Management Support Systems Model for Incident Resolution in FinTech based on Business Intelligence

María Del Carmen Zúñiga[1][a], Walter Fuertes[1][b], Hugo Vera Flores[2][c]
and Theofilos Toulkeridis[1,3][d]

[1]*Department of Computer Sciences, Universidad de las Fuerzas Armadas ESPE, Av. General Rumiñahui S/N, P.O. Box 171 5 231 - B, Sangolquí, Ecuador*
[2]*BI-Solutions, Av. de los Shyris N36-120, Allure Park Building, 170505, Quito, Ecuador*
[3]*Universidad de Especialidades Turísticas UDET, Quito, Ecuador*

Keywords: Business Intelligence, Data Mining, Financial Services, Financial Incident Management, FinTech, Management Support System.

Abstract: Financial technology corporations (FinTech) specialize in the electronic processing of business transactions and compensation of charges and payments. Such operations have a technological platform that connects multiple financial institutions with companies of the public and private sector. In its constant concern for the provision of efficient services, the company created a unit to guarantee the quality and availability of 24x7x365 of its services by granting their clients confidence regarding online-financial environments through high-security timely security standards management of incidents. However, poor management of incident resolution was detected as there are is a lack of tools to monitor transactional behavior or identify anomalies. Consequently, resolution time has been delayed and, therefore, continuity and regular operation of services. In this sense, economic losses are frequent, yet the real loss results in its confidence and reputation. In response to this problematic issue, the current study proposes developing a support model of information management for the appropriate and timely resolution of incidents by analyzing historical information, which allows to detect of anomalies in transactional behavior and improve resolution time of events affecting financial services. The used methodology is ad-hoc and consists of various phases, such as identifying the present situation. Afterward, it builds the solution based on Ralph Kimball and Scrum methodologies and validates its result. With the implementation of the work, the business intelligence model improves incident management by providing indicators for the timely detection of anomalies in financial transactions.

1 INTRODUCTION

With the Internet's initiation, many traditionally developed activities have changed and progressed over time, moving from a manual environment to an electronic environment. A clear example of this development is the financial transactions conducted daily by millions of persons (Gai et al., 2018). Electronic transactions realize the extensive use of technology. However, it requires another element of great importance for its usability, which is trust, being a more challenging issue to build in online environments since transactions are impersonal. The fundamental factor is to promote trust by strengthening the companies' computer systems that provide electronic processing services to feel safe using their digital media or channels. Financial Technology (FinTech), in its constant concern for the effective and efficient provision of its different services, developed a project to mitigate the business's operation risks. Whatever the operational reason, they have a direct effect on the quality and consistency of financial transactions. In this type of financial incident, on several occasions, customers have detected anomalies in the services.

Moreover, since they lack tools to monitor the quality of transactions, the company's personnel use on-demand queries to the database to understand and resolve incidents. This causes poor handling in the resolution of incidents due to the low visibility of indicators that allow monitoring and understanding transactional behavior on time. Even though FinTech

[a] https://orcid.org/0000-0002-2916-2375
[b] https://orcid.org/0000-0001-9427-5766
[c] https://orcid.org/0000-0002-5701-1013
[d] https://orcid.org/0000-0003-1903-7914

Zúñiga, M., Fuertes, W., Flores, H. and Toulkeridis, T.
Management Support Systems Model for Incident Resolution in FinTech based on Business Intelligence.
DOI: 10.5220/0010456402400247
In *Proceedings of the 23rd International Conference on Enterprise Information Systems (ICEIS 2021) - Volume 1*, pages 240-247
ISBN: 978-989-758-509-8

has qualified personnel for incident management, they lack the appropriate tools to monitor service quality. Our research hypothesis establishes that the information management model's implementation will predominantly optimize the resolution times of financial incidents registered in the company.

