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Connected Financial Services in the Automotive Industry: AI-Powered Risk Assessment and Fraud Prevention

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Abstract

This paper presents a method for the application of AI in the design of risk assessment model, under a scheme for provision of financial services within the supply chain to the automotive industry. This scheme can be broadly divided into the procurement and distribution of automotive parts. The case of a dealer receiving a loan in order to pay for stock. The car dealer utilizes a DApp on a blockchain network to apply for a deferred insurance loan. The insurance company provides the loan after the car dealer is authenticated; however, the insurance company's assets are tied up on an insurance contract. The insurance company additionally provides the car dealer with a loan level AI. This AI provides a recommendation as to the credit worthiness of the car dealer, and detects the court-mandated arrest registration of the car dealer's CEO. Obligated to pay back the loan, the car dealer receives a loan from a stock financing service. The car dealer makes automatic returns of the loan based on financial vehicles. This last endowment is the one that will be modeled.

Risk assessment is defined as an identification of the risk tasks involved in a loan against a type of automotive working capital financing. After this, a causal loop diagram is constructed and a stock and flow model proposed. Lastly, a finite impulse response model is designed using a deep neural network. There exist no reports on the use of AI in the modeling of the aforementioned causal structure and, moreover, the type of automotive working capital financial service to be addressed is entirely novel. As such, the methodology is not merely empirical, but one of analytical modeling and modeling of the system structure on the basis of policy computer simulations of total policy commitments for selected rights. In terms of analysis, the credit AI is developed by a chain-based dealer networking platform that assists potential borrowers such as car dealers with credit evaluation.

Keywords: Automotive Financial Services,AI-Powered Risk Assessment,Fraud Prevention in Automotive Finance,Connected Vehicle Financing,Machine Learning for Risk Management,Credit Scoring with AI,Automotive Loan Fraud Detection,Predictive Analytics in Finance,AI-Driven Financial Decision Making,Digital Finance Solutions,Vehicle Financing Risk Analysis,Real-Time Fraud Detection,Financial Technology (FinTech) in Automotive,Secure Automotive Transactions,Smart Contract Technology in Automotive Finance.

1. Introduction

The automotive industry is being fundamentally transformed, and the focus of the companies are shifting from production to services, data, and customer engagement. Connected vehicles equipped with a variety of sensors generate an unprecedented volume of data related to both the vehicle itself and its environment. Some of this data is highly sensitive, containing personal and confidential information about the driver and the passengers, making it a prime target for cyber attackers. Meanwhile, governments are enacting laws tightening data privacy rules and regulating data ownership, limiting the manufacturers' and service providers' possibilities.

On a higher level, with the advent of the Internet of Things (IoT), it has become possible for data science and machine learning approaches to revolutionize decision-making in various industries by analyzing large, semi-structured or unstructured data sets such as driver health, emotion, and current traffic conditions. Work done by can monitor vehicle bus traffic, road traffic signs or hazards, and traffic lights, learning normal behavior using Hidden Markov Models (HMMs) with depth-1 trees. More advanced machine learning techniques can be applied more generally to connected vehicle data, such as Support Vector Machines.

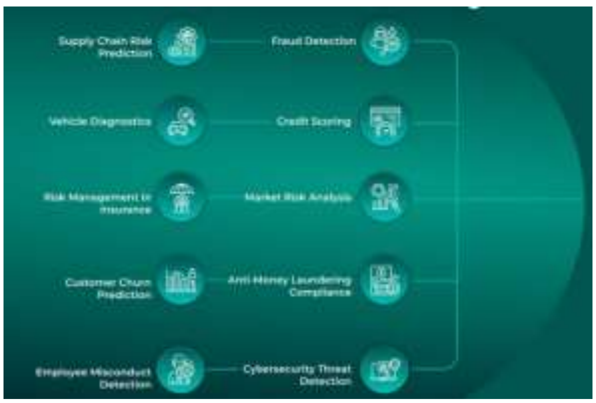

Fig 1: Artificial Intelligence in Risk Management

1.1. Background and Significance

Although already maturing, the real thor of vehicular connectivity technologies is expected in the near future. Auto manufacturers were relatively late to embrace the internet of things and capitalize on the potential connectivity of their products. However, in the last few years it seems that the digital-economy domino effect has also pushed this discipline into the automotive industry, where vehicles are becoming connected from within as well as to the outside world. The motivation to connect vehicles is many-sided. Car OEMs are racing to introduce advanced telematics services, using the internet connectivity of their vehicles as a platform for profitable business models. The current installed base of connected vehicles serves as a relevant platform for a variety of vehicular services, ranging from safety and car health systems to real-time data, entertainment and more. Communication systems are installed in vehicles, like sensors, radars and GASes, or embedded systems like airbags, brakes, throttle, networking components, etc., can cooperate with information provided from smartphones.

This transformation is fueled by innovations in sensing-based technologies (e.g., RADAR, LiDAR, cameras), ride-sharing data-driven services, geospatial tracking and mapping innovations. Nonetheless, it also raises numerous risks to drivers and passengers. For instance, the number of car accidents has increased between 2014-2016. Connected car industry is working according to Vehicle-to-EVERYTHING (V2X) communication technologies to eliminate increasing car accidents. As connected car applications continue to identify and develop for the automotive market, data usage over the connected communication cycle shows incremental growth at the end of 2020. However, at every growth stage of data usage in cars, security and privacy issues are getting increased. Major risk areas found for connected car security are smart devices and IoT, infotainment, traction battery packs and charger. Last, the ECU buffer and hack cars data is the primary question and issue for the automotive sector.

Equ 1: Ad Spend Optimization (Linear Programming)

$$\sum_{i=1}^{n} c_i x_i \leq B$$

Where:

- Z = Total return on investment from advertising campaigns
- r_i = Revenue generated from ad spend in channel i
- x_i = Amount spent on channel i
- c_i = Cost per unit of ad spend on channel i
- B = Total advertising budget

2. Overview of Connected Financial Services

The connected automotive industry has seen its revenue potential shift from hardware sales to services like financing and loans. The technologies supporting the automotive industry shifts to connected financial services, as cars seamlessly connect with financial institutions. The advent of autonomous vehicles has significantly disrupted the automotive ecosystem. With the increasing adoption of autonomous vehicles, the way people own and operate vehicles has to be revolutionized, thereby stimulating the automotive industry to bring revenue to a new trend. To seize used-vehicle sharing, rather than outright purchase, the driver can acquire a more flexible usage of vehicles in which financial assistance becomes essential. In recent years, the revenue of financial assistance in the automotive industry has been overwhelming the sales of vehicles themselves. The uptake of automotive mobility services is a converging trend in the automotive industry that promotes the emergence of connected financial services. Financial services in the connected automotive area range from easy-to-realize insurance to upcoming risk assessment as well as compliance-based loans. These services aim at providing a deep and complete financial solution for each mobility need of the customer.

Carmakers can also partner with third-party insurers, who utilize the connected payment box to estimate the insurance fee on the basis of driving behavior patterns. Risk assessment service using advanced machine learning models, particularly deep learning models, and vast parameters to identify potential risks for vehicle owners. This subsequent improvement includes an off-board cloud server, where tremendous data generated by cars can be processed in as a quick a time as possible. Besides, the deployment of a novel and intelligent algorithm, which is an

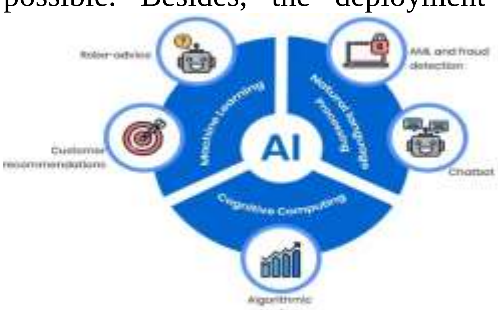

Fig 2: AI in Financial Services

2.1. Research Design

The implementation of AI-powered financial services is of somewhat recent origin but has seen significant growth in recent years. Recent research highlights the potential of AI-powered risk assessment models resulting in an increase in annual revenues and number of loans provided by banks through an enhancement in customer financial assessments. It also proves that the implementation of AI-powered fraud prevention models increases the amount of reported fraud and reduces any wrongful allegations of fraud among bank clients.

Automobiles hold quite a unique position when compared to other consumer goods in terms of investment size. Financing the purchase of a car is hence a good way to increase sales, because consumers find it difficult to pay for the vehicle upfront due to the high price. The increasing necessity of a car in modern society, especially in terms of necessity for independent living situations in most urban areas around the globe is causing automobile markets to grow in size, further accelerating the need for financing. This is why automobile finance was developed in the first place, and why including AI-powered financial services in this area is the focus of research in this paper. The rise of AI-powered financial services is expected to hit the market globally within only 5 years. The development of smart cars, digital wallets, and cryptocurrencies will further escalate this trend. However, until now, there has been a void of research regarding this topic in the automotive industry. It is important to study and note the effects on financial advancement in any union of a new technology and industry to foster constant and sustainable advancement in the automotive industry as well as the financial industry. With the implementation of AI-powered risk assessment and fraud prevention models, financial institutions in the automotive industry are expected to significantly increase client gains, amount of loans, and car sales.

3. The Role of AI in Financial Services

Financial services are the lifeblood of the economy. Without access to credit, businesses cannot expand, entrepreneurs cannot develop goods or services and individuals cannot afford to make significant purchases. With automobiles accounting for 6.7% of UK GDP, financial services in the automotive industry are part of a large and highly competitive market. It is therefore important for businesses in the automotive industry to work effectively with financial service providers to ascertain their ability to provide innovative and competitive access to consumer credit. Connected Financial Services is a three-year project designed to expand, develop and deliver real-time AI-powered risk assessment and fraud prevention solutions, initially within the automotive sector before considering opportunities in other relevant sectors.

Connected Financial Services includes Pivotal Innovations, Capricorn Capital Group, SalesMaster, and the University of Surrey, working alongside partners from the automotive industry and contact centres. This unique innovation partnership aims to press the technology readiness index of AI-powered financial risk and fraud prevention solutions and implement these within the working practices of the automotive and contact centre sectors. It is known as four work packages, each lasting eight months. Work Package 1 involves User Research and Business Case Development and will produce outputs in the form of regular project updates, in-depth user research reports, a public Business Case Summary and a closed part Business Case Approval. Work Package 2 involves Dimension Technologies Platformation, data modelling, customer scoring and fraud prevention training capabilities. Outputs include the definitions, detailed data models, performance evaluations, fraud risk frameworks and technologies. Work Package 3 involves Banking and Credit Integration as well as warm-up workshop, technical capabilities to interfacing and systems integration and a Project Mid-Term sustainability review. Work Package 4 involves User-Trial, Scale-Up, and Market-Validation. Outputs include user-testing reports, a public industry white paper, early-stage human learning product prototypes and a final project report.

Fig 3: Role of AI in Financial Services

3.1. Understanding AI Technologies Artificial Intelligence (AI) is a branch of Financial Technologies (FinTech) dedicated to the development and training of algorithms for the intelligence of machines. AI lays at the forefront in FinTech applications since the vast majority of today's FinTech solutions are based on AI technologies. AI-Assisted Technologies (AT) in FinTech bring an improvement in performance, convenience, or efficiency in terms of handling financial activities. The Financial Services Industry is one of the frontiers where the synergy of AI and FinTech can present notable opportunities. More specifically, the benefits of AI and FinTech applications can be grouped into the following categories.

The Financial Services Industry consists of a multitude of sectors involved in the management of finances in terms of monetary, technological or other related activities. With advances in technology and data management, the industry has gone through a major transformation leading to the advent of the modern age financial services that are accessible and operable purely online. Nevertheless, the financial services industry is facing numerous challenges, particularly due to the omnipresent dangerous activities that are deceiving businesses, organizations, and individuals. For this reason, financial services need to safeguard themselves against the increasing threat of fraudulent activities while simultaneously reducing the risks connected with customer behavior.

These combined factors have given rise to a necessity for innovative AI-Assisted solutions to provide an in-depth risk assessment of new or existing customers. Such demands have triggered a vast scope of research work in developing AI-Powered mechanisms for the risk assessment and fraud prevention of financial services.

3.2. Applications of AI in Finance The AI-driven development of an automotive industry at the connected comprehensive financial services market will redefine how transaction, credit, interest, life, and asset insurances are handled across industrial boundaries. Comprehensive interest in products or programs will change the permeable integration of commercial risks relating to credit, asset, and transaction insurances. As ubiquitous financial services will become a more critical connected service generality, financial institutes will exert more attention to creatively investing in non-financial territories. It has been anticipated the firm, which first concentrates on the realistic surrounding automobile domain, will be in a superior position to expand its market dominance into new financial industries by obviating the cost of being educated about the problems. Moreover, it is also foreseen that financing markets for "used" cars, mobility-related computational analysis, or digital asset management will be significantly grown.

With the advent of FinTech challenger companies, the bank's market share on automotive asset management and inter-dealer funding programs is under threat by entering the automotive retail business on the prevailing connected finance platform. FinTech activity is a concern for mid-cap "wholesale financiers that usually participate in the automotive funding program. With the emphasis on mid-term and long-term asset economics, a data analysis system has been developed, allowing for AI-powered risk assessment and the fraudulent prevention regarding the typical financial structures of transaction assets in the automotive retail sector. The scenario highlights six views on how the financial service market at the (connected) automotive industry will look like in 2030. With the realistic industrial focus, the views are expected to highly facilitate the economic strategy formulation for the macroscopic financial planning, and governmental economic policies such as market regulation, and industrial standardization under the new paradigm of the innovative transaction-based connected service economy.

Equ 2: Recommendation System (Collaborative Filtering)

$$\hat{r}_{ui} = \mu + b_u + b_i + \frac{\sum_{j \in N(i)} (r_{uj} - \mu - b_u - b_j)}{|N(i)|}$$

Where:

- $\hat{r}_{ui}$ = Predicted rating of user u for item i
- μ = Global average rating
- b_u = Bias of user u
- b_i = Bias of item i
- $N(i)$ = Set of users who have rated item i
- r_{uj} = Rating given by user u to item j

4. Risk Assessment in the Automotive Sector

Connected Financial Services is a recent concept of integrating financial ecosystems with different sectors by implementing open APIs and partner networks to provide added-value services for customer and business needs. In the automotive sector, new business opportunities can be obtained for manufacturers, pathways operators, and passengers by providing more smart and connected services and adding intelligent customer journeys. When offering a rental car as a replacement vehicle, it is helpful to streamline the processing of the loaner car request and shorten the request cycle as much as possible. This can be achieved by connecting the core service package system to the customer's dealer management system and by applying a risk assessment model that can quickly evaluate the business partner's credit line adequacy and financial soundness.

The availability of such systems is also expected in the future. The automotive industry is amid a strong transformation phase. Autonomous driving, electrification, and intelligent cloud services are shaping the future developments. These transformation trends can potentially redefine the business models in the automotive industry, turning the classical car sales and service industry into a customer-oriented mobility and smart industry ecosystem. As a consequence, these trends encourage industrial partners to be more seamlessly connected with each other, and connected financial services emerge to enable the realization of such connections. On the other hand, they lead to an enhanced expansion to an open partner network and empowered service capabilities to generate more anthropocentric services and intelligent customer journeys.

Fig 4: Risk Assessment in the Automotive Sector

4.1. Identifying Risk Factors User needs to identify factors that are important for financial institutes to examine when building driving risk assessments. The automotive industry is characterized by the interconnectedness among different services. Physical and traditional services have given way to connected and digital services, and the automotive industry is no exception. Transportation services, including the leasing or rental of vehicles, are increasingly involving entities beyond those that traditionally produce automobiles. The role of banks and other financial institutions is expanding in the global automotive industry. Enhancements in connected transportation services are creating new retail and financial opportunities, and they are also leading to new risks. The biggest challenge to creating successful insurance telematics services in Japan were financial regulations, but those barriers have been removed.

The automotive insurance industry is beginning to devise and implement advanced connected financial services. Payment services for parking fees and other activities related to car navigation are connecting native financial technological services. In regard to connected car risks and safety, financial technology institutions are developing services in the area of liability risk. Insurance premium pricing is more accurately reflecting the driving risk after a car accident that would involve financial aggregation.

Financial technology service providers in the field of AI-powered fraud prevention are cooperating with car navigation providers in order to obtain the big data necessary for driving risk assessment and fraud prevention. This is because information about driving behavior, driving environment, and car shocks is required when conducting a driving risk assessment, and this data is widely available from car navigation providers.

4.2. Data Sources for Risk Assessment

This work aims at the seamless integration of connected financial services in the automotive industry, such as in-vehicle shopping, usage-based insurance or tolling and refueling payments, by reducing risk of usage of such services. The proposed system is able to learn transaction-based diagnostics behaviour and location patterns and detects fraudulent transactions. Furthermore, the proposed framework automates the risk assessment and reaches an optimal balance between a high acceptance rate of applications and low rates of defaults via a supervised learning approach by processing the financial data of a large cohort of consumers. Likewise, the risks are automatically given on the legibility of financial methods with the finances made at a car dealer, controlled for the credit score and the value of the sale. