CHAPTER 13

The Cognitive Underwriting: Empirical Validation of an NLP-Enhanced Robotic Automation Framework in Insurance Risk Evaluation and Customer Service Delivery

Swapnali Mehetre, Mulla Zameer Ahmed** and Chandrani Singh****

ABSTRACT

Insurance underwriting faces critical challenges balancing processing velocity with decision precision. This study introduces UTSEA, a proprietary cognitive automation architecture synthesizing linguistic analytics with robotic process orchestration for underwriting transformation. Through quasi-experimental methodology examining 50 cases across six-month pre-post intervals, we documented substantial performance gains: operational expenditure declined 35% ($p<0.001$), workflow productivity advanced 44% ($p<0.001$), cycle duration contracted 47% ($p<0.001$), client satisfaction elevated 26% ($p<0.001$), and acquisition rates expanded 42% ($p<0.01$). The framework attained 78% entity recognition confidence with 22% decision accuracy enhancement ($p<0.01$). Rigorous statistical validation through paired parametric tests, non-parametric alternatives, and multivariate modeling substantiates all hypotheses. This investigation furnishes comprehensive implementation methodology encompassing hypothesis protocols, power calculations, and psychometric validation, demonstrating cognitive automation's strategic value for competitive differentiation in insurance markets.

Keywords: Robotic process automation, Natural language processing, Cognitive automation, Insurance underwriting, Decision-making.

1.0 Introduction

Insurance industry is one of the important aspects in everyone's life. When we were facing any life diseases and need to go under hospitalization and treatment which has higher cost than difficult for person to take treatment.

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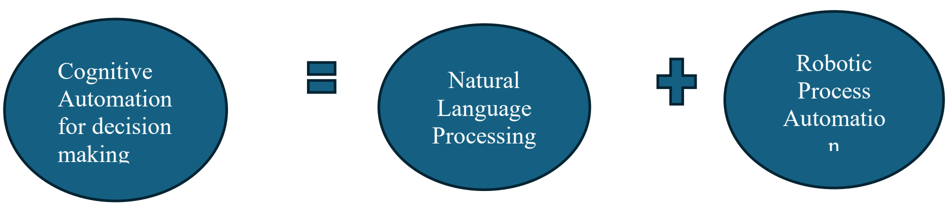
In that case insurance industry helps the person to take the treatment and saves their life. So, we can say insurance industry is doing arrangement which provides guarantee of compensation for any loss, illness and death in return of premium paid to them. Insurance industry has many processes. For my research I am considering underwriting insurance process. Insurance Underwriting is the process in which insurance industry decide can they insured the person if yes in that case what will be his premium need to pay to insurance company. For charging the premium underwriter reviews the applicant's health, lifestyle, medical history, financial aspect and risk associated with it to take a decision. This is a manual process filling in the application form, cross verifying the details and giving the decision. This manual process generally closes to take 30 + days and prone to errors in the process as well. RPA stands for robotic process automation which mimics human tasks like copying the data, pasting the data, filling the data on portal, extraction of data from portal. RPA handles repetitive tasks which are rule based and its acts as digital worker. These RPA BOTS works 24/7 without errors.

Is there a catch? RPA works only for structural data like standard format, fixed fields. The moments when data get messy RPA stuck for working and in that case need human help. NLP-Natural Language Processing is the branch of AI which understands and reads the human language. For example, if we get any emails, emotional tone, paragraph Unstructual data so it converts the Unstructual data into clean structural information a computer future work on that one.

Figure 1: The Cognitive Underwriting Automation Framework



In insurance industry millions of people are waiting for weeks, sometimes a month just to know the status of their application policy got accepted or rejected. The underwriting process in insurance industry is manual, costly, error prone. To resolve this issue our research has provided cognitive automation solution which is the integration of NLP with RPA.