Our primary research question was: Which information management models have been used to solve financial incident deficiencies? In response, a few proposals are framed in the given research topic. Bedford et al., (Bedford et al., 2005), conceptualize an incident as: "the unplanned interruption of an IT service and the reduction in its quality. Also, the failure of a configuration element that has not yet impacted the service is an incident". Bobyl et al., (Bobyl et al., 2018), promotes the continuous development of controls in order to monitor and evaluate the implemented services. Latrace et al., (Latrache et al., 2015) discusses several crucial business processes based on information technology (IT) services because adverse IT incidents can disrupt the business's daily activities and cause adverse effects, such as loss of customer confidence, productivity, and finances. Serna et al., (Serna et al., 2016), argues that information systems have become a fundamental tool to improve complex decision-making processes' efficiency and effectiveness, particularly those in which quantitative variables and large volumes of data intervene. Farahmand (Farahmand et al., 2003), states that an entity needs to have an effective system capable of identifying, evaluating, and monitoring. These studies demonstrate the industry's concern and the scientific community to reduce or even avoid entirely financial incidents.

Therefore, this study proposes a tool with the necessary elements to achieve the transactional behavior of financial services, intending to improve incident management through BI instruments. The development of a BI solution was proposed within this working framework, consisting of analyzing customer needs, developing and configuring visual reports, creating data warehouses, information cubes, indicators, metrics, dimensions, and control boards. These BI solutions are subject to constant changes which the company experiences, so it remains below development. Agile methodologies offer adequate support for BI project management. However, they need to be supported by their BI methodologies for their design and development.

Furthermore, while a traditional methodology allows modeling the processes that cover BI systems' needs, agile methodologies include managing projects quickly and flexibly. In this way, it is possible to apply these two methodologies in the same project. The most popular agile methodology best adapted to BI project management is Scrum (Schwaber and Sutherland, 2013). Scrum, in conjunction with Ralph Kimball's dimensional modeling method (Kimball and Ross, 2011), was used for the development of the solution. Therefore, this research's main contribution is to favor the country's financial sector by developing a tailored system that allows visualizing the status of transactions over time. Hereby, the user can identify variations, which demonstrate the service quality's degradation and allows FinTech to act on time to detect anomalies and resolution of interruptions.

The remainder of the article is organized as follows: Section 2 describes the theoretical framework necessary to obtain a suitable foundation for implementing the solution. Section 3 explains the solution design. Section 4 presents the evaluation of the results. Finally, section 5 contains the conclusions and lines of future work.

2 BACKGROUND

2.1 Business Intelligence (BI)

According to (Ayoubi and Aljawarneh, 2018), BI is an interactive process that explores and analyzes structured information about an area and discovers trends or patterns to derive ideas and draw conclusions. Méndez del Río defines BI as a set of tools and applications to aid decision-making, enabling interactive access, analysis, and multiplication of mission-critical corporate information. These applications provide valuable knowledge about operational information by identifying business problems and opportunities. Users can access large amounts of information in order to establish and analyze relationships and understand trends that will ultimately support business decisions (D'Arconte, 2018). Based on the definitions mentioned earlier, BI is a set of processes that facilitate data integration from various systems, whether internal or external, to facilitate the analysis and interpretation of information through visualization tools to support decision-making and knowledge generation.

Within this context, **information sources** are those where an organization's operational data are recorded. Depending on their origin, they can be internal or external sources, such as **Operational or transactional systems**, including custom-developed applications such as ERP, CRM, and SCM; **Departmental information systems**, which includes forecasts, budgets, spreadsheets, among others; **External information sources**, in some cases purchased from third parties. They are essential to enrich the information about customers.

Additionally, the **Extract, Transform and Load (ETL)** process is responsible for the recovery of data from information sources to strengthen the data warehouse. The ETL process is divided into five subprocesses (Hahn, 2019): **Extraction**, which physically retrieves the data from different information sources. The raw data are available at this time. **Cleanup**, which recovers the raw data and checks its quality, removes duplicates, and, where possible, fixes erroneous values and fills in empty values. In other words, the data are transformed whenever possible in order to reduce loading errors. Hereby, clean and quality data are available. **Transformation**, which retrieves clean, high-quality data and structures, summarizes it in the different analysis models. The result of this process is obtaining clean, consistent, summarized, and useful data. **Integration**, which validates that the data loaded into the data warehouse is consistent with the definitions and formats. It also integrates them into the several models of the different business areas which have been defined through them—finally, **Actualization**, which allows adding the new data to the data warehouse.

