Natural Language Interactions Aided with Data Visualization for Exploring Insurance Claims and Risk Management

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Abstract Analysis of claims and risk management is the key task to avoid frauds and to provide risk management in the life insurance industry. Though visualization plays a fundamental role in supporting analysis tasks of the business domain, exploring user behaviour remains a challenging task. The prevalence of natural language interactions aided with data visualization has become quite the norm. With the increasing demand of visualization tools and varying level of user expertise, it comes as no surprise the use of natural languages interface. However, the design of visual analytics tools aided with natural language interfaces (NLIs) for risk management and claim analysis requires thorough task analysis and domain expertise. In this work, we investigate an alternative approach through a natural language interaction based interactive visualization such as chart, pie, and histogram, which can be applied for analyzing insurance claims and risk management. We design a new visual analytics solution (VAS) named (***InsCRMVis***[1]) aided with NLIs. We present an expert evaluation

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[1] The source code and demo video of the proposed framework are publicly available at https://github.com/rafiqulcse/InsCRMVis.git.

of *InsCRMVis* based on Task Load Index (TLI) questionnaire which is currently the standard measure metrics to investigate the usability (effectiveness, efficiency, satisfaction) for supporting human task performance. To evaluate the performance, we performed a user study of 10 experts which suggest that *InsCRMVis* can provide better insights and assist to IMs in reducing loss and guide to change insurance premium policy. Furthermore, we provide a concise set of guidelines that can be used when visualizing risk to avoid the dangers in the insurance domain. We discuss the challenges associated with the use of a visualization system in the insurance industry, focusing on aspects related to visualization research.

Keywords User interface design · Natural language interfaces · Risk management.

1 Introduction

The financial industry is becoming more complex due to the lack of effective communication between risk experts and decision makers [21]. For example, a recent study of the life insurance industry in Australia examined that managing risk is about more than protecting value [23, 24]. According to the Australian Prudential Regulation Authority (APRA), for the financial years ended in the 12 months to December 2019, net claims expense increased by 12.6%, i.e., from $22.1 billion to $24.9 billion. It is observed that re-insurers have a higher capital coverage ratio than direct insurers [2]. Hence, insurance managers (IMs) need to take proper actions to avoid frauds and to reduce losses [16]. This strong oversight can only be achieved through an effective risks management system (RMS) [28]. Although many forms of business diagrams such as tables, chart and formulas are the common solutions for claim and risks management in the insurance industry, it may be challenging for IMs to find and get the most relevant risks to initiate adequate countermeasures. Therefore, data visualization is an attractive solution to hold effective risk-relevant information between risk experts and decision makers [52, 24, 9].

Visual analytics solutions (VAS) are widely used for different purposes in a large number of applications such as finance, biomedical, education, forecasting research in academia etc. [4, 32, 37, 48, 26]. It enables researchers to gain better insights and to inform decision-maker through the analysis of large scale dataset [11, 51, 25]. Moreover, it expedites knowledge and provides evidence for improved outcomes [29]. For examples, several VAS have proposed focusing on fraud detection and customer monitoring in the last few decades [35, 31, 21]. This visualization allows the stakeholders to meet their demand for identifying suspicious cases where traditional methods fail. However, most of the existing VAS are not effective in the insurance industry because 1) 'claim risk is very difficult to describe and extremely hard to visualize'; 2) decision makers are not well expert the procedure of VAS with outcomes such as diagrams, risk maps, and the impact/likelihood positions of specific business risks. Moreover, existing research on the impact of customer behaviors on visualization processing has

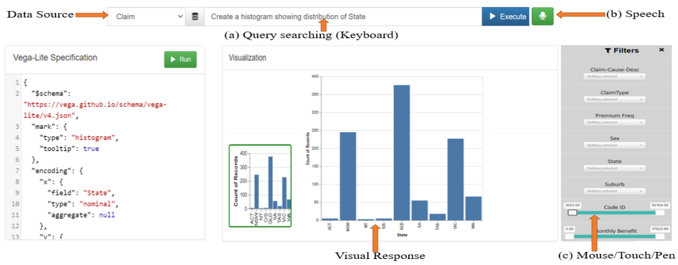

Figure 1: Summary of *InsCRMVis* interface components (Insurance claim and risk management with visual analytics). (a) Query searching, (b) Speech : allow users to freely express query to get visual insights, and (c) Mouse/Touch/Pen: can be supported with visualization.

concentrated on primary insights that are employed in a non-interactive system (e.g., pie and bar charts), while the visualization outcomes on an interactive visualizations system are still limited. Thus, 1) to our best knowledge, there is no research on interactive visualizations system to examine the visualization of risk systemically; 2) interaction approaches only aid the theoretical processes for exploring risk visualization; and 3) previous works only examine either low-level tasks (e.g., value retrieval) or high-level tasks (in specific analysis). Furthermore, there is no research to consider both high-level and low-level task together for decision making. Thus, with the natural language interaction (NLIs), the need for visualizing and monitoring the policyholders claim risk is more urgent than ever before.

