million active workers across large employers and tiered commercial plans, has been modeled to score individual acute hospital admission probability at different prediction horizons (15 to 30, 31 to 60, 61 to 90, 91 to 180, and 181 to 365 days). Different types of models, including traditional logistic regression, generalized linear model, boosting tree, random forest, and neural network models, have been trained and evaluated on different prediction windows.

An ensemble approach has been evaluated by incorporating the probability predictions obtained from the best-performing model and the logistic regression model. Study findings support multilayer perceptron networks to predict hospital admission across different prediction horizons. Deep learning models are found adequate for predicting medical costs, mortality, and readmission separately using data from a project wherein urban populations were studied. The diseases’ ensemble consisted of four popular deep learning models: the Multilayer Perceptron Neural Network, Conditional Survival Neonatal Network, Factorization Machines, and Recurrent Neural Network - Gated Recurrent Unit.

**Equation 2 : Severity of Healthcare Event Prediction:**
Once a healthcare event is predicted, the model can be extended to estimate the severity of the event (e.g., whether it's a minor illness or a major medical emergency) using a regression-based approach.

$$S(\text{Healthcare Event}) = \mathbf{W}_2 \cdot \mathbf{X} + b_2$$

Where:

$S$(Healthcare Event) is the severity score of the healthcare event (a continuous variable indicating the intensity of the medical issue).

$W2$ is the weight vector for the severity model, and $X$ again represents the input features (e.g., age, pre-existing health conditions, destination health risks, etc.).

$b2$ is the bias term for the severity model.

**5. Discussion**

5.1. What We Did We applied neural networks, the backpropagation learning algorithm, regularization of network weights using L2 regularization and early stopping, and dropout regularization in fully connected feed-forward neural networks used to model complex, non-linear functions to predict healthcare costs for travelers. A large number of demographic, policy buy options, and travel-related predictors were explored, including single, interaction, and polynomial degree two (quadratic) and three (cubic) terms. Predictors were dummy-coded and standardized to mean 0 and variance 1. Projected healthcare costs are then used in defining and updating International Travel Coverage plans up to the time of the insured's departure. We tested different neural network structures, including the width of hidden layers and deep neural networks. We searched for a network that best mimics the relationship between predictors and claim costs.
5.2. What We Found Best networks generated a prediction mean average error (MAE) in the range of \$30–\$35. Predictions based on travel-related variables outperform the purchase of travel insurance, which should be determined before the traveler's final decision on travel destination, local coverage, type of travel (leisure or work), or age. Selected predictive interactions help create dynamic International Travel Coverage at different travel costs for scatter plots of predicted cost by groups of variables. Variable dependence is measured and visualized by additive explanations. Dropout was a critical approach in improving the networks' robustness. In particular, scatter plots of predicted healthcare costs generated by an average of 10 different feed-forward neural networks provide estimates of robustness adjusted for group demographic, policy buy, country, and period of application, with liability limits ranging from one to one million dollars.

**5.1. Implications for the Travel Insurance Industry**
There are important implications of the proposed neural network-based models in predicting healthcare needs for travelers in international travel coverage plans for the insurance industry. First, profitability is one of the foremost goals for insurers. Accurate predictions of healthcare needs using the proposed models are of substantial economic interest to the travel insurance industry. Instead of using general risk categories, insurance premiums, and prices can be tailored to reflect the actual amount of healthcare needs. Risk classification is important in the setting of insurance premiums and prices, and insurers have implemented risk classification systems based on standard deviations of aggregate claims. Traditional actuarial risk classification uses similar pricing. In travel healthcare need prediction models, demand for travel insurance can be forecast as a derived demand for healthcare needs in travel destinations.

Second, one of the main characteristics of the travel insurance industry is its need to generate risk communication with not only potential travelers but also travel agencies. By doing so, customers can better take care of themselves and reduce risks. More customized travel health information and current risk assessments are of substantial economic interest for travel agencies to make their business smooth environments for travelers. Insurers, as important players in the service provider industry of international travel health risk management, can properly alert travelers and set up a benchmark for travel risk communication supporting policy recommendations of epidemic management agencies. More effective communication of individual healthcare needs in travel destinations will provide new opportunities for service innovation for established vertical service providers and new entrants to this industry. Such newly established ecosystems and created values are economically substantial for the travel insurance industry.

