Descriptive Analytics for Operational Risk Intelligence in Financial Services

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Abstract: The impacts and consequences of COVID-19 pandemic significantly changed the strategic direction of many industries globally. In the financial services industry operational resiliency of many financial institutions were challenged driving the shift from the traditional risk management approach into the implementation of risk intelligence solutions. Risk experts recognized the importance of using emerging technologies to build the capability to learn from external sources to supplement internal risk management processes as an important factor to support operational resiliency. The purpose of the study is to develop an analytics system that will provide operational risk intelligence from a reliable external source useful for financial institutions to gather external insights and support operational resiliency. It involved stimulation of business need for an analytics system in a selected financial institution to validate insights derived from the system and impact to the operational risk management process. The methodology used is the Knowledge Discovery in Databases (KDD) Process Model appropriate for discovering external risk intelligence. Multiple iterations of system development and evaluation were performed to identify business relevant insights that primarily relate to the business, product, cause, and event types. The overall result of the descriptive analytics revealed new operational risk intelligences that can be presented to various risk management discussions confirmed by the risk experts and focus group discussion participants. Therefore, the stimulation activity of the study helped recognize the need for an analytics system to augment the internal risk management process in the selected financial institution.

Key Words: data analytics; operational risk management; descriptive analytics; risk intelligence; financial services

1. INTRODUCTION

Amidst the COVID-19 pandemic, the traditional risk management approach is proven to be insufficient for financial institutions to sustainably thrive in the rapidly evolving environment. Financial institutions are prompted to focus on improving the company's agility, adaptability, and resilience (Gil, 2021). According to the Financial Stability Board (FSB), "an international body that monitors and makes recommendations about the global financial system", COVID-19 pandemic tested the resilience of the global financial system (About the FSB | FSB, 2019). Additionally, FSB highlighted that the pandemic emphasized the importance of effective operational risk management in financial institutions (FSB, 2021). Thus, institutions are now investing in stronger operational resilience to adapt to the new normal brought by the global pandemic.

In March to September 2020, Deloitte conducted a global risk management survey across 57 financial institutions to determine effects of COVID-19 pandemic and to uncover significant risk management trends that could impact financial institutions over the next two years (GARP, 2021). Global Association of Risk Professionals (GARP), a "leading professional association for risk managers, dedicated to the advancement of the risk profession through education, research and the promotion of best practices globally", analyzed and discussed results of the survey together with experts (About Us | GARP). According to risk professionals, in the next two or more years, partially driven by the economic consequences of COVID-19 and the transition to working from home, financial institutions are anticipated to focus on credit risk, cybersecurity, data management, third-party risk, operational resilience and the use of disruptive technologies like Artificial Intelligence (AI) and machine learning (ML) (GARP, 2021). The global pandemic significantly impacted financial institutions, thus, additional emphasis on building more resilient operational risk management has become a priority (GARP | FRM, 2021). Further, risk professionals recommend that digitalization embedded in risk management should be included in the organizational strategy to evolve for better operational resiliency (GARP, 2021).

According to Global Risk Institute (GRI), an organization that provides practical strategies to help financial services organizations to better manage risks (GRI | GRI Team), operational resilience is key for institutions to arise from the COVID-19 crisis (Baxendale, 2020). In the study of Baxendale in 2020, it was discussed that the problem with the current business continuity in institutions is the gap in planning for the possibility that all its employees and most functions will be performed at home with the "new normal" over an extended period. The regulators emphasized that financial institutions must go beyond disaster recovery and business continuity management but also secure operational resilience (Baxendale, 2020). Some of the guidelines provided by Global Risk Institute in the study are the operational resilience culture wherein learning from past experiences of themselves and others should be practiced, and organizations must move towards being proactive rather than reactive. Also, operationally resilient organizations must be capable of solving problems of the future that require continuous learning both internally and externally (Baxendale, 2020). One of the emerging technologies identified that is foreseen to introduce both challenges and opportunities in the financial sector is machine learning (Rossi, 2022). Thus, risk management insights are expected to be derived from the use of AI technologies to further elevate risk modelling (Rossi, 2022).