2.2 Financial Technology (FinTech)

FinTech has become a common term in the financial industry that describes novel technologies adopted by financial service companies (Gai et al., 2018). We selected FinTech as it specializes in the electronic transfer of funds and information through its products and services for the financial sector. One of its products is the collection and payment service. Due to the variety and complexity of configurations, it is the service that inspired the current study, with the certainty that it will form the basis for future developments in other FinTech services. The interbank collection and payment network allows a financial institution to connect to collection companies through the technological platform, supporting its clients to proceed with their financial contributions. The collection may be realized online and back office.

We consider that **the service indicators** allow knowing the transactionality of financial institutions and their percentage of participation in the interbank network. Below are the service indicators for the collection and payment network: a) Status, which allows knowing the status of transactions (i.e., successful or rejected). b) Response, which allows knowing the reasons why a transaction presents a specific status (e.g., successful, invalid password, funds not available, the client does not exist, destination not available, external decline, etcetera.); and, c) Channel, which refers to the client's channel to conduct their contribution: virtual channel, window.

2.3 Methodologies for the Design and Development of the Solution

Companies need to innovate their way of responding to changes' demands based on constant technological developments. Within this context, agile methodologies appear as a set of working ways oriented towards a dynamic execution that seeks to promote adaptation to change and obtain positive results (Schwaber and Sutherland, 2013). Agile methodologies are based on people and their interactions. They allow adapting the way of working to the project's conditions to manage them flexibly, safely, and efficiently, reduce costs, and increase productivity (Alliance, 2016).

Within this working framework, the development of a BI solution was proposed to analyze the clients' needs, developing and configuring visual reports by creating data warehouses, information cubes, screens, indicators, metrics, and dimensions. Agile methodologies offer support for BI project management. However, they need to be supported by their BI methodologies for their design and development.

Furthermore, while a traditional methodology allows modeling the processes that cover BI systems' needs, agile methodologies encompass methods for managing projects quickly and flexibly, so it is possible to apply these two methodologies in the same draft. The most popular agile methodology best adapted to BI project management is Scrum (Schwaber and Sutherland, 2013). Scrum allows partial and regular deliveries of the final product, prioritized by the benefit they bring to the project client. Scrum is designed for projects in complex environments, where it is required to obtain results quickly, while the requirements are changing, innovation, competitiveness, flexibility, and productivity are fundamental (Malik et al., 2019).

In conjunction with Scrum, Ralph Kimball's dimensional modeling method (Kimball and Ross, 2011)(Macas et al., 2017) was used to develop the solution. This method, also calls the Dimensional Life Cycle of the Business, includes the definition of the technical architecture, the physical design of the database and ETL, and the definition and development of the application. The final phase of deployment allows the application to be available to users for evaluation and production. This cycle is based on four basic principles (Nugra et al., 2016), are focus on the business, building an adequate information infrastructure. At this point, all the necessary elements are provided in order to deliver value to business users. Kimball proposes a method that facilitates simplifying the complexity of the development of Data Warehouse solutions (Kimball and Ross, 2011).

3 RESEARCH DESIGN

3.1 Definition of Roles, Analysis of Data Sources and Definition of Indicators and Metrics

For the development of the solution, three resources were included: Operations Coordinator, Scrum Specialist, and BI Developer. The Product Owner collected user stories and acceptance criteria for each one of them, which became the input to define and write the Product Backlog elements.

Product Backlog collects the requirements to form the product. Instead, the Product Owner is responsible for compiling this list. Based on the business's needs, in the Sprint Planning, it was established that the system is developed in three Sprints, being the user stories with high priority to those which are contemplated in the first instance.

In the Sprint Backlog, the requirements to be developed for the system were specified. In the first Sprint, the initial information gathering tasks were planned, considered essential for proper development. This required the active participation of the Product Owner and the commitment to manage the access and delivery of relevant data to develop the UP Collections and Payments data mart. Table 1 demonstrates the pending list for each Sprint.

