NextGen Scientific Publication
American International Journal of Computer Science and Technology

Volume 7 Issue 1, Pg. No. 28-41, AIJCST-V7I1P103, 2025
https://doi.org/10.63282/3117-5481/AIJCST-V7I1P103

*Original Article*

# AI-Powered Customer 360 in P&C Insurance: Merging CRM, Guidewire, and Behavioral Analytics

***Gowtham Reddy Enjam[1], Komal Manohar Tekale[2]**

[1,2]*Independent Researcher, USA.*

***Abstract:***

*The property and casualty (P&C) insurance is faced with the challenge of failing to handle the growing customer needs, regulatory and competitive businesses. The demand to possess a consistent customer perspective that presents CRM, Guideware policy systems and behavioural analysis have never been greater. The proposed Customer 360 AI-based solution targeted at P&C insurers is suggested in the current paper. The paper cites the design, operational style, how AI was used in merging the different databases in such a way that it could provide meaningful actionable intelligence. It is also in the paper that additional discussion is made regarding principles of behavioral analytics integration which can be useful in enhancing customer experience, risk assessment and management of claims. The paper shows the effectiveness of the implementation of the AI-based Customer 360 model in cross-selling/up-selling strategies, customer retention, and effective business process, basing on the case studies and simulation of the real world. Conclusions demonstrate that the customer satisfaction degree, the policy conversion rates, and predictive ability of claim behavior also significantly increase when insurers approach the demanding strategy of integration. Such aspects as technical conditions, data security issues, and efficient implementation plans are also indicated in the study.*

***Keywords:***

*AI, Customer 360, P&C Insurance, Crm, Guidewire, Behavioral Analytics, Predictive Modeling, Customer Retention.*

***Article History:***

***Received: 16.11.2024***

***Revised: 20.12.2024***

***Accepted: 29.12.2024***

***Published: 08.01.2025***

## 1. Introduction

Property and casualty (P&C), insurance constitutes a very significant part in the provision of financial defense and security to people and companies against any potential loss caused by naturally occurring calamities or accidents or litigation. Even now, with the markers becoming increasingly competitive and digitized, we are beginning to observe a pressure on the insurance entities to offer personalized services, as they strive to not only meet the demands of the customers, but also protect against risky overall risk and regulatory rule violation with the Guidewire, which are typically in autonomous mode. [1-4] The outcome of such system disintegration is an entity of data, disjointed customer data, and bad exposure to individual customer data, sales vehicles. This results in the issue of insurers not having a full picture of customer behaviour, customer decisions and risk exposure and little ability to give personalised services, understand the area of need and be proactive to avoid potential losses. These gaps can be filled by the already growing avenue to behavioral data and the prospects of the further development of the artificial intelligence and analytics, which incorporates a plethora of different data streams converging into one consistent actionable form. Such integration has potential benefits of assisting the insurers in straightening the processes, relations with clients and forecasting on their underwriting, claim and retention approaches. With this threat added to the opportunities that exist through this problem of siloed systems and disjointed data the P&C insurance industry can make a leap towards more data driven, customer centred model of providing better decision making, reduction of inefficiencies in operations and a greater competitive edge in such a dynamically changing industry as innovation and new entrants.

**1.1. Importance of AI-Powered Customer 360 in P&C Insurance**

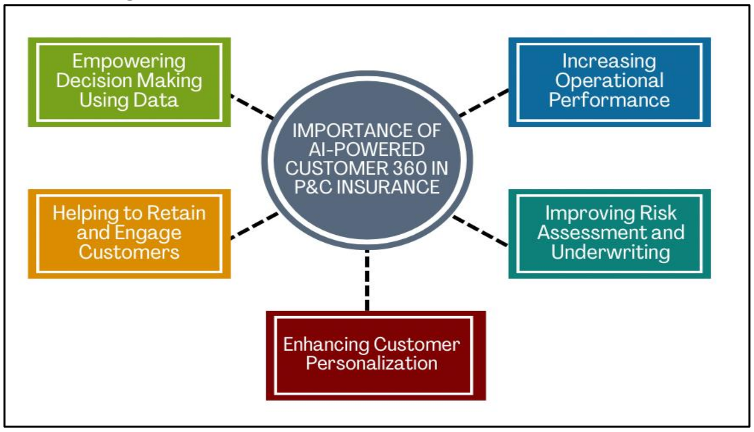


**Figure 1. Importance of AI-Powered Customer 360 in P&C Insurance**

*1.1.1. Enhancing Customer Personalization*

Using AI to drive the customer 360 tools, the insurers are able to have one and comprehensive view of a customer by comparing location of Information retrieved by CRM and policy administration systems (including Guidewire) with behavioral data. The comprehensive strategy will allow the insurers to align their products and services with the individual needs and taste of their consumers and even the category of risks. With a situation of one-on-one interactions, customer satisfaction and loyalty will be improved, not to mention the fact that it will provide an opportunity to attain an individualised marketing and product recommendation, which will ultimately lead to an increase in revenue potential.

*1.1.2. Improving Risk Assessment and Underwriting*

The models created using AI could facilitate predictive modeling of any structured and unstructured data to provide an insight on previous claims, policy and customer behavior in order to identify high-risk policies or clients. This will foster such ability to forecast leading to better underwriting rates that will allow the insurers to charge more accurate policy prices, as well as, control the potential loss. Early identification of the risk patterns also helps in tracking the frauds as well as preventive handling of claims that significantly raise the efficiency and profitability of insurance practices.

*1.1.3. Increasing Operational Performance*

With the help of AI, Customer 360 platforms automatize regular procedures and eradicate information silos by merging processes of the multiple processes a company employs. The real-time dashboards and predictive analytics are used to carry out claims processing, customer service, and fast decision-making on sales. The performance of the process will improve as the employees can work on value added activities and AI models calculate data-related work statistics and repetitive work.

*1.1.4. Helping to Retain and Engage Customers*

The dropout reduction is ensured through the implementation of an AI and analytics platform: the churn risk estimation and customer behavior and preference analysis will help the insurer to maintain proactive retention. Profiling on high-value or at-risk clients is made possible by artificial intelligence, and cross-sell/up-selling can be made achievable through recommendation engines. These functionalities will drive better customer relationships and commitment over time which is significant in a competitive P&C insurance company.

*1.1.5. Empowering Decision Making Using Data*

The Customer 360 model, which was run with the help of AI enables the management to derive actionable knowledge founded on the combination of the structured and behavioral data. These can be applied in strategic choices such as making forecasts on the trends of claims; customer satisfaction and help the insurers manage their resources effectively, address the risks in an effective way and be competitive in a data-driven industry.