The recent development of natural language interfaces (NLIs) with data visualization have drawn immense awareness from the research community, business decision-makers, industries to improve the gain in net profit and have shown considerably better performance via predictive and analytic capabilities [43]. There is one of the most significant reason why NLIs are gaining popularity is because they have the ability to handle large data sets even in situations with limited human and financial resources [15, 44]. Existing NLIs have been used for effective exploration and communication of ideas with various business domains [4, 18]. It has been observed that NLIs can assist users in searching various queries to get insights for exploring a large database. However, by using existing NLIs, when people want to ask the questions of their data, they can have difficulties in generating the desired visual response. Moreover, existing NLIs are often intended for domain experts, have complex interfaces, and still remains ambiguity challenges. Therefore, an appropriate NLIs with data visualization is required (e.g., language-based, speech based, touch based, speech+touch, language+speech+touch) to understand and to explain large-scale dataset, particularly in light of insurance claim and risks management decision support.

The main contributions of this paper is to design a new visual analytic solution (VAS) named *InsCRMVis* through NLIs to visualize policyholders claim and risks in the life insurance industry. Figure 1 illustrates how our system allow the IMs to express their questions and intents more freely to get insights for exploring of 26,817 policyholder's large database of insurance claims and risk management [30]. Additionally, as a solution to this, speech interaction for the conversation and also touch interaction can be supported by a visualization, which allow the IMs to follow up on the current status of policyholders for handling a risky situation [49, 6, 42, 33]. Then, we gathered 169 questions from the teams of IMs and found that our VAS correctly answers 69% of all the questions. For evaluation, we performed a user study of 10 users with three datasets such as questionnaire, demographic, and claim using our VAS. The experts evaluation suggest that *InsCRMVis* can identify the claim risks perfectly and assist the IMs in reducing loss and guide to change insurance premium policy for further development planning, and management. Thus, the **key contributions** of this paper are as follows:

- We introduce a new design space and present an end-to-end framework that allow experts exploring a large database of the policyholders claim behavior for reducing the risk.
- We present results of 26,817 policyholders claim behaviors to expose effects of different visualizations on understanding, distraction, driving performance, expert experience, and risk management.
- We gathered 169 questions in our study from the insurance stakeholders. We find that our system correctly answers 69% of all the questions in our system.
- To evaluate the performance, we performed a user study of 10 experts. The experts evaluations suggest that *InsCRMVis* can provide better insights and assist to IMs in reducing loss and guide to change insurance premium policy.

The paper is organized as follows: Section 2 discusses related work on the NLIs with data visualization for insurance claim and risk management. In Section 3, we describe in details of methodology where data description, data pre-processing, domain characterization and task analysis, and visual analytics solution are described respectively. We illustrate the details of *InsCRMVis* system in Section 4. In Section 5, we present a comprehensive result analysis. We also illustrate user study of the proposed VAS to assess its capacity to inform the relevant variables for exploring insurance claims and risk management in Section 6. Finally, conclusions and future directions are provided in Section 7.

2 Related Work

Natural language interaction for data visualization have been widely explored both within commercial software development and research community. We limit our discussion on existing study related to the topic presented in this paper is divided into three folds: 1) insurance claims and risk management; 2) visualization for claims and risk analysis; and 3) natural language interfaces

(NLIs) with data visualization. In the following section, we review the state-of-the-art in these folds to motivate the need for our proposed VAS.

2.1 Insurance Claims and Risk Management

The exploration of insurance claim and risk management has gained a great attention because a large number of policyholders have brought great loss to insurance companies and society as a whole [23]. Insurance risk management is a branch of financial risk management and it mainly includes life insurance and healthcare insurance [16, 28]. From the existing study, it has been observed that life insurance claim and risk management has attracted more attention than other financial risk management. According to KPMG's life insurance insights 2020, Australian life insurance companies premium revenue decreased by 6.1% to $17.3 billion, compared to approximately $18.4 billion per annum for the 2017 to 2019 period [3]. Moreover, according to Arych, Mykhailo, and Walter Darcy [8], approximately 21%–36% of life insurance claims involve factors of suspected fraud, but only 3% of them are prosecuted. Although researchers have invested great effort to conquer the problem of insurance claims and risk management using various effective risk management methods, these methods are often inadequate to handle the claim and risk management problems [35, 16, 31, 23]. Moreover, existing studies have revealed that there is a need for better quality, more consistent and more transparent data about insurance claims. Also, they lead to poor outcomes to extract new insights in order to make a correct decision. Therefore, there is an increasing demand to improve risk management through design and implementation of a cost-effective, practical, and real business-wide visual analytic solution.