Table 1: List of pending of each Sprint.

Sprint	Activities
1	Data source identification and analysis
1	Definition of management indicators
1	Physical design of DSA data model
1	Physical design of DWH data model
1	DSA and DWH database creation
1	Report model generation (prototype)
2	Design and development of ETLs
2	Create attributes, metrics and cubes
2	Dashboards development for monitoring
3	Channel dashboard development
3	Dev. of transaction response dashboards
3	Creation and setup of the autoload job
3	Incremental bucket loads
3	User testing and tuning
3	Go into production

In this phase of development, we identified the data source analysis, which will constitute the data warehouse construction input. The Financial Services Company has a transactional system developed under Oracle database, Oracle Developer, and Oracle Application.

The Key Performance Indicators (KPIs) are metrics that help identify a specific action or strategy's performance regarding the definition of indicators and metrics. It is possible to identify performance based on the objectives set previously (Midor et al., 2020). For FinTech, the objectives set for monitoring the quality of services are established by the total number of transactions and the transaction status. Therefore, the indicators that they request to analyze for the Collections and Payments Service are Total transactions by Merchant, transactions by Financial institution, transactions by Status, transactions by collection channels, transactions per Transaction response, transactions by type of transaction.

3.2 Physical Model of the Data Staging Area and Data Warehouse

The first step was to design the intermediate layer between the source system and the Data Warehouse (DWH), called Data Staging Area.

Data Staging Area (DSA): The DSA is the central layer that served as storage between the source system and the DWH. It allows managing the data with the origin's structure to facilitate the DWH's denormalized model's integration and transformation. The created structures contain identical fields from the catalogs and transactional table of the data source.

Data Warehouse (DWH): Its function is more complicated than a data warehouse. It is composed of *Dimensions*: Dimensional modeling allowing to contextualize the facts by adding different analysis perspectives. A dimension contains a series of attributes or characteristics through which we can group and filter the data. *Tables of Facts*: Facts are composed of the details of the process; this means that they contain numerical data and measurements (metrics) of the business being analyzed. The technique used to perform the dimensional modeling of the current study is the star model. It is composed of a central fact table called DW_HEC_TRANSACCIONES_COBROS, which is connected through relationships to the dimension tables.

3.2.1 Sprint 1: Prototype Design and Implementation

We developed a prototype that allows users to validate the solution's usability. The technique used was

”visual design,” which consists of the design of the GUI. For this purpose, we created an information cube whose data source was an Excel file with fictitious data. We used the visualization tool available at FinTech.

3.2.2 Sprint 2: ETL Design and Development

The ETL process starts with the DSA tables’ truncation, followed by the transactional system’s data extraction. They are placed in the DSA in order to perform the transformation and cleaning process. Then, they are stored in the data warehouse. In order to perform such a step, we used SQL Server Integration Services (SISS). A SISS package is a work unit in which the elements which participate in the ETL process are created. These elements may be of two types:

- *Control Flows*: They are the program flow control structures. They indicate the sequence with which the ETL elements need to be executed.;
- *Data Flow*: Also known as the stored procedure (SP), which allows defining the start of the load.

The first step in the ETL process is to create a project in Microsoft Visual Studio called pqt_ETL. As the next step, we need to create the data connections to the source, DSA, and DWH. Then, we proceeded with creating the SQL task to truncate all the tables in the DSA to clean them to receive the information from the source. To comply with such intention, we drag the ”Execute SQL Task” object and type the truncation SQL statement.

The elements for the extraction of data from the source tables to the DSA are created one by one using the ”Data Flow Task” object. In this object, we need to configure both the data source and the destination. Once the data extraction is realized, the next step is the cleaning, integrity validation, consolidation, and uploading of the data to the DWH.

3.2.3 Creation of Attributes, Metrics, and Smart Cubes

This task starts with the attributes creation of the dimensions, the relationship between them, and the definition of business indicators, where the relationship of the logical layer and its equivalents in the physical layer is established, i.e., tables and fields of the database.