### 1.2. Merging CRM, Guidewire, and Behavioral Analytics

AI-powered Customer 360 is based on the integration of CRM systems, Guidewire platforms, and behavioral analytics, which allows an insurer to attain a holistic overview of every client. [5,6] Such systems as CRM (Salesforce, etc.) enable businesses to have a great insight into customer-related strategies, attraction, and interaction, enabling tracking the trending communication, service calls, and buying habits. Such systems, however, are mainly concerned with customer interactions and do not provide in detail operation and policy level information. Guidewire platforms on the other hand serve core insurance functions such as policy administration, requests processing and billing. Although Guidewire has strong transactional and operational reporting data, it is usually used independently of the CRM system and these create data silos that do not give a comprehensive view of the customers to the insurers so they can learn how their customers are using the different channels based on their needs. By combining the two most important data sets, the insurance firm can both integrate the operational and customer-oriented data so that all decisions, including those made in underwriting and marketing, are based not only on service history data but also on policy-level insights Intelligent behavioral analytics is a third demonstration of intelligent since it tracks real-time data of customer use and interaction with websites, mobile applications, marketing mail programs, and social networks. These learnings make an insight in asserting how behavioural patterns would otherwise not be determined by traditional CRM or policy data.

The preferences of the customers can be identified through methods like clustering, segments, and also recommendation algorithms which determine their future activities as well as the prospects or risky prospects of their selective treatment. At some point in the future, behavioral analytics coupled with CRM and Guidewire data will allow far more accurate and useful predictive modeling that will allow the insurers to anticipate their customer needs, early warning of the threat of churn and optimize the success of cross-sell or up-sell efforts. These 3 components (CRM, Guidewire, behavioral analytics) appear to address an eternal issue of the insurance data splintered across the industry.

It helps companies eliminate silos and merge all data into a single source of truth, as well as infer insight-generating conclusions with artificial intelligence models. It is more of an integrated approach, though it also makes operations more efficient and accurate in terms of information on the decisions made by the operations, but also customer satisfaction is enhanced as operations are highly personalized, timely, and relevant through highly personalized interactions between businesses and its customers. Lastly, the synthesis of all these multi-facet data onto a unified platform is a thing that is afforded a tactical advantage to the insurers, which can enable it endure its competition in an industry and whose dynamics are quickly evolving with the introduction of data on the grand scale, and as a generator of risk systems development, establishment of a customer relationship, and business development.

## 2. Literature Survey

### 2.1. AI in Insurance

The insurance market is becoming automated with the application of artificial intelligence (AI) maximizing the fundamental functioning and decision making. Machine learning Algorithms have also been applied in the underwriting process of applications which can be done faster and with greater accuracy due to the analysis of large amounts of data which cannot be done effectively by humans. [7-10] machine learning AIs can also be applied to detect Fraud wherein strange patterns will be readily identified in claims which are suspicious; in real-time. In addition to that, AI-based predictive modeling helps insurers to estimate risks more accurately, predict the probability of claims and make policy offers more relevant to different customer segments. The study shows that the implementation of AI may lead to the reduction of operation costs and customer satisfaction and competitive advantages because of a faster and more precise decision-making process (Smith et al., 2021).

### 2.2. Integration of CRM

Customer Relationship Management (CRM) is among the tools that are most relevant in the analysis and control of policyholder relationships. The data platform like Salesforce can gather about their customers, such as preferences, a history of their interactions with them, their communication habits, etc; can provide useful information that an insurer can utilize to improve the quality of their service. CRM combined with policy management systems will provide a unified view of customers without the so-called compartmentalized view of a specific customer by the professionals. It will make it possible to approach marketing personally, to reach out to customers directly, and to provide customer service proactively, among other advantages that will make the retention and customer loyalty more likely. Having a single database of customers, the insurers will be capable of anticipating the needs of customers and making the process easier, not to mention improving the customer experience on a larger scale.

### 2.3. Guidewire Systems

Guidewire sells its primary insurance product line that consists of policy management, claims and billing. It possesses powerful capabilities that enable an end-to-end operational management in an insurance firm and uniformity in the operations across the departments. However, in most instances, Guidewire systems are systems used independently and thus they can create silos of data and fail to offer the full picture of the customer behavior. Without linking the system with the CRM, or other sophisticated analytics tools, the insurance companies may struggle to get some insights based on which they can be able to act on based on the data they receive in Guidewire. This void must be filled so that a holistic view of the customers is achieved whereby the effectiveness of operations can be improved besides data-driven strategic decision making.

### 2.4. Behavioral Analytics

Behavioral analytics examine the tendencies of consumer behaviours in order to make predictions regarding future opportunities and preferences. By clustering, segmentation and recommendation-systems, the insurers will be in a position to ensure they produce what they want to produce, marketing will become easier and the insurers will be in a better position to retain their customers. As an example, an insurer is able to examine trends of policy renewals or claims submissions in a way such that it is able to design interventions that are geared towards the achievement of satisfaction and or reduction of churn. Moreover, cross selling and up selling decisions can also be informed using behavior based insights hence compel companies to sell the right products to the customer, at the right time and into the right customer. The research results reveal that the application of behavioral analytics can make the relationship with the customers positive, as well as enhance the overall efficiency and profitability of the operations.

### 2.5. Integration Challenges

Nevertheless, it has a natural problem, which lies in the fact that regardless of all the benefits of AI, CRM, Guidewire, and behavioral analytics, they are not simple to unite into a united Customer 360 platform. One of them is data heterogeneity as different data formats and sources must be normalized in order to which it is easy to analyse different data. The real-time processing requirements further make the integration even more difficult; insurers require real-time access to the insights to make time-sensitive decisions. The privacy and security concerns cannot be neglected either because the information that is linked to insurance is sensitive, and that it must be controlled. The interpretability of models are also an issue and the insurers are required to clarify that the recommendations obtained by AI are understandable and make sense to the stakeholders. These issues are to be properly addressed in order to reach the maximum of the integrated customer-centric platforms in the insurance market.

## 3. Methodology

### 3.1. System Architecture

The Customer 360 proposed framework presented to insurers will offer an intelligent survey of a customer with a cohesive picture of customers. [11-14] Through the combination of various sources of information, a combination of high-level analysis, and the provision of tangible insights, the framework would aim to optimize activity, customer relations, and choice-making.

#### *3.1.1. Data Layer*

The Data Layer forms the primary basis of the Customer 360 architecture wherein the integration of information through various sources of information (CRM systems, Guidewire policy and claims information, and third-party behavioral datasets), are collected together. It is a layer that makes sure that all the data concerning customers such as demographic, past purchases, interactions and online activities is gathered and standardized. The Data Layer allows having silo-free and clean data that becomes a single source of truth to be consumed downstream and used as the basis of analytics.