2.2 Visualization for Claims and Risk Management

Claim and risk visualization show the systematic and interactive ways such as charts, maps, and conceptual diagrams to enhance the quality of entire risk communication along the claim and risk management cycle. It helps experts and decision makers to improve their understanding and to better deal with ricks in the insurance industry. Visualization and visual analytics have been introduced both in academia and industry: 1) to provide a clear view of customers adverse behavior, transactions monitoring, premium fluctuations, and in complex everyday decision-making [19, 11, 39]; 2) to characterize data, user and task [27, 10, 45]; and 3) discovering imbalances and monitoring risk [14]. Whereas some contributions are domain-specific, e.g., visual animation is adopted to investigate the vast amounts of time-series dataset [53, 7, 46]. To monitor a specific stock market user behavior who has provided adverse trading patterns and to identify the real-time stock marker performances, the 3D treemap is implemented [21, 17]. To detect user adverse behavior, the coordinated specific keywords visualization is developed within the wire transactions [41]. Additionally, various interactive visualization systems are developd to support the stakeholders immediately to make a decision for different business scenarios [55, 13]. The clustering-based visualization system is used in financial risk monitoring, discovering imbalances in financial networks, and for predicting head and neck cancer patients [12, 5, 50]. However, there are very few works on claim and risk management in the insurance domain. Moreover, the existing systems have limitation to investigate a large number of variables and satisfy specific requirements, e.g., measuring new claims costs, number of accidental claims, and number of mental health claims of domain experts. Therefore, in this study, we get an opportunity to fill up the gaps of existing visualization system and to meet the demands of domain experts.

2.3 Natural Language Interfaces with Data Visualization

Natural language interfaces (NLIs) are emerging as a promising paradigm for data analysis with visualization [36]. It is gaining popularity because it helps to improve the usability of visualization systems. Typically, these interfaces respond to user queries by either creating a new visualization and/or by highlighting answers within an existing VAS. It has been explored both within the research community and as commercial software. Existing studies have provided various NLIs based VAS that use well-structured commands to specify visualization. For example, NLIs based VAS such as articulate [47], ConveRSE [22] that supports people to explore how NL affects in the incorporating of digital assistants and recommendation system. DataTone [18] uses to manage ambiguity to let people specify visual response through NL queries and to develop the useful NLIs for data visualization. FlowSense [54] allows user to write query and visualization components to specify system functionality. Eviza [40] incorporates a probabilistic grammar-based approach and a finite state machine to provide an NLIs for an interactive query dialog. Evizeon [20] allows people to support for compound queries, and lexical cohesion with visualizations. The ideas in Evizeon and Eviza were also utilized to describe the Ask Data feature for specifying NL queries in an organized shape in Tableau [1]. From the aforementioned systems it has been observed that NLIs provide an opportunity to ask any questions in generating the desired visualizations using natural language. However, in the insurance domain, there are no NLIs based VAS for the identification of insurance claims and risks management. Therefore, inspiring by the aforementioned visualization system, we leverage data visualization with natural language interactions for exploring insurance claims and risk management.

In summary, the existing research on data visualization for exploring the insurance claims and risk management is very limited. Although few studies have developed interactive visualization system, there is no study on data visualization with NLIs to meet the practical requirements of the risk domain experts in the insurance industry. Thus, to our best knowledge, this is the first

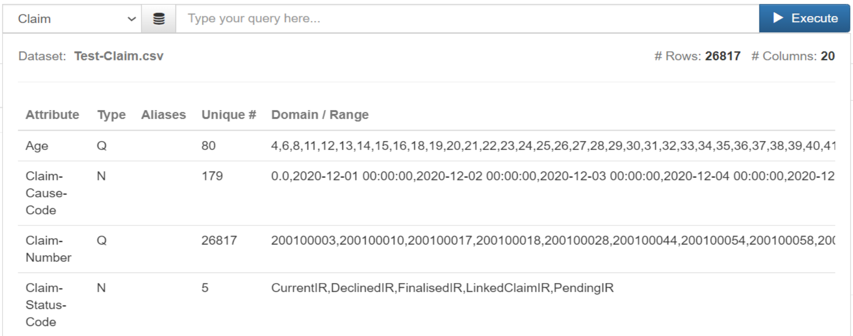

Figure 2: This diagram showing the policyholders claims data sources. County and state level detailed infrastructure.

work using NLIs with visual analytics approaches to address the insurance claims and risk management issues.

3 Methodology

3.1 Data Description

This work uses three types of data collected from an Australian insurance company, including 1) questionnaire data ; 2) demographic data; and 3) policyholders claims. All the attributes of questionnaire dataset are binary where demographic and claim dataset consists of binary, categorical, numerical etc. The attribute descriptions are given in Figure 2. The brief description of each dataset are presented respectively.

Questionnaire dataset: We have acquire the dataset from a screening questionnaire provided by the insurance company that have amassed over 10 years. The questionnaire was considerably large and detailed, containing of 64,000 policyholders and 834 questions ranging from personal, medical, family history, occupational details, lifestyle, etc. with responses labelled 0 for 'No' and 1 for 'Yes'. For example, whether *they drink or not*, *they have cancer or not*, *they smoke or not*, *they have any disease or not*, etc.

Demographic datasets: The dataset have five different attributes including Insurance ID, Gender, Age, Occupation, and Postcode. The 'Gender' attribute contains 'Male' and 'Female'. The 'Postcode' attribute contains the Australian postcode of the applicants residence. The 'Age' attribute contains the age of the applicant in whole years, where the youngest applicant is 3 years old and the oldest is 78 years old. The 'Occupation' attribute contains 18 different categories such as 'T-Trades', 'S-Supervisor of Trades', 'R-Special Risk', etc. As part of the demographic info analysis, we also use Socio Economic Indexes for Areas (SEIFA) data set.

Table 1: Key questions identified in collaboration with domain experts.

RQ1	Why an interactive visual analytic tool is necessary for insurance domain?
RQ2	What are the key factors/contents should be depicted when exploring insurance claims and visualizing risks/risk-related information?
RQ3	For whom our visualization system will monitor or to control risks?.
RQ4	When an interactive risk visualization system can provide benefits and should be considered as a useful tool by the stakeholders?
RQ5	How natural language interfaces (NLIs) can be supported through an interactive visualization system for investigating insurance claims and risk management?

Claim dataset: The customer claim dataset is privately provided by IMs for research purposes only. In total, there are more than $27,458$ claims recorded from 2010 until April 2019. In details, the dataset consisting of $27,458$ claims records of data with containing 37 attributes which occurred all throughout the country. It contains various attributes describing details about each claim where each attribute is associated with multiple answer.

3.2 Data Pre-processing

As mentioned in Subsection 3.1, various information are recorded in the dataset with consisting of various attributes. Since attributes have values on different categories, it may contains missing values. In order to simplify the system to ensure only the most significant data is used, data pre-processing consisted of reducing less important and redundant attributes which offer no benefit to exploration and analysis. As part of data preprocessing, redundant fields that were not eliminated, were combined. Finally, we get in total $26,817$ policyholders information with consisting of 21 attributes to work with for the insurance claims and risk management. Therefore, we applied these cleaned datasets to provide a broader and more comprehensive analysis for exploring claims and risk management in the insurance industry.

3.3 Domain Characterization and Task Analysis

In this work we collaborated with a team of IMs. We have selected the IMs participant based on inclusion criteria of more than ten years of experience. Our task is to understand the problem through a series of interviews and discussions. We gathered several questions that cannot be answered by existing VAS as listed in Table 1. These questions suggest that analysis should be able to inspect the policyholders behavior of both individual and/or groups, as well as able to identify most important variables for exploring insurance claims and risk managements.

We have noticed that our collaborators were concerned not only in observing a comprehensive analysis of policyholders' behavior but also demanded to find specific values and information along the study. It is essential to occupy the insurance claim data without losing detail, e.g., being able to display specific values. As the capability to present response defined the demands for designing a VAS, our design efforts focused on bringing complementary views of various relationships and supporting IMs to examine representative variable in relation to adverse behavior. It is viewed that our VAS has the capability to compare variables in terms of policyholders' behavior. We described our system's properties that can be useful to getting responds to such queries as shown in Section 3.4.

3.4 Visual Analytics Solution

In this section, we present the proposed natural language based framework for risk visualization. Figure 3 illustrate the components of proposed methodology for visual analytic solution (VAS). We aim to cover the scope of risk visualization, that is to say, highlight various purpose, what contents and for whom risk visualization can provide benefits. We consider VAS as a useful tool and provide a checklist of the key factors to consider when visualizing risks or risk-related information.

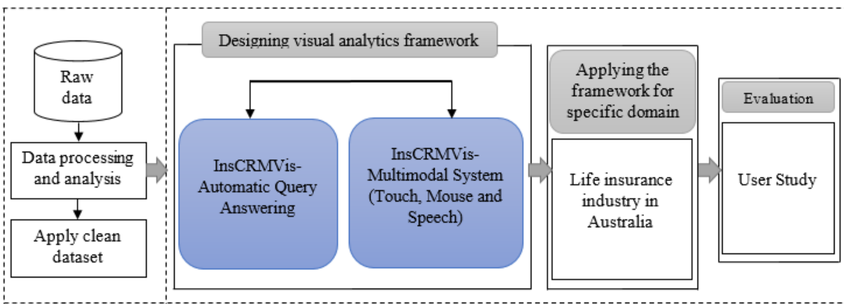

Figure 3: Proposed architecture of NLI based visualization

As illustrated earlier in Table 1, we provide some specific questions where the framework answer these questions of why, what, for whom , when and how the risk-related information should be visualized as shown in Figure 4. Therefore, it is important to start with these questions and then it provides useful possible answers for each one of these questions for the objective of a risk visualization. Through our interface, we can observe this represent a process view of risk depiction; a solution that emphasizes the act of visualizing, rather than just the resulting graphic artifact.

The visual analytic tool consists of four components: 1) data collection and processing; 2) designing visual analytics framework; 3) applying the framework for specific domain; and 4) evaluation. First, we collected dataset to go through for data processing, organizing, and cleaning as described in Section 3.2. This will allow the dataset to be used in the utmost effectiveness as organizing and

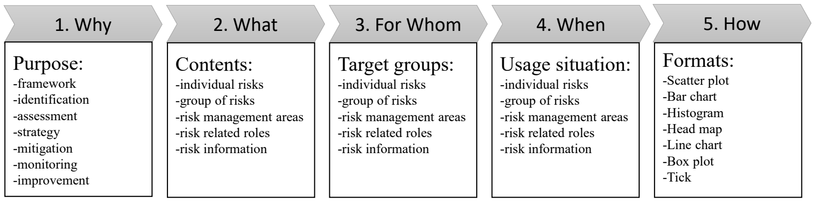

Figure 4: System overview: Key questions of the risk visualization framework.

cleansing make data more reliable and free of duplication. Like many other web application, our visual analytics framework named (*InsCRMVis*) consist of two components: 1) *InsCRMVis*- Automatic Query Answering, and 2) *InsCRMVis*-Multimodal System. The first component of *InsCRMVis* framework allow the user in searching various queries to get insights for exploring a large database, and the second component that allows interacting with various plots in a visualization system through touch, mouse and speech. The panel also have a filter options based on the claim score. Our current VAS framework is applied to the life insurance domain in Australia that allow the IMs to explore insurance claim and risk management. Finally, the domain specific application framework is dependent on expert evaluations to get feedback to assist in reducing profit loss, and guide to change insurance premium policy.

4 System Description

In this section, we present a new design space data visualization architecture namely '*InsCRMVis*' for exploring insurance claims and risk management as shown in Figure 5. The introduced framework combines multiple visualization component such as text, speech, touch etc. that conveys the claim behavior of each policyholders in a consistent representation of the data observations. Our approach is similar to the method proposed by [34]. It integrates multiple natural language processing and visualization techniques into a framework to support risk experts in the investigation of the claim behaviors of policyholders. It holds three main key components such as 1) data interpretation, 2) query analyzer, and 3) visualization generation. In the following, we briefly described how '*InsCRMVis*' use the above key components to design, and use to explore and minimize claim risk?

4.1 Data Interpretation

In this paper, we use insurance claim dataset to infer various types of attributes. For example, our dataset contains the attribute 'Monthly Benefit' with a range values. When we look a temporal information, our system may provide misleading information and lead to make poor decision choices. Thus, to overcome this issue, *InsCRMVis* iterates through the underlying data item

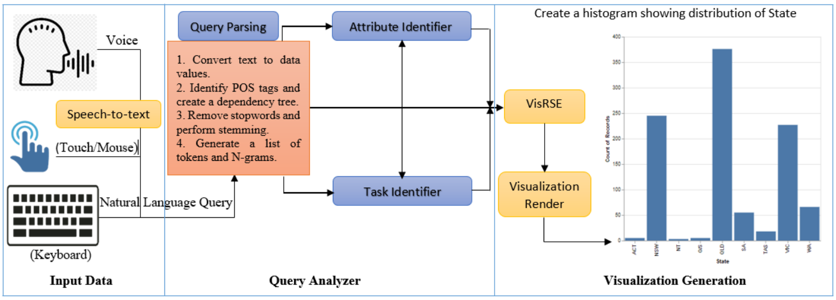

Figure 5: Framework: overview of the interface functionalities such as input data, query analyzer, and finally Visualization generation.

values to derive metadata consisting of the attribute types such as Quantitative, Nominal, Ordinal, Temporal along with values for each attribute in a range. This attribute metadata is utilized for interpreting query to analyze exact tasks and generate appropriate visual response.

4.2 Query Analyzer

Natural language interaction based visualizer should be able to analyze the phrases in the query that are more informative. In particular, to generate a visual response from query, NLIs need to identify the related information such as analytic tasks, data attributes, type of visualization, values as shown in Figure 6. For example, *'Create a histogram showing distribution of M Sex in NSW State'*. In response to this query, the visualization system performs three operations: query parsing, attribute interface and task interface.

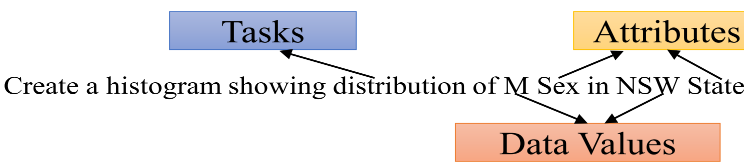

Figure 6: An illustration of query analyzer while interpreting NL queries.