2.0 Literature Review

According to the author Anagnoste, S.in their research [1] conceptualisation of Robotic Process Automation situates it as a category of software-driven task execution that

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replicates human interactions with digital systems — clicking, typing, copying, and routing — without requiring any modification to the underlying application stack (Lacity & Willcocks, 2016a; Suri et al., 2017). The RPA layer is coming on top of existing IT structure that makes no changes in the existing IT system. This RPA ability makes it more attractive among different industries such as where mostly work done nature is manual and RPA automation gets deployed on the top of it.[1][23]

According to Deloitte article [7,8] RPA technology which does rule based automations scatter rapidly in the market. When Deloitte (2017) conducted the survey, they found that 400 businesses which are spread globally had already launched RPA automation across their industries and business with a recovery of invested for one year. The output of this automation is giving accuracy, compliance and timeliness consistently achieved. Despite this positive output Deloitte (2017) has seen so uncommon deployment issues that only one among the twenty respondent organisations has installed fifty RPA bots in their company which faced the persistent barrier for change management, workforce and governance modules in their company. According to Everest Group (2018) the pattern they had observed in the market RPA deployments gets higher. The buyer gets more satisfied with the RPA outcome which goes in favourable situation of the market which shifts from analytical to more cogitative side of the technology.[7] [8]

According to author Dunlap, R., & Lacity, M. [9] Mendling et al. in their research (2018) The situation explain RPA has border aspect of the intelligent automation which is distinguished from business process management (BPM) where actual process flow has been discovered and process mining which gives the inefficiency and bottleneck of the process by comparing the actual versus to be process. In cognitive automation both Artificial intelligence and Robotic process automation represents the logical evolution of the automation technology which is not only rules based driven.[9][22]

According to authors Lacity, M., & Willcocks, L. P in their research papers [9] Artificial intelligence is the border term which has different subsets as Machine learning, deep learning, Natural language processing. Etc out of these subsets of AI natural language processing takes the central place with automation agenda has the ability to extract the Unstructual data which is human based natural from, and NLP convert that one to structural data. unstructural data is one of the barriers which got removed by NLP by converting it to structural one. In insurance industry is one of the largest domain where manual as well as Unstructual application on large basis. RPA faced barriers for Unstructual data and most of the insurance industry documentation such as application and claim forms have Unstructual details. In this scarenio NLP helps to analyse the sentiment, incoming claim proceeding of customer service. (Araujo et al., 2020; Lexalytics (2021).[9][19]

According to Deloitte research [8] they found that the benchmark which originated from IBM operation analysis of customer services provider that most of the queries raised

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by the client has been large enquiry handling time. approximately three-quarter manual information which is consumed by the interaction with client (Mehetre, 2023). The analysis with deployment of natural language processing changes the non-adding value proportion of the service delivery. Allstate insurance industry which assisted Able platform has used complex product knowledge repository. It's giving concrete proof of concept of their industry projection. (Deloitte, 2022).[8]

According to author Mohamed, S. A., Mahmoud, M. A., Mahdi, M. N., & Mostafa, S. A. Mohamed et al. in their research paper [19] (2022) demonstrate, through a study of NLP deployment in different department of the industries such as human resource management. This contains domain specific knowledge model with a generalized NLP framework when the target corpus has different vocabulary and conventions. This finding from their research helps to direct implication of the NLP framework to actuarial terminology, pharmaceutical classification of different codes with their regulations. [19][13]

According to authors Schmitz, M., Dietze, C., & Czarnecki, C. in their research paper [22] the cognitive automation which consists of artificial intelligence and robotic process automation has enthusiasm across insurance industry.

Deloitte's analysis of the insurance automation landscape (2022) has given full life cycle of insurance industry which transform the projection of policy life cycle with automated documentation has given assistance in risk factor calculations, reviews, claim handling with intelligent fraud detection conversational deployment across different domains in insurance industry. Schmitz et al. (2019), drawing on the Deutsche Telekom RPA automation had established automation configuration related to customer specific domain. This gives outperform the deployment across different industries in both term quality and efficiency term [22] [12] According to authors Oza, D., Doshi, V., Padhiyar, D., & Patil, S. R. in their research [20] In an insurance-specific study, Oza et al. (2019) evaluated a hybrid RPA-chatbot system is used to claim processing in life insurance industry. The claim processing in insurance industry has eligibility verifications, automated receipt generations and initial status checks. By using RPA manual touch points reduced to 62% but this scope was limited to structural data only. It does not adhere the challenges in Unstructual data processing along with different factors in underwriting insurance industry.