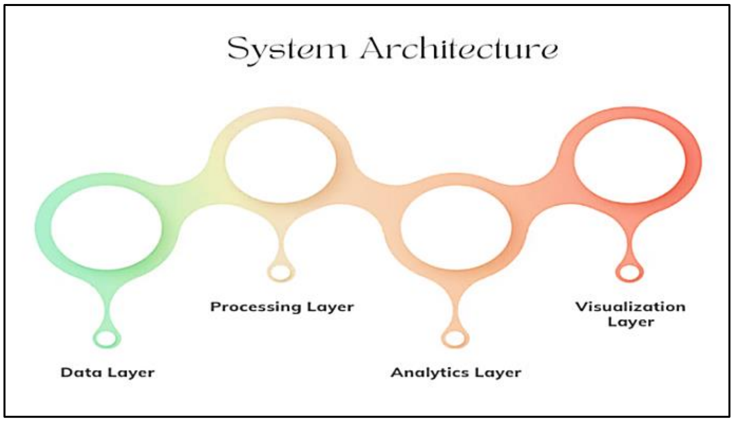


**Figure 2. System Architecture**

*3.1.2. Processing Layer*

Processing Layer involves the translation and processing of the melded data which is to be analysed. Processing pipelines (ETL - Extract, Transform, Load) will clean, enrich and unify information of multiple data sources. The models of AI utilized in this layer to identify patterns, anomalies, and forecast customer behavior include machine learning and prediction algorithms. It is due to this layer that it is possible that the information is arranged correctly, accurate and available to execute sophisticated analytics at the same time as having real-time or near real-time processing capability where needed.

*3.1.3. Analytics Layer*

Analytics Layer takes the processed data and uses it to provide some insights that are applied to make business decisions. It also involves the use of product and service personalization like predictive modeling as a predictor of future needs of customers, segmentation of customers where similar customers are clustered and recommendation engine to create recommendations. Such layer can use the best behavioral analytics and machine learning techniques to forecast how the customers will behave, manage the safety, control the marketing functions, and identify cross-selling or upselling opportunities of the employment possibilities.

*3.1.4. Visualization Layer*

Analysis the Results and actionable intelligence in the Visualization Layer is provided through interactive dashboards and reporting solutions to various stakeholders. Leads can be identified and engagement enhanced through detailed profile of leads, better management of sales and lead generation processes and overall performance of the business in a broad perspective which can be managed by the management levels. The layer aides in making fast judgments since complicated analytics is altered into straightforward visual collections and eases data-centered manner at an organizational-wide scale.

**3.2. Data Collection and Preprocessing**

The variety of data received in numerous sources and its thoroughness is vital to the effectiveness of an AI-based Customer 360 model. In this model, customer data has been defined as one that is collected using CRM systems, Guidewire insurance systems, and third-party behavioural channels to form a complete view of all customers. The information that is recorded in CRM usually involves customer details, contact history, likes and dislikes and Guidewire incorporates structured information that comprises of policy, claim, and billing. Behavioural sources which may include the interaction on the web site, the use of mobile applications and social activity provide more information regarding the manner in which customers interact and engage. The issue with data collection in such heterogeneous sources is a problem as they are not homogeneous as they are structured differently, of different formats, and their granularities are not the same. In order to go over these challenges, an effective preprocessing pipeline is executed to ensure the information is clean, consistent and analytics-focused. The preprocessing begins with missing data or incomplete data which could be encountered as a result of inability to record data once they transpired, empty fields or system crash. They make methods such as imputation, the method of interpolation or deletion of the data according to the circumstance and the importance of their missing values.

After the data normalization process, the data formats are later fine tuned by standardizing the formats of the data across sources i.e. date formats, data currencies, and categorical values so that they are similar in the future analysis. Other elements of such data as outliers and erroneous entries are also built and processed in this manner that will not corrupt the outputs produced in relation to the AI models. There is also the consideration that since insurance statistics are confidential, anonymization and pseudonymization are employed to eliminate any identifying factor, which can identify the membership of certain individuals, without affecting the data with respect to analysis. Using feature engineering is also the means of extracting meaningful attributes, e.g. customer lifetime value, risk scores, engagement measurements, and other items that can enhance the predictive strength of AI models. The framework is a reliable foundation of analytical actions led by AI since it gathers and preprocesses data in their entirety. It also instills confidence in the insights generated besides improving accuracies and interpretability of the models. Last but not least, stringent data preparation would enable the insurers to come up with informed decision-making, develop tailor-made experiences and optimization of operations without breaking the law of privacy of data.

### 3.3. AI Model Design

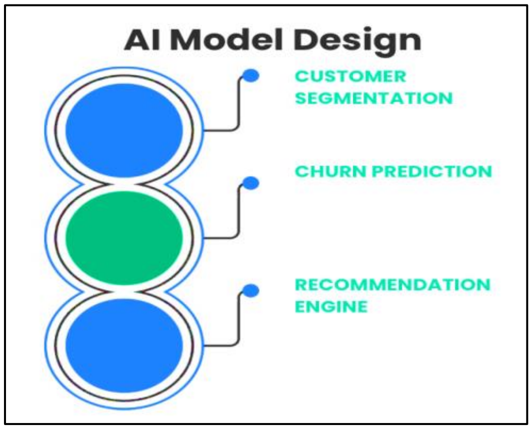


**Figure 3. AI Model Design**

#### *3.3.1. Customer Segmentation*

Customer 360 framework of the AI is about customer segmentation, where insurers can segment their customers based on their behaviour, tastes and their worth. K-means clustering algorithm used is a machine learning algorithm that is unsupervised that classifies customers into different groups of similar characteristics. This way, the policy type, frequency of claim, interaction history and engagement patterns help the insurers to identify the high-value customers, loyal customers and the risky groups. Knowledge of this nature helps in shaping the marketing campaigns that should be targeted by modifying the mode of communicating and optimum utilization of the resources that should therefore offer the right products to the right audiences.

#### *3.3.2. Churn Prediction*

Churn prediction is aimed at informing you about customers who may cancel their policies or go to the competitors. The automatic way of doing this is through the use of Gradient Boosting Decision Trees (GBDT), a supervised machine learning method, because it is possible to model complex non-linear relationships and interactions amid variables. After correlating the past behavior, tendencies in claims, the probability of engagement, and the demographic organizational data, the model puts a churn likelihood over each consumer. Insurers can use personal offerings, loyalty deals, or active engagement to retain those high-risks as they recognize them early thus bettering customer lifetime value through attrition.

#### *3.3.3. Recommendation Engine*

The recommendation engine is setup in such a way that it can increase cross-sell and up-sell in that it can propose relevant products or policy modifications to the customer. Collaborative filtering is one of the most common AI methods in recommendation a system which uses the similarity between customers and how they relate to products to come up with personalized recommendations. Using purchase, claim, and policy preference patterns, the system will be able to recommend complementary policies or upgrades based on the needs of the individual customer. This does not only increase revenues but improves customer satisfaction and attention by providing on-relevant-time and product recommendations.

### 3.4. Implementation

Applying the AI-driven Customer 360 framework uses an amalgamation of contemporary programming languages, large-scale data processing, and visualization to promise scalability, optimum performance, and actionable data. [15-18] The programming language Python is selected as a predominant one owing to the flexibility of data, broad data scientific resources, and coverage of the development of machine learning and artificial intelligence applications. The data manipulation, preprocessing, and modeling is done on libraries like Pandas, NumPy, and Scikit-learn and the creation of advanced predictive and recommendation models is done with TensorFlow and PyTorch. Apache Spark has also been included in the framework to process the huge amounts of the heterogeneous data that are inspired by CRM systems, guide wire, and behavioral data. Spark can support parallelization of ETL process with large datasets and it is able to bring about and enhance promptness in feature engineering and model training. PySpark combines Python and Spark, which means the system can take advantage of both high scalability and high performance and flexibility of clusters that Python offers, and Spark.