In the 2018 MIT Sloan Management Review data and analytics report, it was revealed that the majority of the "analytically mature organizations" or also known as "analytical innovators" uses more data sources to support the organization's data strategy (Brown, 2021). These data sources go beyond the organization's realm "including data from customers, vendors, regulators, and competitors" (Brown, 2021). In the context of risk management, Deloitte's Predictive Risk Intelligence (PRi) offers predictive risk monitoring that is the application of analytics to both the "current and historical information from internal and external sources" with the use of data mining and machine learning capabilities (Deloitte, 2017). In terms of external data sources, there are different reliable platforms available globally that offer financial institutions the capability to share risk events and learn from one another to better manage operational risks. These reliable platforms secure and anonymize the information about the financial institutions to provide operational risk data from all over the world. Also, some of the reliable platforms offer structured data that can be accessed by financial institutions through the different methods that can be integrated to the internal systems. This capability enables financial institutions to learn externally and supplement internal risk management strategy. Bringing external perspective into financial institutions in a real-time manner can significantly contribute to its data and digitalization strategies.

The study aims to develop an analytics system that will provide operational risk intelligence using external data from a reliable platform useful for the selected financial institution called "Company Z" to gather external insights and support operational resiliency. Specifically, the study aims to:

- Extract significant data from a reliable platform to formulate target dataset for the discovery process.
- Pre-process target data and transform to produce accurate results usable for data analysis.
- Stimulate the need for an analytics system using the target dataset relevant for operational risk management.

- Interpret and evaluate insights generated to derive potential knowledge that can be presented.

The study is primarily focused on the operational risk management aspect of the financial services industry, hence, covers operational risks data only. Publicly available operational risk data will be sourced from a reliable external platform trusted by financial institutions globally named "Risk Management System" or "RMS" in the study. Operational risk data from RMS will help financial institutions learn from real-life scenarios in other institutions and in a timely manner. All operational risk events available in RMS, for bank and non-bank sectors, will be extracted and analyzed.

2. METHODOLOGY

The methodology used in the study is the Knowledge Discovery in Databases (KDD) Process Model adapted from Fayyad et al. (1996) with five major steps (see Fig. 1). This was adapted from the study of Chermiti in 2019 on establishing risk and targeting profiles using data mining. However, in the study only four steps were applied given that no further data pre-processing was required for the dataset.

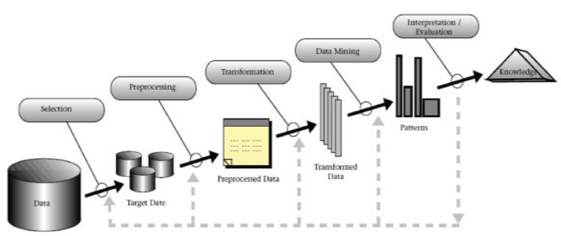

Fig. 1. KDD Process Model, adapted from Fayyad et al. (1996)

2.1 Data Selection

To stimulate the business need for an analytics system in Company Z, the researcher started with the presentation of the initial analytics and query questions to the three selected business risk leaders. The request was to select the top six analytics questions that would be relevant to the business specifically for operational risk reporting and to gather feedback for any additional insights that should be added to the list. Further, a meeting to understand business requirements was held with the divisional lead of ABC. The researcher presented and explained the initial analytics questions and requested the stakeholder to provide top six analytics questions that would be relevant for the business. The stakeholder highlighted that any questions that relate to the business, product, event type, cause, taxonomy, region, and industry sector would be value-adding for the business. Also, the stakeholder agreed to develop the analytics system to understand how the analytics questions will translate to the different visuals on the system.

In terms of data extraction, the researcher performed full data extraction from the platform's interface in CSV format and loaded it into the Power BI report. Also, to manage versions of the analytics system, the researcher employed a version control process for both data and Power BI reports.

2.2 Data Transformation

The researcher performed an exploratory data analysis prior to loading data into Power BI report to determine which fields need clean-up and identify initial data transformations required for any further calculations and presentations in the system.

2.3 Data Mining

The analytics system underwent multiple system development and evaluation iterations with various stakeholders.

2.3.1 First System Development Iteration

Once data transformations were implemented, the researcher started building the home page of the analytics system. Initial design was to have a landing page with the high-level data. Selection of appropriate visuals throughout the system development process were based on the Visual Vocabulary of Financial Times. Several calculated columns and charts were added in the initial design of the system based on the analytics questions defined (see Fig. 2).

Fig 2. First version of the Analytics System

2.3.2 Second System Development Iteration

On the second iteration of the system development, the interface was redesigned to align with the feedback of the stakeholder. Initial concept of the home page was removed including the headers and breadcrumbs, and all visuals were placed on one page. More visuals were added to match all final analytics questions and slicers were enhanced.

2.3.3 Third System Development Iteration

The third iteration of the system development was focused on the enhancement requests gathered from the focus group discussions. However, no further changes on the analytics questions of the system.

Table 1. List of Enhancements in the Analytics System Version 3

Focus Area	**System Enhancement**
Slicer / Customizability	Redesigned system header to add two new slicers for Business level 2 and Product level 2.
	Added new Headline slicer with enabled search functionality to satisfy keyword search requests of stakeholders.
User interface design	Added risk event number renamed as R Link and Date Risk Event Published fields into the *Top Business Risk Events by Loss Amount* matrix. Also, the matrix was extended occupying the entire width of the page before the business and product tiles.
User interface design	Renamed No. of Risks column to No. of Risk Events in the *Top Types by Risk Events & Loss Amount* matrix.
New Features	Added Drill through feature in the risk event number or R Link in the *Top Business Risk Events by Loss Amount* matrix to view risk event details or content.
	Added Drill through feature in the No. of Risk Events in the *Top Types by Risk Events & Loss Amount* matrix to view a short list of risk events.

2.3.4 Fourth System Development Iteration

In the fourth system development iteration, a new visual to present the correlation of the number of risk events per business and the number of risk events per event type was added using a scatter plot in Power BI. Additionally, presentations of the drill through pages were revised based on the feedback gathered during evaluation.

3. RESULTS AND DISCUSSION

The business requirements activity successfully stimulated the business need in Company Z for an analytics system using external operational risk data. Initial recommendation from the business risk lead of FMR to add Taxonomy dimension in the analytics questions and for the business risk lead of ABC to initiate involvement in the initial discussions demonstrated interest in the study. The initial meeting with the business risk lead of ABC was a success and resulted in the identification of top six dimensions that relates to the analytics questions used in the study. Additionally, the risk lead ranked the dimensions by business relevance that is business, product, event type, cause, taxonomy, region, and industry sector. Therefore, it was found that exploratory data analysis and pre-determination of analytics questions presented to the business is an effective way to stimulate business need for an analytics system.

3.1 System Evaluation First Iteration

There were several insights that can be derived from the first version of the External Operational Risk Intelligence System which were presented to the divisional risk lead of ABC. The objective of the discussion was to identify relevant insights for the business from the initial version of the system and gather feedback to improve the system. The approach for all the system evaluations was to conduct focus group discussions (FGD) via zoom meeting. A diverse set of participants from different regions and businesses became part of the FGD.

The first feedback loop was scheduled with the divisional risk lead of ABC. The stakeholder suggested a single page dashboard as an option where all the different visuals are added for easier navigation. Current set of slicers were liked by the stakeholder and emphasized the importance of having all the necessary filters that are easy to use for a customized data view. However, it was also shared that the challenge with external data is not having the same business structure internally. Thus, different combinations of slicers should be used like business and product to derive a similar business view useful for the group.