In order to extract details and adopt more relevant phrases, the query parser first runs a set of NLP block that includes part of speech (POS tags), dependency tree, and N-grams. Followed by query parsing, *InsCRMVis* searches for data attributes that are specified both explicitly and implicitly. Finally, *InsCRMVis* analyzes the remaining N-grams for references to analytic tasks such as correlation, distribution, derived value, trend, and a fifth Filter task as shown in Table 2.

Table 2: Types of query and visualization observed in this study

Query Example	Task	Visualization Type
Show a scatter-plot of age and monthly benefit for policy-holders under the age of 30	Correlation	Scatter plot
Visualize monthly benefit for depression/anxiety of M sex in Australia	Derived Value	Bar Chart
Show me an average sum of amount for QLD State	Distribution	Strip Plot
Create a histogram showing distribution of State	Distribution	Histogram
Show a line chart of claim by state in Australia	Trend	Line Chart
Show me premium frequency of NSW state	Distribution	Histogram

4.3 Visualization Generation

InsCRMVis uses NL4DV toolkit where Vega-Lite is operated as the regulating visualization grammar to visualize up to three attributes at a time. It holds the Vega-Lite marks such as tick, bar, point, line, arc, area, boxplot, text and encodings: x, y, size, color, row, column, etc. [38]. Similar to NL4DV, the combination of Vega-Lite marks and encodings allows *InsCRMVis* to support a variety of popular visualization types like bar, histograms, line, strip plots, pie, box plots, area, and scatterplots [34]. To provide insights related to the query, *InsCRMVis* analyzes the query for explicit requests for visualization types (e.g., 'pie charts', 'histogram', 'box plots') or implicitly infers visualizations from attributes and tasks. To implicitly determine visualizations, *InsCRMVis* utilizes a combination of the attributes, and tasks derived from the query. Then, it complies with the inferred visualizations into a visList. Each object in visList is composed of a vlSpec containing the Vega-Lite specification for a chart, an inferenceType field to highlight if a visualization was requested explicitly or implicitly derived by NL4DV, and a list of attributes and tasks that a visualization maps to.

4.4 Implementation

The *InsCRMVis* system is developed as a web-based application, where Python and Flask is used to develop the back-end to support data processing and analysis. JavaScript is used to implement the front-end where Data-Driven Documents (D3) is used to build visualization views. A combination of HTML, CSS elements provide the interface and the AngularJS framework is used to structure the web application using a model-view-controller paradigm. The web-based front-end is connected with the back-end through a query engine interface where the query engine brings in aggregated data from the back-end based on interactions and user selections on front-end. Figure 1 displays the primary screen of the *InsCRMVis* front-end that comprises a full view for visualizing insurance claim datasets.

5 Results

InsCRMVis visually guides domain experts in finding the claims behavior and reducing risks using various functions described in Section 4. We highlight the following outcomes to the selected motivating examples raised by the questions listed in Table 1. In this study, we performed across 169 questions and we see that our system generates answer 69% correctly.

Identifying and understanding relevant risks (Q1 and Q2): Figure 7 shows a variety of questions and charts generated by our system. We observe that the uses of appropriate VAS can help the stakeholders to gain attention for specific risks, and to provide way how to deal with these risks adequately. For instance, the insurance company can not cut the number of risky policyholders directly. By analyzing different factors with an attractive system for establishing a fair claims management process, a good overview on many relevant business decisions can be established. Thus, the design of a interactive visualization system is important to avoid any complications with factors that are not relevant.

Exploring situations for risk visualization (Q3 and Q4): The exploration of a large database for the risk visualization can provide useful insights for various risk-related purposes. In Figure 4, we provide target groups and usage situation to make sure for whom and when risk information need to visualize to make decision. For example, IMs would most likely to know their risky user to allocate adequate resources for mitigation measures and how their risk are interrelated. In Figure 7, we provide some question answering for identifying risky profile. Furthermore, a claim and risk management outcome would look very different if it intend as a print-out and provide to the risk committee members during a meeting. Therefore, this diversity of application situations illustrated that risk visualization should be used systematically in most risk-related activities.

Comparing the behavior of observations (Q5): In order to investigate how the NLIs can provide the desire visualization responses, in Figure 7 we provide visual response of different question where different modalities of interactions are utilized. For example, “Show me a distribution of Male sex in Lakemba Suburb”, ”What are the Female population at the age 25 in NSW State?”. Based on the provided result, we argue that the combination of different interaction modalities are really promising research direction in achieving desired visual for exploring and refining of data in an interactive systems.