Tableau has been used to derive fan pdf, reporting, and dashboarding on visualization of interactive dashboard and analytical reports to the various stakeholders such as customer service, sales, and management teams. Tableau is connected directly to processed datasets enabling users to view any insight in real-time, view the essential key performance indicators, and watch customer behavior trends. Incorporated dashboards will offer the capabilities to drill down the information so that the stakeholders understand the micro details of customer profiles, policy performance, and the output of the predictive analytics. In the implementation process, automation and repeatability are also installed. The ETL processes, model training, and scoring activities will be executed at a specified frequency in order to ensure that Customer 360 is always updated on the latest information about the customers. Sensitive customer information is protected by the addition of security and compliance (data encryption, anonymization, and realization of access controls) to the system. On the whole, this implementation approach includes an effective analytics engine, scalable processing, and a simplistic visualization to generate a powerful, real-time and practical Customer 360 solution that results in improved decision-making and more engagement with the customer.

### 3.5. Evaluation Metrics

#### *3.5.1. Customer Retention Rate*

Customer retention rate is used to calculate the number of customers who remain in relation with the insurance firm over a period of time. It is a red flag underlying the efficiency of the Customer 360 framework as an AI-driven tool and its effectiveness in retaining customers. It is also through the retention tracking that the insurers can determine the effectiveness of certain interventions, provides and proactive re-engagement strategies. As the retention rate is high the predictive inferences and segmentation interventions are invoked so that they can service the customer well and hence reduce churn, and when the retention rate is low, it is clear that some alterations can be made to the customer service or engagement.

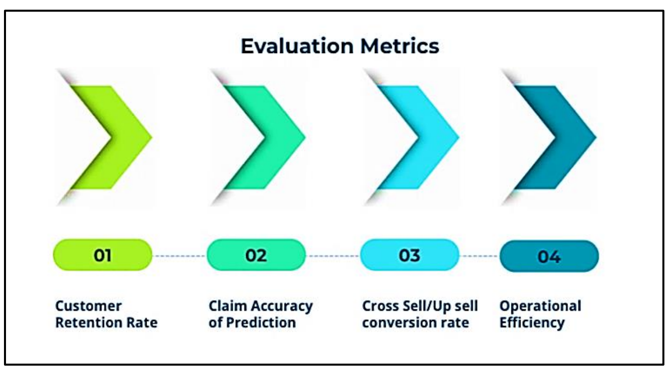


**Figure 4. Evaluation Metrics**

#### *3.5.2. Claim Accuracy of Prediction*

The effectiveness of the AI models in predicting insurance claims is the accuracy with which the prediction of the claims is correct. It is an indicator of the predictability of the specified model to effectively conclude on what policies are likely to make claims and what the amount of the claims will be. Claim predictability is much more beneficial to the insurers because the insurers are in a position to control the risk, maximize reserves, and make improved underwriting decisions. It also facilitates the detection of fraud and planning of operations in that early interventions may be done on potentially high-cost claims. Overseeing the performance and continuously upgrading the originality of the predictions will assist the insurers to reduce the frequency of the financial losses, not mentioning the risk management in general.

*3.5.3. Cross Sell/ Up Sell conversion rate*

The cross sell as well as up sell conversion rate is used to assess the effectiveness of the recommendation engine in compiling additional sales. This KPI tracks the rate of the customers that respond properly to the customized product proposals (the upgrade of the policy, or the complimentary product). The increased rates of conversion will demonstrate the relevance of the recommendations generated by the AI system and their timeliness, which will allow saying that it has the potential to increase the level of revenues and customer satisfaction. Incrementing this measure would also enable the insurers to refine their targeting measures, optimise suggestions and enhance the most profitable customer relationships.

*3.5.4. Operational Efficiency*

Operational effectiveness is used to quantify how the internal processes are transformed by using Customer 360 framework. This is comprised of a reduction in manual data processing, rapid processing of claims, enhanced customer service interactions, and narrowed-down reporting. The efficiency efforts (i.e. a number of man-hours saved) allows the insurers to estimate the pay-off of their investment in the AI integration, and the places and ways through which the automation and predictive analytics will allow saving costs and improving productivity. The enhanced performance under the operations is not only cost-cutting but also helps in accelerating the operations, on top of making sound decisions within the organization.

# 4. Results and discussion

## 4.1. Data Insights

**Table 1. Example Customer Segmentation**

| Segment | % of Customers | Predicted Churn |
|---|---|---|
| A | 25% | 5% |
| B | 35% | 15% |
| C | 40% | 25% |

Integration of CRM, Guidewire and behavioral analytics information provided a 360-degree view of customers that provided the insurers information previously hidden due to the siloed systems. The structure facilitated the ultimate perspective of customer needs, preferences and risk profile through consolidation (policy management, claims, customer interactions, on-line behaviour). A significant lesson of this consolidated data was segmentation of the customers, and there were distinct trends regarding the engagement, behavior with claims and a potential churn. As an example, three key groups of customers have been defined, on their general value, risk measurement and estimated risk of losing a customer to the company, they are A, B, and C. Segment A which is customer base of 25 percent had very low predicted churn of 5 percent which means that this type of customer is very happy, involved and likely to remain in the customer fold. Segment B represented 35 percent of the customers and presented 15 percent estimated churning rates and it represents that this category engages reasonably but with defined retention efforts, result can be even low attrition rates.

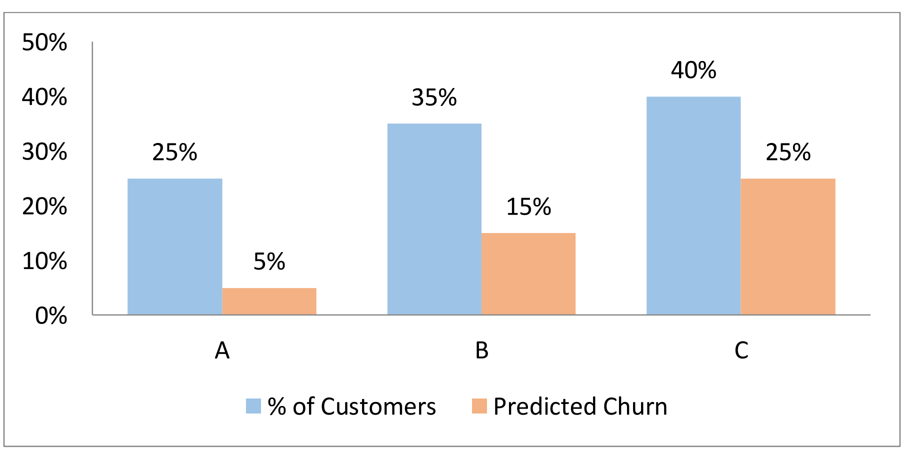


**Figure 5. Graph Representing Example Customer Segmentation**

The most predicted (40 percent of the customer) was segment C, whose churn rate was 25 percent, and thus covered a significant portion of the at-risk customers and thus required to be dealt with by adopting personalized retention strategies such as tailored offers, active communication, and many more. The value of combining such structured policy/claim data with behavioral/interaction analytics would be evident in this experience. In identifying the worth of their customers, an understanding of the extent of risk it is exposing them to and probability of churn in the future, the insurers can target the relevant marketing, retention and cross-sell strategies that will not only increase their revenues but will also help them improve customer satisfaction. The analysis also helps in fact-based decision making in each and every transaction functions including underwriting and claims management, customer service and sales. Altogether, this compound approach can not only help uncover the hidden mechanics of the customer behaviour, but it also can help the insurers to act proactively so that the available resources could be used efficiently and relations with its long-term customers could be improved.