- *Creation of Attributes*: Attributes in Microstrategy are associated with an ID and a description for their Creation;
- *Creation of Facts*: Facts are values by which the business will be analyzed. For the present study, the facts are the number of transactions, transaction amount, commission, number of approved transactions, and rejected transactions. The facts will be used to create the metrics, which will be the elements and attributes for creating the Smart Cube. In the menu Šcheme objectsïn the Facts folder, the metrics are created. The indicators are then created in the ”Public objects” menu. In this step, we need to specify the mathematical operation that will be applied to the event.
- *Creation of Smart Cubes*: In Microstrategy, a dimensional cube (dataset) allows OLAP Services functions in reports and documents, reducing access to the data warehouse.

3.2.4 Development of Dashboards for SP Monitoring and Transaction Status

In this phase, we performed the reports and dashboard development containing the attributes and indicators implemented in the previous section. Also, detailed reports were generated that will be used in order to analyze the transactional behavior of UP’s collection and payment network. The deliverable’s objective was to provide dashboards for the Service Quality Sub-Process to identify the trend of rejection of transactions and unusual increases that may affect UP services. Hereby, a dashboard was provided for the Operations Coordinator to view details such as graphs of total transactions, approved and rejected transactions, annual, monthly, daily amounts, and market share percentages. Next, in Fig. 1 and 2, the developed dashboards are presented:

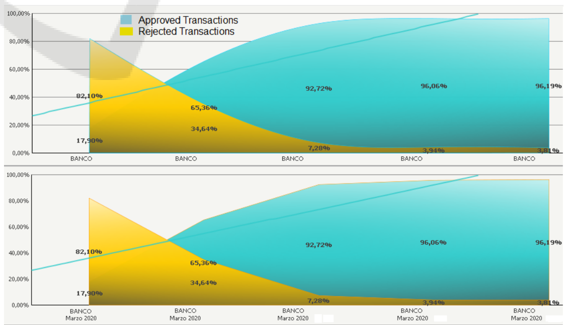

Figure 1: Dashboards Sprint 2.

3.3 Sprint 3: Sprint Goal Development

The results obtained with this Sprint’s execution were: (1) Development of two dashboards that allow to identify the channels with the highest collection of the different types of transaction and visualize the responses, which generate the transaction’s rejec-

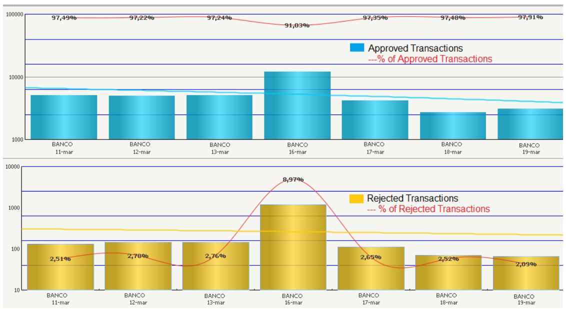

Figure 2: Dashboards Sprint 2.

tion. This analysis will allow the quality area to notify the Account Executive of the news presented for resolution. (2) Creation and configuration of the automatic loading Jobs of both the DWH and Microstrategy cube, i.e., put into production. (3) Conduction of the final tests and completion with the movement towards production.

3.3.1 Channel Dashboard Development and Transaction Response

In this deliverable, we developed the dashboard to identify the channels with the highest collection, classified by type of transaction (i.e., consultation, payments, and reversals). Likewise, the transaction response dashboard was developed, displaying the incidence of error response codes issued by the collecting institution. It should be noted that before the implementation of this study, there were no reports on collection by channel and details of response codes. The tool provides clear and concise information on the channels with the highest collection, recurrence, and error codes, elements which allow the Company to pursue the correct decisions to mitigate errors in the transaction responses and emphasize the use of digital channels. Figure 3 illustrates the dashboards developed:

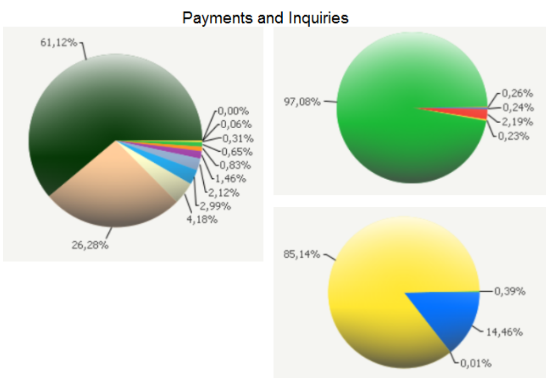

Figure 3: Dashboards Sprint 3.

