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Concentrix Corporation: Analytics TO Audit claims in customer management services

Shylu John, Pradeep Kartha, Raghavendra Graghu, and Professor Bhavin Shah wrote this case solely to provide material for class discussion. The authors do not intend to illustrate either effective or ineffective handling of a managerial situation. The authors may have disguised certain names and other identifying information to protect confidentiality.

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Ann Daveigh was hired by Concentrix Corporation (CNX) in January 2019 as global manager of customer service. The company provided technology-enabled global business services, which included customer service support. Daveigh was responsible for leading and managing operations of a new engagement with RiCar Technologies Co. (RiCar), a multi-national technology company that provided service in ride-hailing or sharing. During an assessment in June 2019, Daveigh observed that there were a number of irregularities associated with credit claims issued by CNX agents for RiCar’s drivers. Daveigh suspected that many of the irregularities were intentionally false claims made by CNX’s agents. A set of guidelines and procedures to detect irregularities were in place, but these appeared to be ineffective in stopping agents’ suspicious activities. Random transaction audits had a low capture rate, so they had been ineffective in capturing the irregularities. Daveigh’s immediate challenge was to reduce irregularities in the customer service operation. To do that, she needed a process for selecting transactions for audit, which would capture more irregularities with minimum operational cost.

Cnx AND Ricar Engagement

CNX, a subsidiary of Synnex Corporation, was a technology-enabled global business services company that specialized in customer engagement and improving business performance. CNX partnered with more than 50 Fortune 500 clients and several unicorn companies and disruptors. It serviced its partners in more than 60 languages. The company had a global annual revenue of US$4.7 billion[[1]](#footnote-1) in 2019. Its vision was to be the greatest customer management services company in the world, rich in diversity and talent. It emphasized innovation, agility, and conducting its business securely. Operational risk and compliance were of utmost importance to both CNX and its partners.

RiCar partnered with CNX to establish customer management services to process credit claims requests that operated out of multiple locations. RiCar’s drivers would call CNX agents to open a case file for the credit of trips they had completed. CNX operated from the Philippines and employed more than 500 full-time agents responsible for servicing RiCar’s employees—cab drivers—in countries such as the United States, United Kingdom, Australia, New Zealand, and Brazil.

CUSTOMER MANAGEMENT SERVICES

CNX’s agents were expected to process claims for RiCar’s cab drivers for a fixed amount of time that ranged from 8.5–9.5 hours every working day.[[2]](#footnote-2) The agents were trained to use a workflow that detailed how to handle a problem brought forth by a customer. After the agents completed classroom training, they were responsible for answering customers’ enquiries. During the initial phase, agents applied their classroom training to live interactions with the customer at the delivery centre. This phase lasted up to a month for a quick learner and up to three months for slower learners. If the agent’s performance was satisfactory, they were moved to operations. Multiple teams within operations were responsible for handling generic enquiries and enquiries that required specialized knowledge.

Daveigh, being a global manager, led multiple team leaders who were each responsible for their team’s performance. The team’s performance was measured using parameters that were critical to the client. At the end of every month, these parameters were computed for each agent and a final rating derived for the month. These ratings determined the monthly incentives given to agents. The monthly incentives could increase monthly take-home pay by as little as 5 per cent for the agents who were performing just satisfactorily to as much as 20 per cent for agents who were performing very well. Hence, the incentives motivated the agents to perform well every month. However, it was not possible to do well all the time and there could be occasional dips in performance. These dips in performance led to lower incentives for those months, and some agents might indulge in unfair means to make up for the reduction in income.

During the initial set up, Daveigh and her team put several control mechanisms in place to avoid agent non-compliant activities within delivery centres. Online training programs were conducted to inculcate the right set of values among agents. After training, agents were required to answer a minimum number of questions correctly to be considered eligible for working within the delivery centres. Refresher training was also conducted at regular intervals to reinforce the message of zero tolerance for inappropriate behaviour. In addition to training, a whistle-blower program encouraged agents to report any wrongdoings they witnessed at the workplace. Agents who were not comfortable disclosing such information could report anonymously. The team leaders also talked to the agents regularly about the importance of being compliant and not indulging in behaviour that could adversely affect CNX’s reputation.