### 4.2. AI Model Performance

**Table 2. AI Model Performance**

| Metrics | Improvement |
|---|---|
| Churn Prediction | 92% |
| Recommendation Engine | 88% |
| Claims Prediction | 85% |

#### *4.2.1. Churn Prediction*

A remarkable result of 92 percent accuracy was recorded on the churn prediction model and it measures the effectiveness of the model in predicting the likelihood of certain customers to leave the insurer. With the use of historical interactions, use of policy and patterns of behaviour, the model will help to identify the early signs of attrition. With such a high degree of accuracy, it is possible to implement the proactive methods of retention, i.e. make a customer a special offer or communicate through the targeted message, which makes customer turnover be reduced and client lifetime be extended. The performance of the model shows that AI-based predictive analytics can contribute greatly to the decision-making of customer retention.

#### *4.2.2. Recommendation Engine*

The recommendation engine has achieved a level of 88% accuracy, which generates an indication that this level within the recommendation engine is quite effective in recommending applicable cross-sell and up-sell opportunities. The system can use collaborative filtering and evaluate trends that identify the behaviour and preferences of the customers to make a personalised product recommendation. This enables insurance providers to get the most out of revenue generation as well as satisfying more customers by offering customized services. The effective work of the recommendation engine shows that AI can effectively lead to targeted marketing and browsing of high-level customers.

#### *4.2.3. Claims Prediction*

The claims prediction model attained the accuracy of 85 percent, which means that it can determine the potential claims and anticipated levels of claims with great precision. With the help of policy details, historical assertions, and customer conduct studies, the model assists insurers in the determination of high-risk policies, reserves, and possible fraudulent activities within the business. Due to the proper prediction of claims, more efficient risk management will be ensured along with more efficient operational management that will be brought due to the ability to manage plans and allocate resources more accurately. The findings prove that AI is valuable to improve both financial and operational decision-making in insurance procedures.

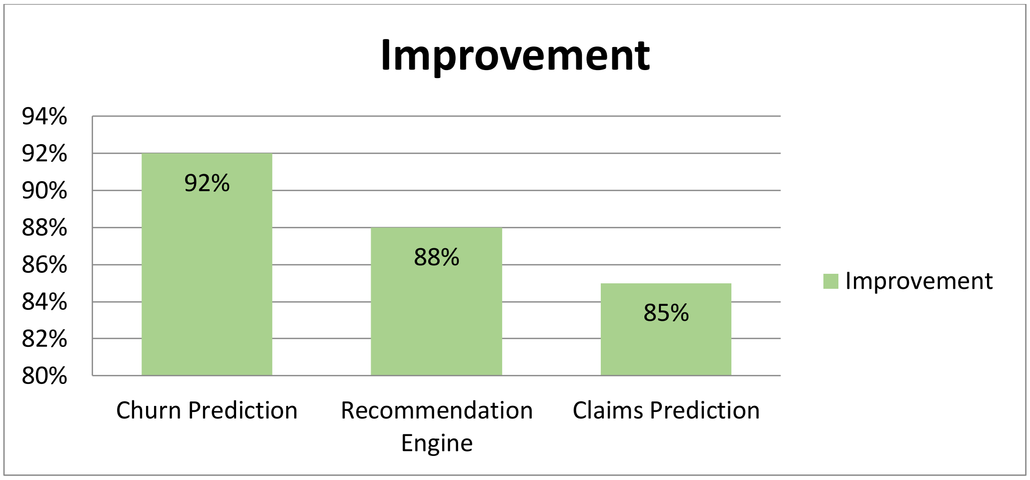


**Figure 6. Graph Representing AI Model Performance**

### 4.3. Discussion

The overall AI-based Customer 360 solutions introduce the insurance companies to a radical change by allowing another level of personalization, retaining customer and operation efficiency. CRM in combination with Guideset and behavioral information results in integrated aggregated detail information about all customers that can be tapped by the insurers to make more informed and proactive decisions. The main strength of this approach is the possibility of dividing the customers with the assistance of AI as it could define not only high-value customers that contribute to the most to the revenue but also high-risk customers that are prone to churning. This will help insurers to be discriminating in such segmentation where they will be able to offer personalized outreach, personalized promotion and customization of the policy. This will help the insurers to gain more loyalty and reduced attrition. Behavioral analytics can alleviate this insight further since it examines tendencies in the communication, adoration, and happiness of the consumer with the business; data not gather in the typical demographic or buy data. By using the example of tracking activity on the sites, mobile device apps and reacting to offers made in the promotion efforts should assist the insurer determine customer inclinations and to offer relevant offers at the right time. The other significant benefit of the framework is the integrated dashboards that enable the company to enjoy real-time awareness on customer behavior, the performance of the policies, and other predictive analytics outputs.

Such dashboards assist the Customer service departments, the sales departments and the management to be aware of the trends, key performance indicators and respond promptly when an emergency arises within the organization hence increasing efficiency in the operations. The decision-making process is more responsive and information driven and AI models maintain the insights updated based on the latest customer data. Overall, the Customer 360 approach based on AI can address the loopholes in interoperability between systems, eliminate data silos and present the insights based on the data to enhance customer experiences and business performance. Predictive modeling, segmentation and recommendations systems help insurers to optimize engagement, minimise risk and maximise revenue. This holistic attitude towards its practices may not only enhance the customer relations but also render the insurers worthy to compete in a fast evolving and data-driven market. The combination of AI, behavioral insights, and real-time visualization can be viewed as the paradigm of considering customers, whose behavior can be described using the behavioral insights, and visualized in real-time.

## 5. Conclusion and Future Work

It has defined a comprehensive customer 360 with AI driving in the property and casualty (P&C) insurance segment that captures the data fields to include the CRM systems, Guidewire systems, and behavior analytics to offer a consumed insight of all customers in a complete and actionable manner. With the integrated diverse data sets, the framework will resolve long term data issues of focused information fragmentation and data silos and allow the insurers to enhance their capacity to interrelate with people as individuals, predictive model as well as attain operational efficiency. The forecasted model of AI that were incorporated into the model, including churn prediction, recommendation engines, claims forecasting, demonstrated extraordinarily high levels of accuracy, which means that machine learning can refine the decision-making process of underwriting, claims management and customer retention.