3.4 Creation of Load of Jobs

In this phase, the package was published in the System Integration of SLQ Server (Server, 2020), and we created the daily extraction job below the following criteria: *Daily ETL execution*: This was necessary to extract the information based on the accounting date of the previous day. Also, we performed the configuration of notifications of success or failure for the ETL and smart cube in Microstrategy. *Incremental Bucket Loads*: It consists of performing the incremental loads of the historical data of the transactional table of the data source. *User Testing*: In order to ensure that the solution is quality-driven, certification tests were conducted with the Product Owner to gain user acceptance. *Transfer to Production*: This activity consisted of publishing the developed dashboards in the production environment and granting permissions to the users created for this purpose. *User training*: With the launch of the product, the user training for the correct practice of the product was finally performed, with relative success.

In summary, Figure 4 represents the complete deployment cycle of model implementation. As previously explained, it starts with collecting user stories and prioritization to obtain the product backlog. The dimensional model's development follows the interaction of one to three of the sprints to finally execute the model's implementation.

4 EVALUATION OF RESULTS

4.1 Comprehensive Daily Monitoring

The Comprehensive Monitoring dashboard allows users to observe the percentage of the number of approved and rejected transactions, supporting FinTech collaborators to identify unusual increases per day by financial institutions and businesses to realize immediate action. Fig. 5 indicates the daily comprehensive monitoring dashboard.

4.2 Rejected Transactions

Figure 6 illustrates the rejected transactions according to each month's collections during the year 2019 until May 2020. The rejections registered in 2019 tend not to present more significant variability. Even though a growing trend is visible as of July, reaching its peak in December with 402,025 rejected transactions compared to only about 209,631 in January of the same year. This means that the actions given to the causes

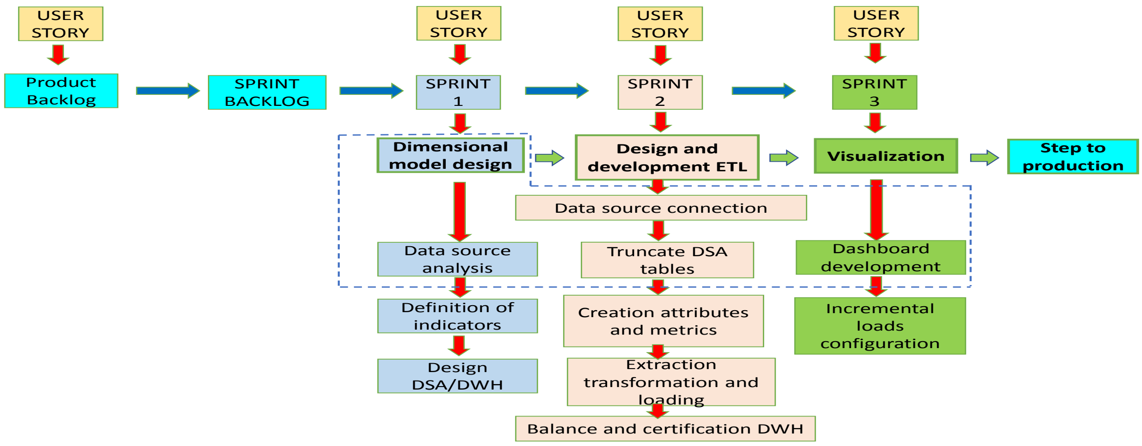

Figure 4: A complete deployment cycle of model implementation.