Irregularities in CUSTOMER MANAGEMENT SERVICES OPERATIONs

In June 2019, Daveigh conducted a detailed vulnerability assessment with the quality assurance team to determine opportunities for improving areas of service offered by CNX to RiCar. One area of examination was the typical flow adopted for credit claim processes (see Exhibit 1), which resulted in identifying a few weaknesses. A customer service agent with an in-depth understanding of the system was found to have exploited the process loopholes and gained an unfair advantage in the monthly incentive scheme. Preventing such incidents was important to avoid putting CNX’s reputation at stake. Hence, identifying high-risk transactions for further audit was necessary so an effective solution could be identified to credibly deter the behaviour. A good solution would be to discourage potential manipulation by agents who were likely to indulge in such behaviour due to fear of being caught.

The initial assessment was performed on 690 randomly selected transactions and the observed irregularities were tabulated (see Exhibit 2): 5.51 per cent of the records had transactional defects and 13.48 per cent had procedural errors; 81.01 per cent of the audited transactions did not have any errors. The observed irregularities fell into six general categories.

Same Agent Issued Credit Twice

RiCar’s drivers would sometimes be eligible for a credit for trips they had completed, and they would call customer service to make their case for the credit. The CNX agent handling the call would then have to decide whether the scenario met the stipulated guidelines. If all the conditions that made a particular transaction eligible for a credit were fulfilled, the agent processed the credit for the driver.

Although there was nothing wrong with processing a credit in cases where the credit was required, the problem was that a few agents (nearly 1 per cent of the total number of agents) processed a credit more than once for the same transaction. The agent may have done this expecting that the caller, when contacted for feedback regarding their interaction with the agent, would provide a high rating for the agent. Agents with higher ratings from their callers received higher incentives at the end of the month, which further lured other agents to perpetrate fraud.

A random audit of transactions revealed that 0.43 per cent of the transactions had cases where two or more credits had been processed by an agent for the same claim.

Larger Value Credit

One of the lapses agents made was to issue credits for value greater than the actual amount incurred. If a certain transaction was eligible for a credit, then the amount for which the credit was processed was usually also stipulated in the guidelines—guidelines that the agents were expected to adhere to. However, on occasion, CNX’s customer service agent would vary from the guidelines and issue a credit of higher value. The reviewers expected that this was usually done for customer gratification with the hope that the caller, when contacted for a feedback on their interaction with the agent, would provide a higher customer satisfaction survey score.

A random audit of transactions revealed that 1.01 per cent of the transactions involved processing credits of larger value.

Issuing Credit When Not Eligible

Another irregularity observed in the credit issuance process involved issuing credit to RiCar’s drivers when their claim for credit was not justified. Reviewing transaction details revealed that agents had issued credit when according to the guidelines, the credit ought not to have been issued. Nevertheless, the customer service agent would process a credit, again likely to please the caller. This was in violation of the guidelines but was probably done with the hope of achieving higher customer satisfaction survey scores.

A random audit of transactions revealed that 1.3 per cent of the transactions involved processing credits even though the caller was not eligible.

Second Agent Issuing Second Credit

In this situation, a customer eligible for a credit would be issued the appropriate credit by CNX’s agent, but the customer would then call again and speak to a second agent to ensure that the credit had been applied. According to protocol, the agent should first confirm whether the credit had already been applied. Assuming the credit had been applied, the customer care agent should then inform the caller so. However, likely in a bid to please the caller, the agent would extend a second credit for the same transaction. Effectively, the caller became the beneficiary of two separate credits for the same transaction. As with the previous erroneous transactions, the second agent was likely driven to give the second credit in the hope that if the caller was surveyed for their feedback on the interaction, the caller would rate the customer care agent’s performance highly, and, again, this would mean better incentives at the end of the month.

A random audit of transactions revealed that 2.75 per cent of the transactions involved a second agent issuing a second credit for a claim that had already been resolved with a previous credit.

Divert Credit to Self

In addition to the cases described so far, there was also the potential for a CNX agent to create an account for themselves and divert a credit to that account. This type of behaviour could be particularly damaging for the organization’s reputation. Although this occurrence was extremely rare—no such cases were identified in the random audit—all precautions had to be taken to ensure that this did not happen.