The integrated dashboards also helped achieve the latest knowledge of the customer behaviour and organisation performance to respond promptly and with adequate information. The overall findings confirm the assumption that a holistic data-driven approach that relies on the application of artificial intelligence and analytics is indispensable when it comes to contemporary insurers that need to achieve an improved customer satisfaction rate, reduce attrition, and increase their resources management. The framework may allow the insurers to develop customer-focused strategies by providing information on high value/high risk customer segment to maximize revenue, minimize risk, and improve productivity of the operational processes.

A number of research and real-life opportunities are available in the future that can be exploited to take further steps in implementing this research. One of these themes is to witness the application of real-time AI models that will be capable of making on-demand decisions and will hence allow insurers to respond in real-time to the fluctuating customer behaviour or unfolding conditions of claims activity. This can lead to a significant improvement in its customer experience and reducing risk management. The other route that could be explored is that the deep natural language processing (NLP) can be applied on unstructured customer communication (such as emails, chat transcripts and social media comments) and provide more information on the sentiment, needs and emerging trends.

Moreover, additional enhancement of risk assessment could be provided by integrating the Internet of Things (IoT) data, i.e., smart home sensors (e.g., sensory data) in the home, or telematics. Finally, the importance of data privacy and security will remain dynamic, and in the future, these problems as well should be covered. It might be possible to train some of the AI models with distributed data sets (e.g., with the federated learning technique), without compromising sensitive customer information and strike a balance between the functions of analytics and regulatory rules as well as ethical limitations. By hitting these paths, insurance organizations can now seek means to amplify the overall potential of Customer 360 systems and administer trust, inventiveness, and robustness in an increasingly competitive and technology-driven insurance setting.

## References

[1] Goyal, R. Customer Segmentation and Personalization in Insurance: A Business Analysis Approach. IJLRP-International Journal of Leading Research Publication, 5(8).
[2] GhorbanTanhaei, H., Boozary, P., Sheykhan, S., Rabiee, M., Rahmani, F., & Hosseini, I. (2024). Predictive analytics in customer behavior: Anticipating trends and preferences. Results in Control and Optimization, 17, 100462.
[3] Chakladar, R. D. (2023). The Transformation of P&C Underwriting Through Data and Analytics. North American Journal of Engineering Research, 4(3).
[4] Reddy, A. S. (2024). Beyond the Claims: Emerging AI Models and Predictive Analytics in Property & Casualty Insurance Risk Assessment.
[5] Guidewire to Bring the Power of Salesforce CRM to P&C Insurance, guidewire, 2017. online. https://www.guidewire.com/about/press-center/press-releases/20170927/guidewire-bring-power-salesforce-crm-pc-insurance
[6] The role of AI in P&C insurance claims and policy optimization, online. https://www.ust.com/en/insights/the-role-of-ai-in-p-and-c-insurance-claims-and-policy-optimization
[7] Karppanen, V. (2024). Leveraging ai-enabled personalization in customer relationship management.
[8] Almubarak Ali, M. A., Elmubarak, Y. A., & Salim Babiker, M. A. (2024). The Role of Artificial Intelligence in Risk Management and Underwriting Optimization in the Insurance Industry. Pakistan Journal of Life & Social Sciences, 22(2).
[9] Riikkinen, M., Saarijärvi, H., Sarlin, P., & Lähteenmäki, I. (2018). Using artificial intelligence to create value in insurance. International Journal of Bank Marketing, 36(6), 1145-1168.
[10] Reddy, A. S. (2023). Multi-Cloud Data Resilience: Implementing Cross-Platform Data Strategies with Snowflake for P&C Insurance Operations.
[11] Alia Shkurdoda, Insurance data 360: Sync your business data ecosystem, eliminate silos and see ultimate efficiency at scale, online. https://www.griddynamics.com/blog/insurance-data-360
[12] Roppestad, S. B. (2024). Artificial Intelligence in Insurance-A Case Study of Business Operations and a Theoretical Model of Information Balance (Master's thesis, Oslo Metropolitan University).
[13] Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., ... & Machtynger, L. (2020). Artificial intelligence (AI) in strategic marketing decision-making: a research agenda. The Bottom Line, 33(2), 183-200.
[14] Pan, S. L., Tan, C. W., & Lim, E. T. (2006). Customer relationship management (CRM) in e-government: a relational perspective. Decision support systems, 42(1), 237-250.
[15] Payne, A., & Frow, P. (2016). Customer relationship management: Strategy and implementation. In The marketing book (pp. 439-466). Routledge.
[16] Boadu, K., & Achiaa, A. (2019). Customer relationship management and customer retention. Customer Relationship Management and Customer Retention (October 20, 2019).

