MHIVis: Visual Analytics for Exploring Mental Illness of Policyholder's in Life Insurance Industry

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***Abstract*—Stakeholders in the insurance industry are committed to yet lack the timely and actionable information for alleviating policyholder's mental health concerns and the industry's mental health climate. Existing research has revealed that personal data, such as depression, anxiety, and stress, can provide deeper insights into policyholder's mental health states. However, such data remain unexplored for supporting stakeholders' and government goals. In this paper, we design an interactive visualization system to provide deeper insight into policyholder's mental health states and performs recommendation reasoning. Our study has three implications: (i) insurance data are potentially useful for understanding policyholder's mental health; (ii) a dashboard-like visual representation is helpful for the decision-making of Stakeholders; and (iii) recommendations on how the government can improve the mental health of Australians. We conclude by reporting an informal evaluation of the effectiveness of our system and remarking on the future directions in system design.**

***Index Terms*—Mental health analysis, data visualization, recommendation reasoning, insurance recommendation.**

I. Introduction

Mental Health Illness (MHI) is a significant issue in the Australian landscape, with an ever-increasing number of cases [4]. Almost one in five Australians within the age range 16 to 85 have mental health illnesses problems, and most of us experience it at some point in their life. Indigenous Australians are known high-risk groups, which experience a suicide rate more than double those of non-indigenous Australians [4]. Therefore, it is evident that MHI is a growing issue within the Australian climate, with a significant number of cases every year.

Recently, economic activity and development have prioritized MHI as a new and squeezing challenge for each country [10]. People with MHI brings forth a financial imbalance, superfluous working spirit, alongside affecting their professional and personal life [19], [16]. For instance, in 2018, approximately 18% of adults of the USA suffered from MHI, as suicide becomes the 10th leading cause of death in the US [23]. In another study of 2019, they examined almost 10,000 records of IT workers where 58% of workers are mentally sick [9]. Therefore, to understand the MHI of Australian people, we consider a local life insurance policyholder's MHI, which is a very sensitive and impressionable matter. It includes depressive disorders, anxiety disorders, eating disorders, schizophrenia, and bipolar disorder which are very common within women and men. In the life insurance industry, it has been shown that policyholder's with mental illness have three times higher rates to claim for benefit compared with individuals who do not have a mental illness [22], [18]. This kind of enduring behavior is referred to as underwriting sometimes, and a key to ensuring the economic viability of the insurance industry, which causes a great impact on the economy [11], [18]. Additionally, surrounding the policyholder's claim data source, there was a potential lack of interpretability. Therefore, to reduce this leading problem with proper counselling and ensuring a healthy environment, there is an urgent need to identify a group of professional people in a specific age-range and their living areas (dangerous) in Australia to help with special considerations and profitability of those experiencing mental illness.

ata visualization systems are widely used for different purposes such as recommendation systems, text analysis, mental health analysis, sentiment analysis, etc. In many fields, such as finance, education, and fostering research in academia [12], [14]. In the literature, there are very few of visualization research works available to explore the MHI of users globally. Existing dashboard such as Visualizing Mental Illness (VMI)[1], Nigeria Health Map (NHM)[2], National Health Accounts (NHA)[3], HIV Atlas[4], and Global Behavior Disorders (GBD)[5], are suitable for gaining various mental health-related statistical results. However, they largely ignore the intrinsic relationships between mental illness and the user's profession. Furthermore, the majority of those existing tools are leading to a lack of interpretability for their recommendations, which makes them less attractive in many applications, especially in decision making. Therefore, how to visualize the policyholder's mental health behaviors and why certain information's are recommended remain open problems.

To address the aforementioned limitations, in this work, we design a new visualization dashboard, which ensures flexibility, efficiency, and exhibits the correct path to take

[1]http://humanosphere.org/global-health/2013/06/visualize-mental-illness
[2]https://vizhub.healthdata.org/health-map/nigeria
[3]https://vizhub.healthdata.org/nha/
[4]https://hiv.ihme.services/
[5]https://vizhub.healthdata.org/gbd-compare/