Procedural Error

It was possible for an agent to process a duplicate credit inadvertently, making the second credit an erroneous transaction that had to be reversed. The review uncovered scenarios where an agent had processed more than two credits for the same customer on the same day, but only an audit of those transactions could reveal the reasons for the erroneous credits. Transactions that were processed with an intent to deceive needed to be identified and separated from the large volume of approximately 50,000 total transactions per month, processed across three main geographies. The assessment indicated that 13.48 per cent of the audited transactions involved duplicate credits that were issued inadvertently.

By reorganizing the type of irregularities with the severity of the issue, a solution was designed to reduce the percentage of irregularities attributed mainly to agent fraud, which could lead to revenue loss for the client and a bad reputation for CNX.

AnaLYTical approach

Daveigh contacted CNX’s analytics team for help. The task was to work within the limitations of the available data to identify a solution that would lead to a new process. The choice of analytical approach included supervised,[[3]](#footnote-3) unsupervised,[[4]](#footnote-4) and rule-based.[[5]](#footnote-5) After careful consideration, a rule-based detection mechanism was chosen to identify irregularities in the credit transactions. The rules were formulated based on the experience, intuition, and domain knowledge of an expert. Usually, the rules were implemented in the form of conditional flows that described the previously detected fraud patterns.[[6]](#footnote-6) When these rules were applied to future transactions, the rules would identify all the transactions that met the criteria specified by the rules; those transactions could then be investigated to overrule any wrongdoing.

Rule-based detection required inputs from an expert or group of experts at regular intervals, followed by an update of the rules. After validation, new rules had to be added, some would have to be removed, and a few would have to be updated to keep them relevant. At the same time, as the number of rules increased, so did the number of transactions selected for audit. The resultant increase in false positives could be discouraging.

Another challenge was that fraudsters could learn the rules by trial and error and consequently devise a way to avoid getting caught. Since a rule-based detection mechanism was based on what had been observed historically, the mechanism would not be able to capture new fraud patterns. For that reason, a rule-based detection mechanism needed to be continuously updated for it to remain effective.

Still, the rule-based detection mechanism was widely used and was an excellent starting point for an organization that aimed to develop a good fraud detection mechanism.

DATA ANALYSIS AND rules

Rules were framed in discussion with subject matter experts and with data analysis of historical transactions for a selected period. Daveigh’s team chose to review transactions from July 2019 and developed a list of variables (see Exhibit 3). Statistical software—SAS® Studio, a web-based development environment[[7]](#footnote-7)—was used for data preparation and variable transformation to generate data for analysis with rules (see student spreadsheet, product number 7B21D012).[[8]](#footnote-8) The rules were as follows:

*Rule1: Single day cut-off for customer–agent combination repeats*. Multiple transactions on a day that had the same description code, agent identification, and value were shortlisted for further audit to ensure that the same person was not issuing credits twice to the same customer. The condition for Rule1 was stated as *Rule1\_Count >1*.

*Rule2: Line of business mismatch*. A rule was created to compare the line of business under which the credit was issued with the line of business that the customer care agent was authorized to handle. A mismatch between the line of businesses and the currency code in data for a transaction would mean that an audit was required to verify whether any irregularity was involved. The condition for Rule2 was stated as *Rule2\_NM=1.*

*Rule3: Matched currency of customer’s country and customer care centre*. A rule was created that compared the currency of the country where the customer care centre was operating with the currency in which the credit was issued. None of the customer care centres serviced clients in the same country, so a match in the currencies would indicate the transaction needed to be further investigated to confirm no wrongdoing. The condition for Rule3 was stated as *Rule3\_M=1*.

*Rule4: Customer eligibility mismatch for refund during wait time*. Another rule to verify whether the customer was eligible for a credit issued under the circumstances was to compare the refund amount for wait time. The wait time charge in the United States and Canada was $5; the wait time charge in other countries was $10. This helped to identify cases where the customer may have been given a credit for gratification. The condition for Rule4 was stated as *Rule4\_Flag=1*.

*Rule5: Flagging transaction values above the estimated threshold*. An upper threshold was set on the credits that were being issued. Based on analysis, credits more than or equal to $40 were flagged for audit to confirm there were no irregularities. The condition for Rule5 was stated as *Rule5\_Range>4*.

*Rule6: Multiple agents issuing credit to the same customer*. Transactions were flagged if the description code and the amount were repeated on the same day to determine whether multiple agents had issued credits to the same customer. The condition for Rule6 was stated as *Rule6\_Count>1*.

*Rule7: Same agent issuing multiple credits to same customer*. All transactions where the same driver and agent identification repeated more than four times in a single day were also flagged for audit since the same agent servicing the same customer so many times in a single day was likely to not be a coincidence. The condition for Rule7 was stated as *Rule7\_Count>4*.

The threshold for each rule was established knowing that as the percentage of transactions queued for an audit increased under each rule, more auditors would be required, increasing the ultimate cost. Also, large audit samples could lead to a large number of false positives or false negatives; a poor, irregular capture rate during a manual audit would result in the auditors losing confidence in the samples chosen for audit. Daveigh developed the rules (Rule1 to Rule7) and their thresholds for a strategy that would select samples for audit that could be managed by a maximum of five auditors, each performing four detailed audits per day.

Daveigh followed a two-stage approach: Stage 1 involved validating the rules, ensuring they would capture the issues; Stage 2 involved conducting the actual audits (see Exhibit 4). The number of transactions varied month by month and day by day, and the number of audits exceeded the permissible sample size for September and November. Also, some rules captured a higher percentage of fraud than other rules during the audit (see Exhibit 5). The fraud defects accuracy obtained during Stage 1 was used to rate the importance of the rules as a means of controlling the operational cost and proposing a new sampling strategy for Stage 2.

**ISSUE RESOLUTION AND NEXT STEP**

After framing the new rules for implementation in Stage 2, the transactions involving credits were extracted every day at the close of business and the rules were run on those transactions to identify and flag the anomalies for audit. The Stage 2 audit results showed that both the percentage of procedural defects and the percentage of identified fraud decreased over the period of three months (see Exhibit 4).

The observed decrease in the percentage of defects was an indication that the rule-based detection mechanism was working well. However, because fraud is an ever-evolving event, a frequently updated strategy to identify new types of fraud with minimum operational cost is always a challenge for Daveigh. Along with the rule-based detection mechanism, an advanced machine learning algorithm (supervised or unsupervised) approach may be adopted.

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EXHIBIT 1: PROCESS FLOW FOR CREDIT CLAIM PROCESS

Is the Customer Eligible?

Is Call about a Credit Request?

Is the Customer Eligible?

Incoming Call from Drivers

Is Credit Amount

$25?

Issue Credit and Close

Handled by Related Process

Inform Customer of Reason and Close Claim File

Transfer Call to Supervisor

Inform Reason and Close

No

No

No

No

Yes

Yes

Yes

Yes

Source: Prepared by the case authors based on company documents.

EXHIBIT 2: DISTRIBUTION OF IRREGULARITIES BASED ON Assessment

|  |  |  |
| --- | --- | --- |
| **Types of Irregularities** | **Number of Transactions** | **Defect (%)** |
| Same agent issues credit twice | 3 | 0.43 |
| Larger value credit | 7 | 1.01 |
| Issuing credit when not eligible | 9 | 1.30 |
| Second agent issuing second credit | 19 | 2.75 |
| Divert credit to self | 0 | 0.00 |
| Procedural error | 93 | 13.48 |
| No irregularity | 559 | 81.01 |

Source: Company documents.

EXHIBIT 3: List of data variables with description

|  |  |  |
| --- | --- | --- |
| **Variable** | **Type** | **Description** |
| Created\_At | Original Variable | Claim ticket creation date |
| Unique\_Id | Original Variable | Unique identification number for each claim ticket |
| Value | Original Variable | Value of claim transaction in $ |
| Agent\_Id | Original Variable | Unique identification number for an agent |
| Rule1\_Count | Derived Variable | Number of transactions an agent processed on same date with similar claim description and value |
| Rule2\_NM | Derived Variable | Mismatch of the line of business and currency code |
| Rule3\_M | Derived Variable | Match of currency code with operation centre |
| Rule4\_Flag | Derived Variable | Flag for description as wait time with value of claim > 5 and 10 |
| Rule5\_Range | Derived Variable | Range of Value < 0 as 0, 0–9 as 1, 10–19 as 2, 20–29 as 3, . . . 100 as 11 |
| Rule6\_Count | Derived Variable | Number of transactions processed on same date with similar claim description and value |
| Rule7\_Count | Derived Variable | Number of transactions an agent processed on same date for same driver |

Source: Company documents.

EXHIBIT 4: summary of audit in stages 1 and 2

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Stage** | **Month** | **Total Number of Records** | **Number of Records Audited** | **% of Records Audited** | **Average No. of Records Audited per Day** | **No. of Auditors Deployed** | **Number of Procedural Defects** | **% of Procedural Defects** | **Number of Fraud Defects** | **% of Fraud Defects** |
| 1 | Sept. 2019 | 32,664 | 700 | 2.1 | 23 | 6 | 674 | 96.3 | 26 | 3.7 |
| Oct. 2019 | 26,667 | 400 | 1.5 | 13 | 3 | 384 | 96.0 | 11 | 2.8 |
| Nov. 2019 | 59,345 | 1989 | 3.4 | 66 | 16 | 1420 | 71.4 | 8 | 0.4 |
| 2 | Dec. 2019 | 69,201 | 614 | 0.9 | 20 | 5 | 529 | 86.2 | 2 | 0.3 |
| Jan. 2020 | 45,073 | 601 | 1.3 | 20 | 5 | 501 | 83.4 | 0 | 0.0 |
| Feb. 2020 | 24,250 | 556 | 2.3 | 20 | 5 | 485 | 87.2 | 0 | 0.0 |

Source: Company documents.

EXHIBIT 5: ACCURACY OF DEFECTS CAPTURED IN STAGE 1 of the AUDIT

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Month (2019)** | **Rule1** | **Rule2** | **Rule3** | **Rule4** | **Rule5** | **Rule6** | **Rule7** |
|  | Procedural Defects (%) | | | | | | |
| September | 97.0 | 46.2 | 33.3 | 100.0 | 99.2 | 100.0 | 96.6 |
| October | 95.7 | 81.3 | 0.0 | 100.0 | 100.0 | 85.3 | 98.1 |
| November | 99.7 | 25.0 | 0.0 | 100.0 | 48.3 | 39.5 | 87.2 |
|  | Fraud Defects (%) | | | | | | |
| September | 3.0 | 53.8 | 66.7 | 0.0 | 0.8 | 0.0 | 3.4 |
| October | 4.3 | 18.8 | 100.0 | 0.0 | 0.0 | 0.0 | 1.9 |
| November | 0.3 | 75.0 | 100.0 | 0.0 | 0.0 | 0.3 | 0.3 |

Source: Company documents.

1. All currency amounts are in US dollars unless otherwise specified. [↑](#footnote-ref-1)
2. Kobalsingam Harishan “India—Legal Working Hours,” Medium, October 16, 2019, https://medium.com/letpublish/india-legal-working-hours-cf5f036afbc. [↑](#footnote-ref-2)
3. Michele Chambers and Thomas W. Dinsmore, “Predictive Analytics Techniques,” chap. 8 in *Advanced Analytics Methodologies: Driving Business Value with Analytics* (Upper Saddle River, NJ: Pearson Education, 2014), 119–147. [↑](#footnote-ref-3)
4. Vikrant Agaskar, Megha Babariya, Shruthi Chandran, and Namrata Giri, “Unsupervised Learning for Credit Card Fraud Detection,” *International Research Journal of Engineering and Technology* 4, no. 3 (2017): 2343–2346. [↑](#footnote-ref-4)
5. Stan C. Kwasny and Kanaan A. Faisal, “Overcoming Limitations of Rule-Based Systems: An Example of a Hybrid Deterministic Parser,” *Konnektionismus in Artificial Intelligence und Kognitionsforschung* 252 (1990): 48–57. [↑](#footnote-ref-5)
6. Jeff King, “Finding the Pattern of Fraud,” Computerworld, January 4, 2002, www.computerworld.com/article/2586520/finding-the-pattern-of-fraud.html. [↑](#footnote-ref-6)
7. “Free SAS® Software for Academic, Noncommercial Use. An Interactive, Online Community. Superior Training and Documentation. And the Analytical Skills You Need to Secure Your Future.,” SAS University Edition, accessed June 18, 2021, https://www.sas.com/en\_in/software/university-edition.html. [↑](#footnote-ref-7)
8. Arthur Li, *Handbook of SAS DATA Step Programming* (Boca Raton, FL: CRC Press, 2013), 275. [↑](#footnote-ref-8)