Journal for Re Attach Therapy and Developmental Diversities
eISSN: 2589-7799
2023 November; 6 (10s) : 2222-2232

**5.2. Limitations and Future Research Directions**

**5.2. Future Research Directions and Conclusion**

The results suggest that using a neural network-based approach results in better models. The models will help actuaries better estimate insurance coverage guarantees and will enable insurers to develop a risk assessment and underwriting model that is less dependent on qualitative information. Developing this type of model is important, given the high number of travel insurance claims and the high costs associated with them, which can change as a result of demand for insurance and changes in travel. Natural disaster models can be used not only to advise the insured but also to inform potential travelers about travel decisions they will face, thus reducing the overall burden of natural disasters and the cost of emergency assistance. As the models underline that older age, male sex, and a greater number of short-term, single-journey travel insurance products sold by travel agencies increase the level of healthcare services required abroad (and, consequently, health insurance claims), health insurance companies should be able to focus more on older members who buy insurance products and provide travel advice and health services closer to departure and during the trip to develop new insurance services with travel agencies. They may also conduct a cost analysis of the medical services provided in tourist country hospitals that travelers can use and maintain. The cost comparison of these services can be retrieved by the insured through an integrated mobile app, which includes the nearest healthcare agreements negotiated between the insurance company and the service providers in the tourist country.

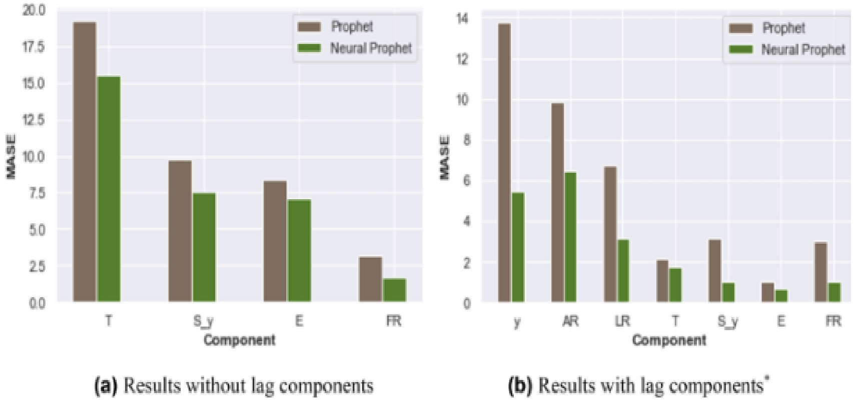


**Fig 5 : Predictive healthcare modeling for early pandemic assessment leveraging deep autoregressive neural prophet**

## 6. Conclusion

In this paper, we have examined the problems that insurance providers face with providing health coverage for their clients all over the world. We present a novel series of approaches that use deep learning and other predictive modeling techniques to improve the speed at which insurers can assess potential travelers for pre-existing medical conditions that might increase their claims risk. We engaged in human-centered research methods, interviewing healthcare and travel insurance professionals to build out a comprehensive, real-world applicable predictive model for use in assessing new applicants. Through the application of big data practices, we demonstrate the ability of our model to capture and reveal useful patterns that a knowledgeable human can recognize as consistent with reality, if not already visualized by a current risk assessment process. We also note that future research could focus on improving the data collection process. Additionally, one direction for further work focusing on this problem area could be examining the merging of disparate data formats, such as electronic healthcare records with travel histories. Furthermore, focusing on more domain-specific preprocessing could lead to speaking specifically to a limited domain, and must be cautioned that the model contains reliance on this step, assuming that the reclassification to generalize medical or healthcare terms is easy for the preprocessing technician. While we acknowledge the possibility of more domain-specific preprocessing leading to a deeper understanding of the problem hidden within the data, we still stand firmly behind our approach of training larger, more complex models with unrefined data. This approach presents a quick and effective way to gain understanding and can complement more targeted investigations. In precision medicine, more specialized approaches are necessary to reveal the most insightful details. But we submit that a first pass with more general models can play a vital role in setting up success for those carefully targeted models.

### 6.1. Summary of Findings

A fundamental problem facing trip planners is the difficulty of forecasting whether a traveler is likely to experience adverse health conditions requiring medical consultations while visiting international destinations. It is necessary to optimize the targeting of care and increase travelers' awareness of the type of services they may expect to find and how the foreign healthcare system works. This study used a dataset including travelers' personal and trip details and their health complaints after returning, to model factors related to generating potential medical consultations before international travel. Travel insurance data are collected to estimate the risk of incidents occurring among travel activities and then used to determine the price and contract for the policy. We used binary classifiers to classify whether the policyholder made a medical consultation during the trip and the number of medical consultations during the trip. Random forests and neural networks demonstrated strong performances concerning both tasks. Suggestions for implementing the models in an operational environment are presented.

The ultimate objective of this study is to identify predictive patterns that are indicative of healthcare consult needs during international travels using travel, demographic, and situational factors of hundreds of thousands of travelers. By doing so, insurers can better tailor the trip-specific health benefit products, provide travelers with additional healthcare assistance and support, and better target their marketing efforts. The study uses predictive analytics to solve a complex real-world business problem in the insurance industry. Throughout the report, we discussed two tasks for crafting a possible care alarm system. The first task has been named "Medical Consultation Risk" and provides information to the insurance company on which policyholders are more susceptible to needing a medical consultation and consuming the assistance benefit from the plan should they have an adverse health event. The primary intent is to help insurance companies better understand the medical risks of the travelers they serve. The second task identifies which policyholders needed to access foreign health facilities and during how many days of their trips. By identifying who will use it, the second task can help arrange for healthcare networks and medical evacuation services as well as designate the countries, problems, and populations in which the models can be more viable, important, and economical.

We have found that bagging and boosting techniques were not able to increase the predictive performances when compared to the baseline models. Nonetheless, the more sophisticated random forests and neural networks demonstrated strong performances in problems. This can be due to the representation of the information in the problem, as in bagging or boosting, we are trying to build models exploiting variations and similarities, thus diversity between the trees in the ensemble with a total focus on the improvements complementary to all the models. We are analyzing which profiles have multiple predictions in all the baseline models as a compulsive and empirical view and if this pre-class of policyholders has a clear characteristic or tendency. According to Principal Component Analysis, we verified if the problem is, in fact, difficult. We also tested to obtain a probability threshold necessary to perform the classification in the models for the field of risk management during the incremental launch of these predictive models. Finally, we questioned policyholders about their health complaints observed during the trip before the visit to the healthcare provider and if the policyholders would seek assistance from their assistance insurance plan, if any. The results suggest policies for the expansion of the coverage list and suggestions to minimize future problems.

### 6.2. Practical Applications and Recommendations

Practical Applications Understanding the factors that contribute to the traveling public's urgent medical needs has important applications. These range from important data applications in the hands of health planners to advice by potential travelers, physicians, and travel insurance plan adjusters who establish rules for individuals to obtain an international travel insurance policy. With advancements in technology and the increasing use of neural networking as a method in health research, we investigated and demonstrated the effectiveness of neural network-based models of the most common medical conditions in travelers. We explained and demonstrated the practical application of these models to inform travel healthcare clinicians, insurance plan caregivers, and administrators about international travel. Recommendation for Future Studies Investigations that conducted this study had limitations based on retrospective database structure, such as variance of pre-hospital needs by flight company and season, and the impact of day and time of the week. There are numerous unconsidered questions in our study concerning travel-related risk factors, such as the duration of the trip, the number of persons accompanying the traveler during the trip, the destination of the trip concerning the public health infrastructure, the conditions for travelers, the presence of recent travel history, and the use of seasonal and necessary vaccines. The high-risk population groups have been defined in different studies as senior travelers, as well as adventurous and long-term travelers. Our databases did not provide information about the travelers' demographic and travel history characteristics, limiting our evaluation of the healthcare needs defined by age, gender, and trip type. We need to gather more detailed databases parallel with travel history for the definition of healthcare needs and compare different databases to identify standardized and routine definitions for regular use. The most reliable data sources in database studies are centered on a near-real-time online registry, and supplementary comparisons between different data sources should be conducted on the quality of emergency medical services. The reduction of errors in underestimating the true scenario and the quantification of bias may thus vary. The limitations of our study, along with many more questions that have not been answered, are part of non-identified, unmeasured, or non-managed variants of the parameters considered as a result of omitted variables. But the utilization of international travel insurance not only for passengers, airport communities, flight crew, and other travelers, but also for paying road costs and traffic violations, naturally and training nicotine habituation or weight-loss courses, or reimbursing health care needs, constitutes logical topics for future study. Agencies that currently mainly provide flight insurance with travel access will have their liability competition and insurance prices evaluated on a free market basis and internationally. When agencies can indirectly gather health data of potential travelers in the same market, their health policies can thus be changed.