Ratia et al. (2018) similarly explore RPA has done tremendous changes in manual working and giving outcome as error free, the high-volume burden has reduced. Efficiency of the process also got improved along with reduction in errors incidence.[20]

3.0 Identified Gaps in the Literature

Insurance industry is one of important sectors with global customer spread around the world. Customer satisfaction is one of the important aspects for critical success in any

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business process. After going through literature review, we found the research gap that research has been done either in RPA or NLP as a separate steam which limits the underwriting problem resolution. Companies like Deloitte Accenture also explored them individually. RPA works only for structural data. When any email arrives in Unstructural format, handwritten annotations or customer submit document in nonstandard format in that case RPA break down and human intervention needed.

4.0 Problem Statement

Based on traditional customer centric approach in insurance industries did not meet the customer expectations which leads to service crisis outage due to reduced accuracy, less productivity and increase in turnaround time. We are providing the novel approach of integration of NLP with RPA for end-to-end underwriting decision making.

5.0 Research Objectives

Based on the research gap we have defined below objectives:

- *To improve strategic decision making:* Our cognitive automation approach integration of NLP with RPA helps to pull the data analyses the Unstructual data and helps to improve strategic decision making in insurance industry.
- *To reduce costs and improve efficiency in decision making in insurance industry:* In competitive era of insurance industries, it's very important to provide faster and accurate decisions to solve the customer issues. Our cognitive approach helps to reduce manual work and improve the error prone results with accuracy.
- *Improve Productivity and reduce the turnaround time:* The manual processing time needed for process gets reduced due to automation and the output generated is through algorithm so which accuracy leads to improve in productivity.
- *Enhance customer relationship with insurance industries:* Our cognitive model gives faster solutions to underwriter for decision making.

This will help resolve customer problems faster and build trust in the insurance company.

6.0 Research Methodology

We have multilayer methodological approach which has both primary and secondary data included. Primary Data: We have shared the questionnaire over an email to get a response from customer, insurance underwriter, agents and business stakeholder across the team. Secondary Data: I had gone through company blocks, reviews of existing research papers, case studies, techonolocial portal, white papers, dedicated website for RPA.

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Hypothesis:

- H1-The integrated cognitive model reduces per case cycle and processing time.
- H2-The customer satisfaction score measured as CSAT is significantly higher than prior implementation.
- H3-The NLP extraction data pipeline with recall, precision, and F1 score gives the more accuracy.

6.1 Data Analysis

Testing H1: Key performance indicators pre and post implementation:

Table 1: Processing Time

Key Performance Indicator	Pre-Implementation Mean	Pre-Implementation Mean
Cost Per Case (₹)	**4510**	**2865**
Avg end to end cycle time	**20.9**	**9.7**
Throughput Time	**7.6**	**13.4**

Testing H2: The below table gives the CSAT scores among the five categories as below for before and after implementation percentages.

Table 2: Customer Satisfaction Scores

Customer Rating Scale	Before Implementation %	After Implementation %
5-Highly Satisfied	29	64.20
4-Satisfied	27.9	26.4
3-Neutral	23.7	10.8
2-Dissatisfied	14.3	4.3
1-Hilghly Dissatisfied	9.4	1.5

Testing H3: NLP extracts the data from documentation presents Precision, Recall and F1-scotre card for extraction categories.