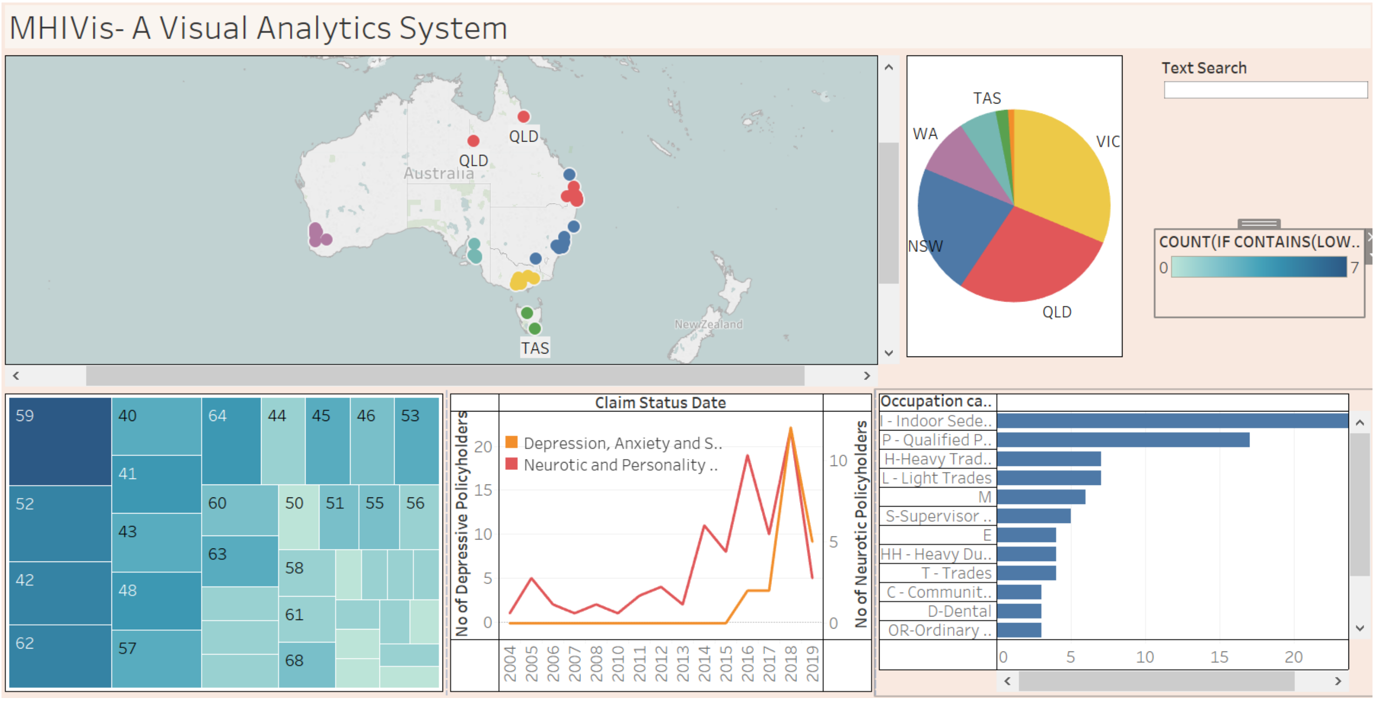

Fig. 1. MHIVis: A Mental Health Illness Visual Analytics System for Insurance Industry

proper actions. Our proposed system, named Visual Analytics for Exploring Mental Health Illness (MHIVis), allows the stakeholders to type different text queries such as "Find top 3 MHI states" in a search box within a dashboard. Fig. 1 illustrates how our system helps the stakeholders to understand policyholder's MHI. By analyzing ten years of data of a total 31,800 policyholder's, the dashboard is showing a multiple-coordinated view of MHI information around Australia. Here, we decided to analyze mentally ill policyholder's region, age, and profession, followed by typing the query 'your text'. In response, the system analyzes the query to generate the answer with multiple coordinated views. Furthermore, we have compared our dashboard with five different dashboards to show how our MHIVis system could improve the efficiency in discovering knowledge and better facilitate the decision-making process. Therefore, our work makes the following three key contributions:

- First, we present an observational study aimed to focus on the mental health illness of policyholder's for visual data analysis.
- Second, a visual analytics system named 'MHIVis' is presented that allows stakeholders and researchers to understand of policyholder's mental health illness.
- Finally, we provide three concrete design implications for stakeholders derived from our findings.

The outline of this paper is organized as follows. In section 2, we review existing work related to our study. In section 3, we present the design methodology, and in section 4, we briefly discussed the visualization results to evaluate the performance and explore the potential for further and related research. Finally, in selection 5, we provide a conclusion.

II. Related Work

We focus on the particular problem of understanding of policyholder's mental health illness, and how stakeholders solve problems using information visualizations. In this section, we discuss two parts of work that relate to this problem. First, we set the research gap by outlining existing research efforts to articulate the 'mental health illness' using a visualization tool in the life insurance industry. Second, we discuss two 'information visualization process' research efforts that we're able to uncover work practices previously and briefly discuss how we drew in our work.

Mental Health Assessment: Globally, mental health illness is responsible for 32% of years of disability [23]. In particular, mental health illness (MHI) is the main reason for claiming injury compensation in Australia [18]. Persons with this illness face a higher risk of premature mortality. Additionally, mental illness can have a deleterious effect on the physical and psychological health, the productivity of the work of an individual [20], [5]. Therefore, there is no doubt that mental illness has brought huge challenges and controversy for the insurance industries.

Assessing the mental health illness associated with any insurance applicant is a core business characteristic of the insurance market. In the case of life insurance, it has been shown that the quality of care for mental illness has not increased to the same extent as that for physical conditions [18]. One study in the United States reported that psychiatric language usually varied from doctor to doctor, which leads to confusion in the interpretation of the diagnosis of a specific mental illness [1]. These risk assessments also referred to as underwriting, are key to ensuring the economic viability of the insurance industry [4]. Underwriting mental health conditions can be challenging due to their complexity, particularly when applying for disability benefits [1], [4], [10]. When considering the negative experiences of mental health customers in applying for and/or claiming insurance benefits, it is necessary to consider the personal information and risk assessments of mentally ill patients in the community. Additionally, how these pieces of information make psychiatric patients inequalities for a long time in insurance application and claim outcomes [11]. However, sometimes stakeholders are confused to deal with the complexities of mental health illness and observe which individuals are engaged, which are disengaged, and those who are in between. Therefore, our works to provide design implications of a dashboard for insurance administrators that visualize policyholder's data relating to support a better understanding of policyholder's mental health illness.

Visual Interfaces for Stakeholders: Previous work on visualizing MHI has often focused on supporting the Stakeholders in exploring user's interest by visualizing thread structures [15], [13], [6]. Several tools were developed to provide a visual overview and allows stakeholders to navigate the mental health states of users [3], [2], [17]. However, such visualizations do not analyze the intrinsic relationships between mental illness and age range with policyholder's professions. Moreover, the above works have a lack of interpretability for recommendations to make a decision. Therefore, how to visualize the policyholder's mental health behaviors and why certain information's are recommended is a timely concern.

In summary, the existing research on MHI visualization in the insurance industry is limited, and there are very few studies that have designed advance dashboards to meet the practical requirement of the stakeholders. Additionally, a very limited amount of datasets have been used in the existing literature. To deal with aforementioned challenges, in this study, we have studied a different domain (life insurance policyholder's MHI) and created a new dashboard by analyzing ten years data of a total 31,800 policyholder's to visualize the MHI and to provide some recommendations to reduce company losses, increasing service quality, improving risk adjustments and allowing for the improvement of insurance premium policy.

III. METHODOLOGY

This section describes how MHIVis is employed as a designed dashboard for discovering, designing, implementing, and deploying. Additionally, the details on data collection and processing are also included in the section for the representations of practical implications of the design.

A. Data collection and processing

This work uses three different types of the dataset such as 1) policyholder's relational data, 2) policyholder's claim behavior, and 3) SEIFA Index based demographic data. The datasets have been collected from different data sources. First, we collect the questionnaire-based relational data used in

TABLE I
DATASET DESCRIPTION

Features description	Values
Total number of relational dataset users	31,800
Total number of demographical dataset users	53,793
Total number of claim dataset users	4,200
Total number of mental illness policyholder's	139
Number of depressive, anxiety & stress policyholder's	79
Number of neurotic & personality disorder policyholder's	60

this paper from one of the local life insurance companies in Australia. After collecting the raw data, the questions and user's information were arranged and stored into the N*M matrix where rows indicate the user's information and columns represent the different questions. Our primary dataset contains a total of 31,800 rows and 834 columns. To do our research work, we also collected policyholder's claim behavior data from the same insurance company. Additionally, to estimate the prior potentials, we collect the demographic information of each user's from available SEIFA index demographic dataset (age, sex, profession, location, population, etc.) [21]. The dataset provided by the client has many attributes that could be used to gain insight into Australia's mental health. Hence, data had to be sourced from online datasets and merged with the existing dataset (refer to Table 1). It is integral that the datasets found online are integrated and linked up with other datasets. However, some of these attributes were deemed to be irrelevant as they could not assist in understanding Australia's mental health. As the dataset was sourced from different sources, there were instances of missing values. If these missing values were not handled adequately, incorrect analysis of the data can be made, which could have a detrimental flow-on effect. Therefore, the software library pandas in the python environment were used to explore, investigate, and understand the original dataset provided by the client. These irrelevant attributes were removed entirely from the dataset.

B. Design and Function of MHIVis

This is designed to support stakeholders for exploring the mental health illness of policyholder's. According to Hoque et al. [7] our design study focused on four-stage of the design framework: **1) Discover:** in this stage, it covers the needs, problems, and requirements of stakeholders. **2) Design:** After reaching a shared understanding of the MHIVis, we explored the design space of text analytics with multiple coordinated visualizations to support policyholder's. **3) Implement:** We developed a new dashboard for stakeholders where stakeholders could effectively compare mental illness data between different age and professional policyholder groups. **4) Deploy:** Following several pilot studies and corresponding refinements, we deployed our design dashboard as a tool. Therefore, to analyze insurance data for exploring mental health illness of policyholder's, the following steps are carried out:

Free text search: There has been a recent surge of considerable attention in data visualization research by free teach