**7. References**

[1] Avacharmal, R., Gudala, L., & Venkataramanan, S. (2023). Navigating The Labyrinth: A Comprehensive Review Of Emerging Artificial Intelligence Technologies, Ethical Considerations, And Global Governance Models In The Pursuit Of Trustworthy AI. Australian Journal of Machine Learning Research & Applications, 3(2), 331-347.
[2] Chintale, P., Korada, L., WA, L., Mahida, A., Ranjan, P., & Desaboyina, G. RISK MANAGEMENT STRATEGIES FOR CLOUD-NATIVE FINTECH APPLICATIONS DURING THE PANDEMIC.
[3] Mahida, A. Explainable Generative Models in FinCrime. J Artif Intell Mach Learn & Data Sci 2023, 1(2), 205-208.
[4] Mandala, V. (2022). Revolutionizing Asynchronous Shipments: Integrating AI Predictive Analytics in Automotive Supply Chains. Journal ID, 9339, 1263.
[5] Perumal, A. P., & Chintale, P. Improving operational efficiency and productivity through the fusion of DevOps and SRE practices in multi-cloud operations.
[6] Kommisetty, P. D. N. K. (2022). Leading the Future: Big Data Solutions, Cloud Migration, and AI-Driven Decision-Making in Modern Enterprises. Educational Administration: Theory and Practice, 28(03), 352-364.
[7] Bansal, A. Advanced Approaches to Estimating and Utilizing Customer Lifetime Value in Business Strategy.
[8] Korada, L., & Somepalli, S. (2023). Security is the Best Enabler and Blocker of AI Adoption. In International Journal of Science and Research (IJSR) (Vol. 12, Issue 2, pp. 1759–1765). International Journal of Science and Research. https://doi.org/10.21275/sr24919131620
[9] Avacharmal, R. (2022). ADVANCES IN UNSUPERVISED LEARNING TECHNIQUES FOR ANOMALY DETECTION AND FRAUD IDENTIFICATION IN FINANCIAL TRANSACTIONS. NeuroQuantology, 20(5), 5570.
[10] Vaka, D. K. " Integrated Excellence: PM-EWM Integration Solution for S/4HANA 2020/2021.
[11] Mahida, A. (2023). Machine Learning for Predictive Observability-A Study Paper. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-252. DOI: doi. org/10.47363/JAICC/2023 (2), 235, 2-3.
[12] Mandala, V., & Surabhi, S. N. R. D. (2021). Leveraging AI and ML for Enhanced Efficiency and Innovation in Manufacturing: A Comparative Analysis.
[13] Chintale, P. (2020). Designing a secure self-onboarding system for internet customers using Google cloud SaaS framework. IJAR, 6(5), 482-487.
[14] Bansal, A. (2022). REVOLUTIONIZING REVENUE: THE POWER OF AUTOMATED PROMO ENGINES. INTERNATIONAL JOURNAL OF ELECTRONICS AND COMMUNICATION ENGINEERING AND TECHNOLOGY (IJECET), 13(3), 30-37.
[15] Korada, L. (2023). AIOps and MLOps: Redefining Software Engineering Lifecycles and Professional Skills for the Modern Era. In Journal of Engineering and Applied Sciences Technology (pp. 1–7). Scientific Research and Community Ltd. https://doi.org/10.47363/jeast/2023(5)271
[16] Avacharmal, R. (2021). Leveraging Supervised Machine Learning Algorithms for Enhanced Anomaly Detection in Anti-Money Laundering (AML) Transaction Monitoring Systems: A Comparative Analysis of Performance and Explainability. African Journal of Artificial Intelligence and Sustainable Development, 1(2), 68-85.
[17] Dilip Kumar Vaka. (2019). Cloud-Driven Excellence: A Comprehensive Evaluation of SAP S/4HANA ERP. Journal of Scientific and Engineering Research. https://doi.org/10.5281/ZENODO.11219959
[18] Mahida, A. Predictive Incident Management Using Machine Learning.
[19] Perumal, A. P., Deshmukh, H., Chintale, P., Desaboyina, G., & Najana, M. Implementing zero trust architecture in financial services cloud environments in Microsoft azure security framework.
[20] Bansal, A. (2021). INTRODUCTION AND APPLICATION OF CHANGE POINT ANALYSIS IN ANALYTICS SPACE. INTERNATIONAL JOURNAL OF DATA SCIENCE RESEARCH AND DEVELOPMENT (IJDSRD), 1(2), 9-16.
[21] Laxminarayana Korada, & Vijay Kartik Sikha. (2022). Enterprises Are Challenged by Industry-Specific Cloud Adaptation - Microsoft Industry Cloud Custom-Fits, Outpaces Competition and Eases Integration. Journal of Scientific and Engineering Research. https://doi.org/10.5281/ZENODO.13348175
[22] Avacharmal, R., Sadhu, A. K. R., & Bojja, S. G. R. (2023). Forging Interdisciplinary Pathways: A Comprehensive Exploration of Cross-Disciplinary Approaches to Bolstering Artificial Intelligence Robustness and Reliability. Journal of AI-Assisted Scientific Discovery, 3(2), 364-370.
[23] Chintale, P., Korada, L., Ranjan, P., & Malviya, R. K. ADOPTING INFRASTRUCTURE AS CODE (IAC) FOR EFFICIENT FINANCIAL CLOUD MANAGEMENT.
[24] Mahida, A. A Review on Continuous Integration and Continuous Deployment (CI/CD) for Machine Learning.