6 User Study

To observe how the visual responses generated by VAS on the measures of trust, and usefulness, we conducted a user study which help us to understand the penitential utility of proposed framework. The primary aim of our study was to examine how real users would use the *InsCRMVis* system and what their

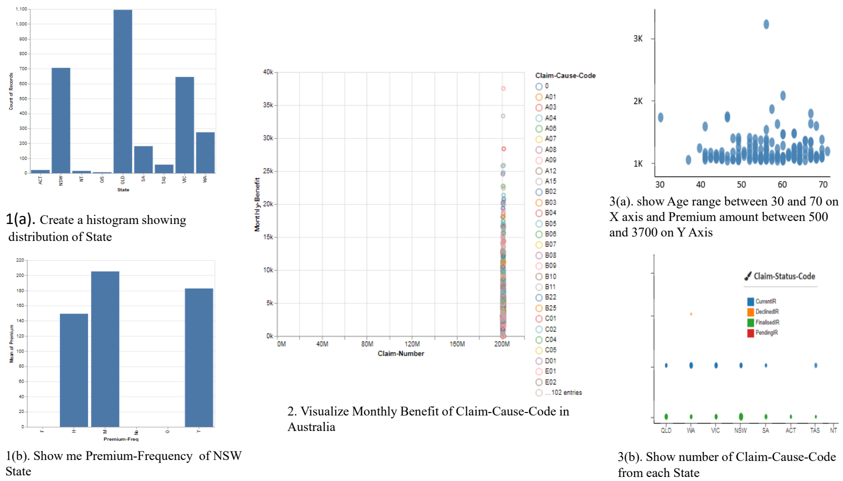

Figure 7: Sample questions with answers generated by our system. Answer in Q1(a), and Q1(b), for query searching, Q2 for speech and Q3(a), and Q3(b) for touch/pen/mouse.

reaction to use multi-modal interaction techniques for exploring various queries with several visual views. Thus, the evaluation questions were generated based on the aforementioned key questions (Q1, Q2, Q3, Q4, and Q5) in provided in Table 4. Finally, we performed the study in web-based environments to enhance the system validity, since participants can work in their own.

6.1 Participants

We performed our user study with 10 participants. Of the total 10 participants, 7 men and 3 women were between the age of 20 and 59 years. The users were recruited through emailing lists. Those participants were mostly students, and teachers in universities and stakeholders who had expertise of risk management in insurance industry. Additionally, participants were mostly familiar with basic data visualizations (e.g., bar charts, line charts, etc.) as they frequently read them as part of their study or work. Those participants recommended potential feedback.

6.2 Study Design

In order to validate the performance of *InsCRMVis*, a TLI questionnaire was administered. Detail study was conducted to investigate how to visualize an information to gain a better insights. To visualize the effectiveness of VAS, we implemented five different visualization observations which provide distinct characteristics such as status position (mouse), text input visualization, speech

Table 3: User study response for output visualization to post-study questionnaires.

Input	Interaction	User response (with %)	O1	O2	O3	O4	O5	O6	O7
		Strongly agree (0.13%)		✓					✓
		Agree (0.27%)	✓		✓		✓		✓
Mouse	Clicking menu	Neutral (0.27%)		✓		✓		✓	✓
		Disagree (0.07%)				✓			
		Strongly disagree (0.07%)			✓				
		Strongly agree (0.13%)	✓		✓				
		Agree (0.27%)		✓	✓		✓		✓
Keyboard	Text entry	Neutral (0.20%)		✓		✓		✓	
		Disagree (0.13%)		✓				✓	
		Strongly disagree (0.07%)							✓
		Strongly agree (0.13%)		✓		✓			
		Agree (0.13%)	✓		✓				
Speech	Talking	Neutral (0.27%)	✓		✓		✓		✓
		Disagree (0.07%)	✓						
		Strongly disagree (0.07%)				✓			
		Strongly agree (0.13%)		✓		✓			
		Agree (0.20%)		✓		✓			✓
Touch	Touching menu	Neutral (0.20%)			✓	✓		✓	
		Disagree (0.20%)	✓				✓		✓
		Strongly disagree (0.13%)			✓		✓		
		Strongly agree (0.20%)			✓	✓		✓	
		Agree (0.27%)	✓		✓	✓		✓	
Pen	Clicking menu	Neutral (0.33%)	✓	✓		✓	✓		✓
		Disagree (0.13%)			✓		✓		
		Strongly disagree (0.13%)	✓			✓			

input visualization, touch, and pen input visualization as shown in Table 3. In Table 4, the provided key observation questions were selected to contain satisfactory statements on how our system works and how text/speech/touch output should be structured to avoid distraction. Afterwards, we collected free form responses about what the participants considered relevant to the usefulness of our system. The study took about 10 minutes and all participants work in automotive research.

6.3 Discussion

In this study, participants rated seven different measures on a standard five points such as strongly disagree, disagree, neutral, agree, and strongly agree. The results of these questionnaires are presented in Figure 8. We noticed that the majority of the responses were dominated by positive ratings. In particular, most participants agreed that the tool is useful and it enabled them to find interesting insights from the data quickly. More important, 6 out of 10

Table 4: Key observations identified in collaboration with domain experts where expert responses 1, 2, 3, 4, and 5 indicate strongly disagree, disagree, neutral, agree, and strongly agree respectively..