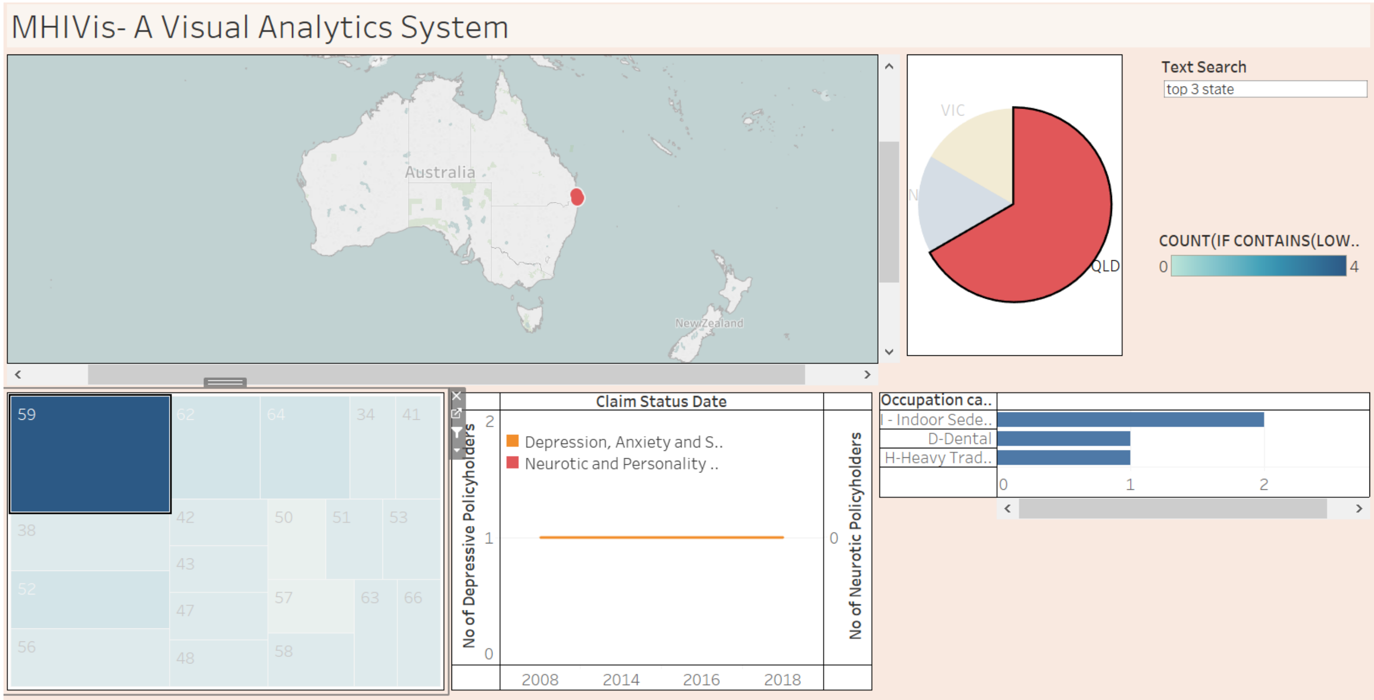

Fig. 2. The result of the free-text searching with multiple coordinated views

search. Generally, these visualizations respond to user queries by either creating a new visualization within an existing visualization in the dashboard. In this strategy, the system first tokenizes the text to find the list of words in the query. For example, given the query 'your text', the system will find a list of queries from the data table and generate result in the dashboard.

Multiple coordinated views: In this strategy, we particularly focus on how our system allows selection within multiple views of the dashboard and use the frame-based dialogue actions to generate the answer. For example, if you want to find how many 59 years old mental health policyholder's are in QLD and what is there profession?. So, our system will first find how many mental illness policyholder's are in QLD, then find how many there are at 59 years old and finally will find out what is their profession.

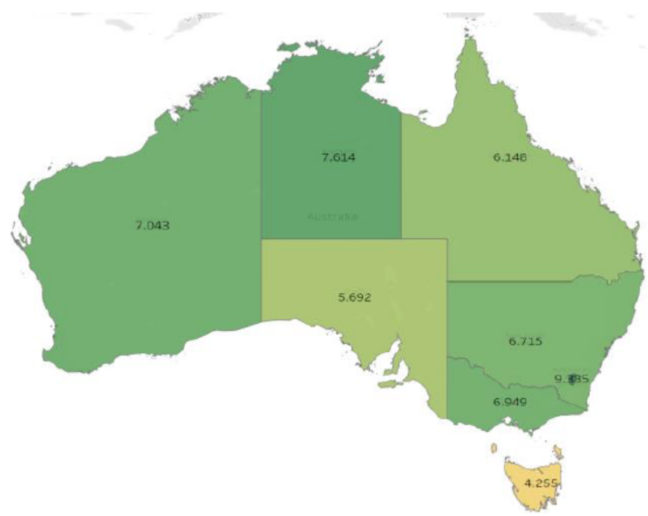

Fig. 3. The demographic information of policyholder's in different states

IV. Result and Discussion

In this section, competing tools, and the findings of our dashboard for visualizing the mental health illness information's of policyholder's are discussed respectively.

A. Competing Tools

Tableau allows the stakeholders to investigate the relationships within a plethora of graphs in the dashboard [8]. During the initial exploration of the dataset, we aimed to understand whether mental illness is influenced by the categories in the variables. Therefore, to understand the potential utility of our system, in Table 2, we compared MHIVis with five different visualization tools, including VMI, NHM, NHA, HIV Atlas, and GBD. These five tools are chosen because they also visualized information in the relevant areas, i.e., VMI in discovering mental health problems which include depression, drug, anxiety, and alcohol, etc. around the world, NHM in visualizing Nigeria health conditions with a limited dataset, NHA in visualizing national health account around the world, HIV Atlas in exploring the burden of HIV with a visualization scenario, and GBD in comparing different situations of mental health illness. Although existing tools are designed to visualize various information in the dashboard, to have a fair comparison of existing tools, we designed a new dashboard, including free-text searching with multiple coordinated views.

TABLE II
FEATURE COMPARISON

Features of dashboard	VMI	NHM	NHA	HIV Atlas	GBD	**MHIVis**
Visualization with global map	✓	✓	✓	✓	✓	✓
Visualization within age group	✓	×	×	×	✓	✓
Visualization with occupation category	×	×	×	×	×	✓
Review previous status across time/year	✓	✓	✓	✓	✓	✓
Free text searching with multiple views	×	×	×	×	×	✓

Notes: (✓) indicates the presence of feature selections and (×) indicates that it does not visualize the feature outcome.