[17] Future Trends in Insurance CRM: AI, Automation, and Predictive Analytics, decerto, 2024. online. https://www.decerto.com/post/future-trends-in-insurance-crm-ai-automation-and-predictive-analytics
[18] Xu, X., & Zweifel, P. (2020). A framework for the evaluation of InsurTech. Risk Management and Insurance Review, 23(4), 305-329.
[19] Rusum, G. P., Pappula, K. K., & Anasuri, S. (2020). Constraint Solving at Scale: Optimizing Performance in Complex Parametric Assemblies. *International Journal of Emerging Trends in Computer Science and Information Technology*, *1*(2), 47-55. https://doi.org/10.63282/3050-9246.IJETCSIT-V1I2P106
[20] Pappula, K. K., & Anasuri, S. (2020). A Domain-Specific Language for Automating Feature-Based Part Creation in Parametric CAD. International Journal of Emerging Research in Engineering and Technology, 1(3), 35-44. https://doi.org/10.63282/3050-922X.IJERET-V1I3P105
[21] Rahul, N. (2020). Optimizing Claims Reserves and Payments with AI: Predictive Models for Financial Accuracy. *International Journal of Emerging Trends in Computer Science and Information Technology*, *1*(3), 46-55. https://doi.org/10.63282/3050-9246.IJETCSIT-V1I3P106
[22] Pappula, K. K., Anasuri, S., & Rusum, G. P. (2021). Building Observability into Full-Stack Systems: Metrics That Matter. *International Journal of Emerging Research in Engineering and Technology*, *2*(4), 48-58. https://doi.org/10.63282/3050-922X.IJERET-V2I4P106
[23] Pedda Muntala, P. S. R., & Karri, N. (2021). Leveraging Oracle Fusion ERP's Embedded AI for Predictive Financial Forecasting. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *2*(3), 74-82. https://doi.org/10.63282/3050-9262.IJAIDSML-V2I3P108
[24] Rahul, N. (2021). Strengthening Fraud Prevention with AI in P&C Insurance: Enhancing Cyber Resilience. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *2*(1), 43-53. https://doi.org/10.63282/3050-9262.IJAIDSML-V2I1P106
[25] Karri, N. (2021). Self-Driving Databases. *International Journal of Emerging Trends in Computer Science and Information Technology*, *2*(1), 74-83. https://doi.org/10.63282/3050-9246.IJETCSIT-V2I1P10
[26] Rusum, G. P. (2022). WebAssembly across Platforms: Running Native Apps in the Browser, Cloud, and Edge. *International Journal of Emerging Trends in Computer Science and Information Technology*, *3*(1), 107-115. https://doi.org/10.63282/3050-9246.IJETCSIT-V3I1P112
[27] Pappula, K. K. (2022). Architectural Evolution: Transitioning from Monoliths to Service-Oriented Systems. *International Journal of Emerging Research in Engineering and Technology*, *3*(4), 53-62. https://doi.org/10.63282/3050-922X.IJERET-V3I4P107
[28] Jangam, S. K. (2022). Self-Healing Autonomous Software Code Development. *International Journal of Emerging Trends in Computer Science and Information Technology*, *3*(4), 42-52. https://doi.org/10.63282/3050-9246.IJETCSIT-V3I4P105
[29] Anasuri, S. (2022). Adversarial Attacks and Defenses in Deep Neural Networks. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *3*(4), 77-85. https://doi.org/10.63282/xs971f03
[30] Pedda Muntala, P. S. R. (2022). Anomaly Detection in Expense Management using Oracle AI Services. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *3*(1), 87-94. https://doi.org/10.63282/3050-9262.IJAIDSML-V3I1P109
[31] Rahul, N. (2022). Automating Claims, Policy, and Billing with AI in Guidewire: Streamlining Insurance Operations. *International Journal of Emerging Research in Engineering and Technology*, *3*(4), 75-83. https://doi.org/10.63282/3050-922X.IJERET-V3I4P109
[32] Karri, N., & Pedda Muntala, P. S. R. (2022). AI in Capacity Planning. International Journal of AI, BigData, Computational and Management Studies, 3(1), 99-108. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V3I1P111
[33] Tekale, K. M., & Rahul, N. (2022). AI and Predictive Analytics in Underwriting, 2022 Advancements in Machine Learning for Loss Prediction and Customer Segmentation. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 3(1), 95-113. https://doi.org/10.63282/3050-9262.IJAIDSML-V3I1P111
[34] Rusum, G. P., & Anasuri, S. (2023). Composable Enterprise Architecture: A New Paradigm for Modular Software Design. *International Journal of Emerging Research in Engineering and Technology*, *4*(1), 99-111. https://doi.org/10.63282/3050-922X.IJERET-V4I1P111
[35] Pappula, K. K. (2023). Reinforcement Learning for Intelligent Batching in Production Pipelines. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *4*(4), 76-86. https://doi.org/10.63282/3050-9262.IJAIDSML-V4I4P109
[36] Jangam, S. K., & Pedda Muntala, P. S. R. (2023). Challenges and Solutions for Managing Errors in Distributed Batch Processing Systems and Data Pipelines. *International Journal of Emerging Research in Engineering and Technology*, *4*(4), 65-79. https://doi.org/10.63282/3050-922X.IJERET-V4I4P107
[37] Anasuri, S. (2023). Secure Software Supply Chains in Open-Source Ecosystems. *International Journal of Emerging Trends in Computer Science and Information Technology*, *4*(1), 62-74. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I1P108
[38] Pedda Muntala, P. S. R., & Karri, N. (2023). Leveraging Oracle Digital Assistant (ODA) to Automate ERP Transactions and Improve User Productivity. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *4*(4), 97-104. https://doi.org/10.63282/3050-9262.IJAIDSML-V4I4P111
[39] Rahul, N. (2023). Transforming Underwriting with AI: Evolving Risk Assessment and Policy Pricing in P&C Insurance. *International Journal of AI, BigData, Computational and Management Studies*, *4*(3), 92-101. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V4I3P110
[40] Tekale, K. M., Enjam, G. R., & Rahul, N. (2023). AI Risk Coverage: Designing New Products to Cover Liability from AI Model Failures or Biased Algorithmic Decisions. International Journal of AI, BigData, Computational and Management Studies, 4(1), 137-146. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V4I1P114
[41] Karri, N., Jangam, S. K., & Pedda Muntala, P. S. R. (2023). AI-Driven Indexing Strategies. International Journal of AI, BigData, Computational and Management Studies, 4(2), 111-119. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V4I2P112
[42] Rusum, G. P., & Pappula, K. K. (2024). Platform Engineering: Empowering Developers with Internal Developer Platforms (IDPs). International Journal of AI, BigData, Computational and Management Studies, 5(1), 89-101. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I1P110

[43] Pappula, K. K., & Anasuri, S. (2024). Deep Learning for Industrial Barcode Recognition at High Throughput. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *5*(1), 79-91. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I1P108

[44] Rahul, N. (2024). Improving Policy Integrity with AI: Detecting Fraud in Policy Issuance and Claims. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(1), 117-129. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I1P111

[45] Reddy Pedda Muntala , P. S. (2024). The Future of Self-Healing ERP Systems: AI-Driven Root Cause Analysis and Remediation. International Journal of AI, BigData, Computational and Management Studies, 5(2), 102-116. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I2P111

[46] Jangam, S. K., & Karri, N. (2024). Hyper Automation, a Combination of AI, ML, and Robotic Process Automation (RPA), to Achieve End-to-End Automation in Enterprise Workflows. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(1), 92-103. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I1P109

[47] Anasuri, S., & Pappula, K. K. (2024). Human-AI Co-Creation Systems in Design and Art. International Journal of AI, BigData, Computational and Management Studies, 5(1), 102-113. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I1P111

[48] Karri, N. (2024). Real-Time Performance Monitoring with AI. *International Journal of Emerging Trends in Computer Science and Information Technology*, *5*(1), 102-111. https://doi.org/10.63282/3050-9246.IJETCSIT-V5I1P111

[49] Tekale, K. M. (2024). AI Governance in Underwriting and Claims: Responding to 2024 Regulations on Generative AI, Bias Detection, and Explainability in Insurance Decisioning. International Journal of AI, BigData, Computational and Management Studies, 5(1), 159-166. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I1P116

[50] Pappula, K. K. (2020). Browser-Based Parametric Modeling: Bridging Web Technologies with CAD Kernels. *International Journal of Emerging Trends in Computer Science and Information Technology*, *1*(3), 56-67. https://doi.org/10.63282/3050-9246.IJETCSIT-V1I3P107

[51] Rahul, N. (2020). Vehicle and Property Loss Assessment with AI: Automating Damage Estimations in Claims. *International Journal of Emerging Research in Engineering and Technology*, *1*(4), 38-46. https://doi.org/10.63282/3050-922X.IJERET-V1I4P105

[52] Pappula, K. K. (2021). Modern CI/CD in Full-Stack Environments: Lessons from Source Control Migrations. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *2*(4), 51-59. https://doi.org/10.63282/3050-9262.IJAIDSML-V2I4P106