Headers in the initial version showing an increasing or decreasing trend of the number of risks and loss amount were considered not very relevant to the business because the metrics are not associated with the company's risk management performance. Further, the insights presented that can be derived from the matrices showing the list of recent risk events by loss amount and risk events by product were considered relevant and aligned with the coverage of the monthly risk forums. For the trend of the number of risk events and loss amount analytics, it was considered of low importance to the business, hence stakeholder suggested to make it smaller or placed at the lower section of the system. Additionally, insights derived from the distribution of risk events by event type and all other analytics related to the business, product, risk events, and cause were considered very useful for the business. However, fixed coverage of 12 months data for the analytics may be too broad.

Overall, it was found in the first iteration that all analytics related to the business, product, event type, and cause were relevant for the business. Also, some analytics were identified to be non-value adding specifically the trend of the number of risk events and loss amount and should be removed in the next iteration. Further improvement in the design interface of the analytics system will also be implemented to improve user experience. Lastly, there should be flexibility in the data coverage, hence date slicer will be added in the next iteration.

3.2 System Evaluation Second Iteration

In the second version of the analytics system there were more visuals added that aimed to provide more insights to stakeholders. The new version includes visuals that answers all analytics questions identified.

A total of four focus group discussions were held with multiple stakeholders around the globe which was the first roll out of the analytics system to other businesses in the selected group. Similar to the first system evaluation, the objective of the focus group discussions was to identify relevant insights useful for their risk management discussions and gather feedback for further system improvement.

The overall design uplift of the analytics interface was liked by the stakeholder and commended the tile slicers for the business and products which makes navigation easier. Divisional risk lead of ABC approved the new version of the system which can already be used in the monthly risk forums. The first use-case was as a self-service tool to determine relevant risk events for inclusion in the monthly business risk forums. Other use-cases are yet to be identified by other business stakeholders based on the analytics available in the system. New version was endorsed to be rolled out to other divisions in the selected group. Thus, the researcher requested from the other two divisional risk leads initially identified to nominate individuals who can explore the new External Operational Risk Intelligence System. A total of four risk managers were nominated across ANZ, Asia, EMEA, and Americas regions and in different divisions.

Overall outcome of the focus group discussions was positive with the intent to use the analytics from the system into multiple risk reporting in various businesses in the group. All charts providing insights related to the analytics questions presented were considered meaningful, hence will be retained in the system. A common challenge raised was the comparability to the business structure but mapping data using business and product filters can be used as a solution. Additional features like the detailed view of risk event information and short list of risk events were found to be pertinent for the stakeholders. Several enhancements in the slicers are also necessary to provide more flexibility to users to slice and dice data. Lastly, minimal enhancements on the user interface like renaming of the field title and resizing of visuals are needed for better user experience.

3.3 System Evaluation Third Iteration

Some analytics experts from a globally recognized academic institution reviewed the analytics system presented by the researcher. The implementation was commended with a few revisions recommended on the analytics system. First recommendation was the implementation of a correlative chart or analysis and additional drill down features. It was emphasized by the analytics expert the importance of presenting all possible analysis to the business as part of the developer's role. Second recommendation was to correct the implementation of drill through in the analytics system. Drill through functionality should be able to provide users a different perspective of data rather than the details only. Therefore, additional visuals and pages will be added in the next system development iteration.

3.4 System Evaluation Fourth Iteration

In the fourth system evaluation two of the previously selected focus group discussion participants were involved in the evaluation because most of the change requests came from the FMR and ADV risk managers.

Overall, the fourth version of the system is considered more useful and meaningful for the business that can already be used in risk-related activities and discussions. It contains all relevant visuals useful for the business to derive meaningful external operational risk insights. Further, all the necessary slicers that will help the business customize data at a granular level were made available on the fourth version of the system. Lastly, the navigation techniques implemented like drill through and drill down provided an overall better user experience.

4. CONCLUSIONS

The selected group for the study has the most diverse set of businesses and products in the financial institution and requires stringent oversight to better manage risks. However, there was a little oversight on external operational risks and heavily relied on learning from internal risk events. To address one of the problems cited in the study and to become a more operationally resilient business, the development of an analytics system helped bring external operational risk data from a globally recognized reliable platform to the institution. Also, the first objective of the study was met through the extraction of a full dataset of operational risk events from the RMS platform in CSV format that is loaded into the analytics system. The dataset contains significant data like risk event loss amount, causes of risk events, different event types, and business and product categories. The dataset forms the target dataset of the study used for the knowledge discovery process and supports the institution to learn from external sources. Furthermore, the second objective of the study was met through implementation of data clean-up and other data transformations in the analytics system to maximize the usability and produce an accurate result for the risk intelligence.

It is empirical today for financial institutions to explore and maximize the application of analytics to transition from a traditional risk management to risk intelligence. Studies have shown that many risk professionals look to develop more sophisticated tools to effectively manage operational risks in a rapidly changing environment. However, another problem identified in the study and similar to other financial institutions, the selected institution of the study had little awareness and knowledge on how to maximize the use of available external operational risk data. Additionally, expertise on developing analytics systems specifically to analyze external data was not easily accessible within the institution. Thus, to address the problems and to meet the third objective of the study, the researcher stimulated the business need to develop an analytics system in the selected financial institution to help with the operational risk management. Concept of an analytics system was proposed through some analytics questions identified using the target dataset. Multiple system development iterations were performed that included focus group discussions with risk experts to improve the analytics system called "External Operational Risk Intelligence System". The last objective of the study, which is the interpretation and evaluation of the analytics system, was performed multiple times as part of the iterations to refine insights that can be presented by the business. It was found that the system can be utilized and supplement internal operational risk analytics for several business risk discussions.

The most prevalent insights identified by risk experts during focus group discussions are related to the business, product, event types, and causes. Secondary dimensions are the insights related to the taxonomy, region, and industry sector. However, the analytics system can be further improved if a common language between external and internal systems can be established to improve comparability of data. First is the mapping of the business internally which can be accomplished by selecting appropriate business and product data from the external platform. Second is the mapping of the taxonomy internally which can be through the risk event type and cause data from the external platform. Lastly, mapping of entities can be done through the region data from the external platform.

Several insights can be derived from the analytics system by slicing and dicing data with the use of the available filters. There is also drill through functionality which allows users to view data in different perspectives. Once relevant filters are applied in the system, users can interpret visuals by analyzing the trends, correlation of various data points, distribution, or deviation. One significant new knowledge derived from the analytics system was the top causes driving the risk events in the Trading & Sales business each month are Processes and People / Staff. The insight was obtained by filtering business level 1 with Trading & Sales value and analyzing the trend chart for risk events and loss amount per cause.

It is recommended that the analytics system be tested in other financial services or business groups in the selected financial institution like retail banking and asset management. This will further improve the useability of the system to better manage operational risks across all services in the financial industry. Also, this will help financial institutions comply with the regulatory obligations to become a more operationally resilient company. A quantitative way to measure success of managing risk in financial institutions with the help of an external operational risk intelligence system should be defined.

Furthermore, it is recommended to integrate the risk intelligence derived from the external platform into the internal risk analytics systems to obtain a holistic operational risk perspective. Advanced analytics can also be explored to identify significant risk factors that can be used to predict operational risks internally. This will further help financial institutions maximize the use of external data to prevent occurrence of similar risk events internally. It is also recommended to expand external risk perspective by integrating data from other reliable external platforms that may involve mining of unstructured data from the web. It will allow advanced analytics systems to learn better with more data.

5. ACKNOWLEDGMENTS

This study is dedicated to Almighty God, our families and loved ones. Sincere gratitude goes to all the mentors at De La Salle University Manila and the risk experts from the selected financial institution who generously shared invaluable knowledge, expertise, and time for the completion of this research study.

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