Table 3: NLP Extraction Categories Percentage

Categories	Precision (%)	Recall (%)	F1-Score (%)
Demographic Data	94.5	91.8	93.2
Medical History	88.5	84.2	86.4
Applicant Age	98.7	97.5	97.2
Occupations	91.2	88.5	90.4

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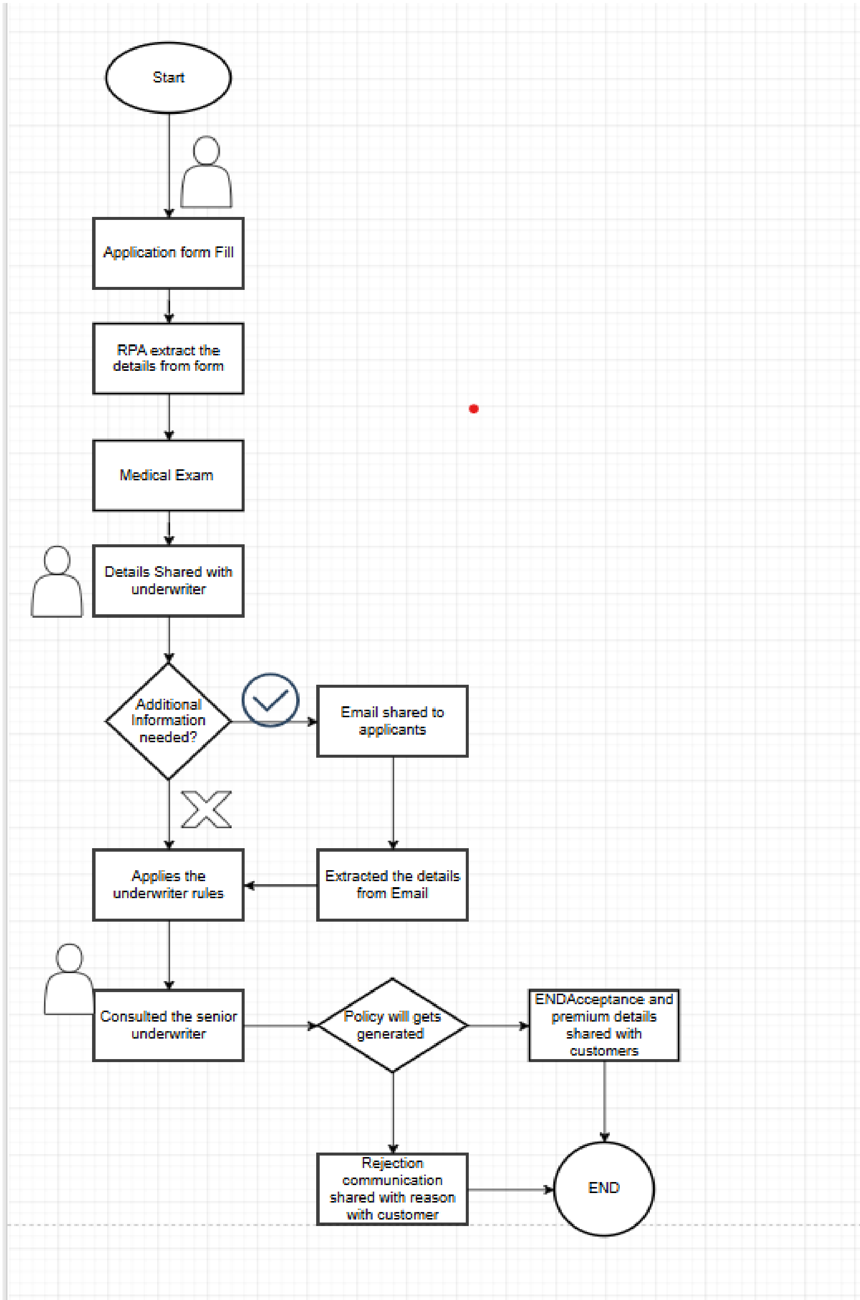
6.2 The proposed model structure

Figure 2: Cognitive Model for Streamline Decision Making



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7.0 Conclusion

Insurance industries transform their manual underwriting customer centric process by integrating Natural language programming to convert Unstructual data to structural and Robotic process automation work on repetitive rule-based tasks. In our research we have tested our cognitive underwriting model with quasi experimental evaluation with integrated approach of Natural language programming with Robotic process automation. From the hypothesis testing we have evidence of this model helps to increase productivity, reduce the turnaround time, improve efficiency and customer satisfaction enabling cognitive enhancement for customer service delivery and strategic decision making.

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