[25] Perumal, A. P., Deshmukh, H., Chintale, P., Molleti, R., Najana, M., & Desaboyina, G. Leveraging machine learning in the analytics of cyber security threat intelligence in Microsoft azure.
[26] Bansal, A. (2023). Power BI Semantic Models to enhance Data Analytics and Decision-Making. International Journal of Management (IJM), 14(5), 136-142.
[27] Korada, L., & Sompepalli, S. (2023). Leverage Teams Phone to Migrate Your Contact Center. In Journal of Artificial Intelligence, Machine Learning and Data Science (Vol. 1, Issue 1, pp. 897–901). United Research Forum. https://doi.org/10.51219/jaimld/laxminarayana-korada/216
[28] Avacharmal, R., Pamulaparthyvenkata, S., & Gudala, L. (2023). Unveiling the Pandora's Box: A Multifaceted Exploration of Ethical Considerations in Generative AI for Financial Services and Healthcare. Hong Kong Journal of AI and Medicine, 3(1), 84-99.
[29] Vaka, D. K. (2020). Navigating Uncertainty: The Power of 'Just in Time SAP for Supply Chain Dynamics. Journal of Technological Innovations, 1(2).
[30] Mahida, A. (2023). Enhancing Observability in Distributed Systems-A Comprehensive Review. Journal of Mathematical & Computer Applications. SRC/JMCA-166. DOI: doi. org/10.47363/JMCA/2023 (2), 135, 2-4.
[31] Chintale, P. SCALABLE AND COST-EFFECTIVE SELF-ONBOARDING SOLUTIONS FOR HOME INTERNET USERS UTILIZING GOOGLE CLOUD'S SAAS FRAMEWORK.
[32] Bansal, A. (2022). Establishing a Framework for a Successful Center of Excellence in Advanced Analytics. ESP Journal of Engineering & Technology Advancements (ESP-JETA), 2(3), 76-84.
[33] Korada, L. (2023). Leverage Azure Purview and Accelerate Co-Pilot Adoption. In International Journal of Science and Research (IJSR) (Vol. 12, Issue 4, pp. 1852–1954). International Journal of Science and Research. https://doi.org/10.21275/sr23416091442
[34] Vaka, D. K. "Artificial intelligence enabled Demand Sensing: Enhancing Supply Chain Responsiveness.