B. Findings

To investigate and identify the group of mentally ill policyholder's, stakeholders, such as insurance managers (IMs), need to have a comprehensive understanding of policyholder's personal information. Therefore we design a dashboard to visualize detailed policyholder's of mental illness that perfectly contribute to discovering knowledge. Our dashboard was designed to be user-friendly, simple, also in-depth to allow a thorough exploration of the MHI of policyholder's in Australia. This tool could be easily used by stakeholders, such as insurance managers (IMs). Our design dashboard will facilitate to search a text query in a box and shows the result with multiple coordinated views within a dashboard. Furthermore, it gives both a zoomed-out and zoomed-in services of the Australian mental health landscape, such as the details of the mental disorders in different postcodes. As shown in Fig. 2, explores the MHI of Australia as a whole, with details regarding Australia's spending. The map itself can be further zoomed in to see different postcodes, regions, and states in more detail. Additionally, Fig. 2 reveals a more detailed image of Australia through the use of exploring the mental health risk of regions, postcode, profession, and age group.

The analysis in Fig. 2 is necessary for insurance managers in designing appropriate policy packages for the future. For example, Indoor sedentary, Heavy Trades, and Qualified professional policyholder's are tending to claim for more benefits. Additionally, in Fig. 3 we outlined the postcode of all policyholder's per state. We also examine the geographical visualization of mental health patients counts for the different states in Australia. We can see VIC, NSW and QLD have the highest patient count, while Tasmania has the lowest patient count. However, the geographical size of MHI information provides a misleading argument. It is noted that the indigenous population has a much higher chance of suffering from mental health issues. NSW and QLD have the highest amount of Aboriginal and Torres Strait Islanders. While this patient count may seem high, in comparison to their population, this is a low number. As we used publicly available data on the Indigenous population, and thus, meaningful conclusions cannot be made.

Our analysis of 'state information with mental illness policyholder's by age group' and 'state information with mental illness policyholder's by profession (Fig. 2) suggests that IMs should pay more attention to the (25-54) range of policyholder's in NSW and VIC. In particular, NSW and VIC are the most popular location because they are highly developed states in Australia. Policyholder's tend to stay in these states, which can generate considerable benefit them. QLD is also a high-potential destination, where high-risk policyholder's tend to spend a long time. Therefore, IMs can investigate and develop appropriate business strategies among policyholder's when they provide insurance service facilities and reduce insurance loss.

In essence, we provide several recommendations, such as a study should be conducted into the mental health of Indigenous Australians to understand their mental health risk better, availability of required large scale datasets to provide a more accurate and in-depth understanding of the Australian mental health climate. Although, earlier research reveals several possibilities of self-tracking data in mental health, however, in our study, we also highlighted the opportunities where self-tracking of mental health user can complement each other in order to fulfil their various unmet needs. The study also revealed stakeholders desire for comprehensive dashboard which is better streamlines to meet the requirements and constraints of stakeholders role and their work environment. We have the following **key recommendations:**

- QLD has the second-highest mental health risk and the highest population out of all the states. Thus, QLD needs to spend significantly more to help provide targeted support towards high-risk regions and postcodes.
- The study suggests that (25-54) range of policyholder's are considerably higher than others. Thus, IMs should pay more attention to policyholder's in NSW, VIC, and QLD.
- We noticed that the average age of the mental illness policyholder's derived between 35 and 45 years old. Therefore, the risk of mental illness claim behaviors for this population can be reduced by considering other factors as well.
- For larger dataset, behavior preference could be used to improve the performance of adverse claim selection.

V. CONCLUSION AND FUTURE WORK

We presented a new visualization system demonstrating that policyholder's data, can have the potential to improve policyholder's MHI if it is shared with stakeholders such as insurance managers. Our study demonstrates how the system can help stakeholders to effectively utilize multiple interactions complement together. We summarize the contributions with three design implications from the study: 1) identifying mental illness policyholder's can potentially be a very useful source that not only help to support the stakeholders goals but also government's; 2) the future dashboard should be able to adequately manage the bias as well as intelligibility issues in the visual presentations; 3) there could some ethical issues around the dashboard design that may need to protect privacy and data confidentiality of policyholder's.

In the future, we would like to incorporate more input data (mental health with other claims data) to display various factors for exploring information visualization. We will also enhance our free text searching modality by natural language processing methods based on the sequence-to-sequence model. Finally, we will evaluate our system with real user case studies to understand the potential utilities of our dashboard with multiple coordinated views.

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