No	Category	Question	Mean (μ)	Std. Dev (σ)	Min.	Max.
Q1	Interactive	The system let me interact the way I naturally wanted to	2	0.63	1	5
Q2	Insight	I would like to use this system frequently	2	0.63	1	5
Q3	Insight	I found using the combination of mouse, keyboard, speech, touch, and pen to be useful for exploring data visualization	2	0.89	1	5
Q4	Insight	The system enabled me to find interesting insights from the data quickly	2	0.63	1	5
Q5	Speed	I found the answer to my queries that I have about the data	2	0.89	2	5
Q6	Confidence	I found the system was easy to use	2	1.09	1	5
Q7	Confidence	I found the system useful for exploring data visualization	2	1.41	2	5

participants found the combination of multiple input modalities to be useful for exploring visualizations.

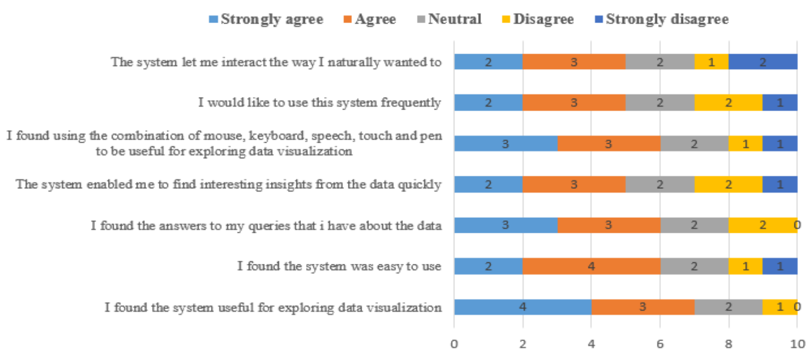

Figure 8: Post study ranking for output visualization and opinion position.

Table 3 shows the performance of various input visualization components such as mouse, text, touch etc. Every concepts is built upon this system. We found the visual responses generated by our system with text query are more significant than the traditional visual outcomes. Additionally, the use of speech and touch were evaluated as both rational and alluring. It is noted that during the conversation with domain experts about the system status, 75% participants positively responded to go for visualizations of the output text.

They informed that full text more convenient for the utilization than keywords. Additionally, variations in speech output were mostly accepted. Moreover, two third of 10 participants each suggested multi-modal actions are also appealing to identify visual responses. Thus, participants' comment mainly belonged to the user interface, which should be robust, interactive, and smart.

At the end of the study, we provide series of guidelines that IMs can follow when attempt to visualize risks. The following are the key guidelines:

- Representation of simple text query/conversation can be more flexible to make productive use of visualization in risk management.
- Use of upto three attributes from the dataset are comparatively more informative to domain experts.
- Use of unnecessary elements in a visualization may cause confusion because of various expectations.
- Various types of risks should be depicted using different queries/symbols.
- The primary risk information should be distinguished from secondary or less important information.

The above mentioned experts feedback and user studies ensure the effectiveness of our VAS in insurance claims and risk management. We have noticed several other challenges that should be addressed such . Even though proposed framework provided good outcome and is valuable for risk visualization, however, there is enough spaces for improvement. For example, people intent to get visual response using a variety of keywords where proposed framework fails to visualize sometime which requires to use transformer (BERT and RoBERTa etc.) based word embedding methods. The resulting explanation may provide better insights, however, proposed framework dost not provide any explanations for generating visual responses. In addition to this, there is still enough space for improvement and to take place with specific guidelines for risk insights visualization.

In summary, we present a web based visual analytics tool aided with query searching, speech, and touch for insurance claims and risk management. We primarily focus on how our system capable of supporting the IMs. We concluded that full text query searching has advantages to provide interesting insights. Additionally, domain experts preferred the presence of visualization through speech.

7 Conclusions and Future Work

We presented a web-based visual analytics solution (*InsCRMVis*) that contains a suite of interactive visualizations, designed with consideration for the task requirements of risk management domain experts. To our best knowledge, this is the first work using natural language interactions with data visualization to address the policyholders claims and risk management in the insurance industry. In this study, we conducted meetings, interviews, and observational sessions to understand their analysis workflows. Our system supports analyzing multiple types of insurance datasets such as relational, claim, and demographical. We find that people ask questions and our system provide useful visual insights. Our automatic question-answering pipeline achieves an overall accuracy of 69%. Finally, we provide a qualitative evaluation of *InsCRMVis* by domain experts based on several use-cases to demonstrate the usefulness of this system in different application scenarios.

In future, we plan to add visual analytics support for collaborative data analysis such as underwriting, mental health analysis, adverse selection etc. While N-Gram approach generates visualization of multiple types of data and convey how the corpus provide a better response, the visual analytic requires advanced technique such as transformer (BERT, RoBERTa etc.) and offer little variations in style. Thus, applying transformer may help address such limitations.

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