[53] Pedda Muntala, P. S. R. (2021). Prescriptive AI in Procurement: Using Oracle AI to Recommend Optimal Supplier Decisions. *International Journal of AI, BigData, Computational and Management Studies*, *2*(1), 76-87. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V2I1P108

[54] Rahul, N. (2021). AI-Enhanced API Integrations: Advancing Guidewire Ecosystems with Real-Time Data. *International Journal of Emerging Research in Engineering and Technology*, *2*(1), 57-66. https://doi.org/10.63282/3050-922X.IJERET-V2I1P107

[55] Karri, N., & Jangam, S. K. (2021). Security and Compliance Monitoring. *International Journal of Emerging Trends in Computer Science and Information Technology*, *2*(2), 73-82. https://doi.org/10.63282/3050-9246.IJETCSIT-V2I2P109

[56] Rusum, G. P., & Pappula, K. K. (2022). Federated Learning in Practice: Building Collaborative Models While Preserving Privacy. *International Journal of Emerging Research in Engineering and Technology*, *3*(2), 79-88. https://doi.org/10.63282/3050-922X.IJERET-V3I2P109

[57] Pappula, K. K. (2022). Modular Monoliths in Practice: A Middle Ground for Growing Product Teams. *International Journal of Emerging Trends in Computer Science and Information Technology*, *3*(4), 53-63. https://doi.org/10.63282/3050-9246.IJETCSIT-V3I4P106

[58] Jangam, S. K., & Pedda Muntala, P. S. R. (2022). Role of Artificial Intelligence and Machine Learning in IoT Device Security. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *3*(1), 77-86. https://doi.org/10.63282/3050-9262.IJAIDSML-V3I1P108

[59] Anasuri, S. (2022). Next-Gen DNS and Security Challenges in IoT Ecosystems. *International Journal of Emerging Research in Engineering and Technology*, *3*(2), 89-98. https://doi.org/10.63282/3050-922X.IJERET-V3I2P110

[60] Pedda Muntala, P. S. R. (2022). Detecting and Preventing Fraud in Oracle Cloud ERP Financials with Machine Learning. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *3*(4), 57-67. https://doi.org/10.63282/3050-9262.IJAIDSML-V3I4P107

[61] Rahul, N. (2022). Enhancing Claims Processing with AI: Boosting Operational Efficiency in P&C Insurance. *International Journal of Emerging Trends in Computer Science and Information Technology*, *3*(4), 77-86. https://doi.org/10.63282/3050-9246.IJETCSIT-V3I4P108

[62] Karri, N. (2022). Leveraging Machine Learning to Predict Future Storage and Compute Needs Based on Usage Trends. International Journal of AI, BigData, Computational and Management Studies, 3(2), 89-98. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V3I2P109

[63] Tekale, K. M. (2022). Claims Optimization in a High-Inflation Environment Provide Frameworks for Leveraging Automation and Predictive Analytics to Reduce Claims Leakage and Accelerate Settlements. International Journal of Emerging Research in Engineering and Technology, 3(2), 110-122. https://doi.org/10.63282/3050-922X.IJERET-V3I2P112

[64] Rusum, G. P., & Pappula, K. K. (2023). Low-Code and No-Code Evolution: Empowering Domain Experts with Declarative AI Interfaces. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *4*(2), 105-112. https://doi.org/10.63282/3050-9262.IJAIDSML-V4I2P112

[65] Pappula, K. K., & Rusum, G. P. (2023). Multi-Modal AI for Structured Data Extraction from Documents. *International Journal of Emerging Research in Engineering and Technology*, *4*(3), 75-86. https://doi.org/10.63282/3050-922X.IJERET-V4I3P109

[66] Jangam, S. K., Karri, N., & Pedda Muntala, P. S. R. (2023). Develop and Adapt a Salesforce User Experience Design Strategy that Aligns with Business Objectives. *International Journal of Emerging Trends in Computer Science and Information Technology*, *4*(1), 53-61. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I1P107

[67] Anasuri, S. (2023). Confidential Computing Using Trusted Execution Environments. *International Journal of AI, BigData, Computational and Management Studies*, *4*(2), 97-110. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V4I2P111

[68] Pedda Muntala, P. S. R., & Jangam, S. K. (2023). Context-Aware AI Assistants in Oracle Fusion ERP for Real-Time Decision Support. *International Journal of Emerging Trends in Computer Science and Information Technology*, *4*(1), 75-84. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I1P109

[69] Rahul, N. (2023). Personalizing Policies with AI: Improving Customer Experience and Risk Assessment. International Journal of Emerging Trends in Computer Science and Information Technology, 4(1), 85-94. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I1P110

[70] Tekale, K. M., & Enjam, G. reddy. (2023). Advanced Telematics & Connected-Car Data. *International Journal of Emerging Trends in Computer Science and Information Technology*, *4*(1), 124-132. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I1P114

[71] Karri, N. (2023). ML Models That Learn Query Patterns and Suggest Execution Plans. *International Journal of Emerging Trends in Computer Science and Information Technology*, *4*(1), 133-141. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I1P115

[72] Guru Pramod Rusum, "Green ML: Designing Energy-Efficient Machine Learning Pipelines at Scale" *International Journal of Multidisciplinary on Science and Management*, Vol. 1, No. 2, pp. 49-61, 2024.

[73] Kiran Kumar Pappula, "Transformer-Based Classification of Financial Documents in Hybrid Workflows" International Journal of Multidisciplinary on Science and Management, Vol. 1, No. 3, pp. 48-61, 2024.

[74] Rahul, N. (2024). Revolutionizing Medical Bill Reviews with AI: Enhancing Claims Processing Accuracy and Efficiency. International Journal of AI, BigData, Computational and Management Studies, 5(2), 128-140. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I2P113

[75] Pedda Muntala, P. S. R., & Karri, N. (2024). Evaluating the ROI of Embedded AI Capabilities in Oracle Fusion ERP. International Journal of AI, BigData, Computational and Management Studies, 5(1), 114-126. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I1P112

[76] Sandeep Kumar Jangam, Partha Sarathi Reddy Pedda Muntala, "Comprehensive Defense-in-Depth Strategy for Enterprise Application Security" International Journal of Multidisciplinary on Science and Management, Vol. 1, No. 3, pp. 62-75, 2024.

[77] Anasuri, S., & Rusum, G. P. (2024). Software Supply Chain Security: Policy, Tooling, and Real-World Incidents. International Journal of Emerging Trends in Computer Science and Information Technology, 5(3), 79-89. https://doi.org/10.63282/3050-9246.IJETCSIT-V5I3P108

[78] Karri, N., & Pedda Muntala, P. S. R. (2024). Using Oracle's AI Vector Search to Enable Concept-Based Querying across Structured and Unstructured Data. International Journal of AI, BigData, Computational and Management Studies, 5(3), 145-154. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I3P115

[79] Tekale, K. M. (2024). Generative AI in P&C: Transforming Claims and Customer Service. International Journal of Emerging Trends in Computer Science and Information Technology, 5(2), 122-131. https://doi.org/10.63282/3050-9246.IJETCSIT-V5I2P113