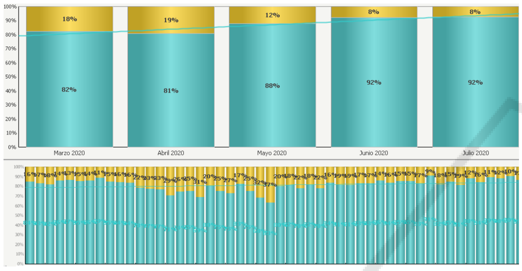

Figure 5: Daily Comprehensive Monitoring Dashboard.

which generated these rejections were not enough to reduce this behavior.

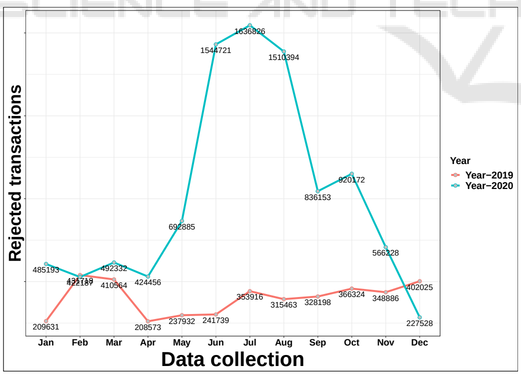

Figure 6: Dashboard of rejected transactions.

Contrarily, in the year 2020, significant variability in the data is visualized since it presents a significant growth, from May (692,885) to July, which reaches the highest value of about 1'636,826. This is due to the pandemic confinement, as the use of online collection services increased drastically. The analysis of transactional behavior through the application dashboards allowed us to deduce the outstanding contribution to take actions and mitigate the causes that motivated this increase.

4.3 Return of Investment (ROI)

Considering that the present study was developed on the existing infrastructure in FinTech, the ROI was focused on the development and implementation costs of the software solution and the quantification of the benefits in two years. For this purpose, in principle, the hourly rate that the collaborators involved in the BI project invest monthly was established, whose function was to analyze information to manage incidents related to the Collections and Payments service quality.

Specifically, the total monthly hours each team member would use to generate the indicators and analysis to manage the quality improvement of the services were considered, such as Operations Leader, Operations Coordinator, BI Coordinator, Coordinator of Quality, summing up of about 1,143.75 USD. This work's implementation costs are included, such as External Consulting for 8,000 USD and Development for 6,000 USD. Besides, implementing a BI project requires resources, both for the implementation phase and the solution's maintenance (operation). The BI coordinator's proportional value is considered the main item for the operation; this meant that the costs related to maintenance amounted to a total of about 600 USD.

In order to deliver a benefit value as close as possible to the national reality, the calculation was performed considering macroeconomic figures such as inflation and active interest rate. As of January 2020, the central bank records an active interest rate of 9.14%, while inflation is recorded at 0.23%. Therefore, a discount rate of 9.4% is estimated. With these inputs, the discount rate was calculated at 9.4%. Figure 7 demonstrates the cost/benefit behavior for two years and reveals the investment's profitability. Additionally, it indicates that during the first year, the project's costs are higher than the benefits, which means that person-hours were lacked to be used efficiently. However, this behavior changes from the breakeven point, where the costs are approximate 14,982 (USD), and the benefits are 15,946.4 (USD). Therefore, the lower the investment costs, the greater the benefit obtained for the project. We deduced that person-hours are better used to analyze information based on the implemented model with these results.

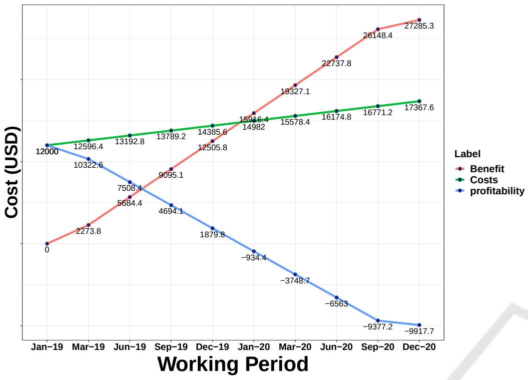

Figure 7: The behavior of cost/benefit and ROI.

5 CONCLUSIONS

The present study focused on implementing a BI system with the necessary elements to achieve the transactional behavior of financial services visible, intending to improve incident management through BI instruments. Hereby, management indicators were identified, which allowed us to evaluate, understand, and value transactional behaviors and trends through a graphic representation. This resulted in a useful tool that provides insights for employees who need to manage anomaly detection and resolution. The system's implementation was able to be delivered in a shorter time since the agile methodology for project management Scrum was used combined with Kimbal's dimensional modeling methodology, allowing collaborators to hold a support tool for managing their work. As future work, a new version's deployment is planned to take competitive advantages that these platforms provide, such as data streaming and massive queries.

REFERENCES

Alliance, S. (2016). Learn about scrum. *Saatavissa: https://www. scrumalliance. org/why-scrum [Viitattu 9.7. 2016].*

Ayoubi, E. and Aljawarneh, S. (2018). Challenges and opportunities of adopting business intelligence in smes: collaborative model. In *Proceedings of the First International Conference on Data Science, E-learning and Information Systems*, pages 1–5.

Bedford, P., Millard, S., and Yang, J. (2005). Analysing the impact of operational incidents in large-value payment systems: A simulation approach. *Liquidity, Risks and Speed in Payment and Settlement Systems–A Simulation Approach*, pages 247–74.

Bobyl, V. V., Dron, M. A., and Taranenko, A. (2018). Operational risks: Assessment and ways of mitigation.

D'Arconte, C. (2018). Business intelligence applied in small size for profit companies. *Procedia computer science*, 131:45–57.

Farahmand, F., Navathe, S. B., Enslow, P. H., and Sharp, G. P. (2003). Managing vulnerabilities of information systems to security incidents. In *Proceedings of the 5th international conference on Electronic commerce*, pages 348–354.

Gai, K., Qiu, M., and Sun, X. (2018). A survey on fintech. *Journal of Network and Computer Applications*, 103:262 – 273.

Hahn, S. M. L. (2019). Analysis of existing concepts of optimization of etl-processes. In *Computer Science On-line Conference*, pages 62–76. Springer.

Kimball, R. and Ross, M. (2011). *The data warehouse toolkit: the complete guide to dimensional modeling.* John Wiley & Sons.

Latrache, A., Nfaoui, E. H., and Boumhidi, J. (2015). Multi agent based incident management system according to itil. In *2015 Intelligent Systems and Computer Vision (ISCV)*, pages 1–7.

Macas, M., Lagla, L., Fuertes, W., Guerrero, G., and Toulkeridis, T. (2017). Data mining model in the discovery of trends and patterns of intruder attacks on the data network as a public-sector innovation. In *2017 Fourth International Conference on eDemocracy & eGovernment (ICEDEG)*, pages 55–62. IEEE.

Malik, Z. H., Farzand, H., Ahmad, M., and Ashraf, A. (2019). Tour de force: A software process model for academics. In *Intelligent Computing-Proceedings of the Computing Conference*, pages 885–901. Springer.

Midor, K., Sujová, E., Cierna, H., Zarebinska, D., and Kaniak, W. (2020). Key performance indicators (kpis) as a tool to improve product quality. *New Trends in Production Engineering*, 3(1):347–354.

Nugra, H., Abad, A., Fuertes, W., Galarraga, F., Aules, H., Villacis, C., and Toulkeridis, T. (2016). A low-cost iot application for the urban traffic of vehicles, based on wireless sensors using gsm technology. In *2016 IEEE/ACM 20th International Symposium on Distributed Simulation and Real Time Applications (DS-RT)*, pages 161–169.

Schwaber, K. and Sutherland, J. (2013). The scrum guide: The definitive guide to scrum: The rules of the game.(2011). *Available: scrum. org*.

Serna, M. A. A., Arias, J., Gómez, J., Lopera, F., and Arbeláez, L. (2016). Information system for the quantification of operational risk in financial institutions. In *2016 11th Iberian Conference on Information Systems and Technologies (CISTI)*, pages 1–7.

Server, G. S. (2020). Sql server integration services.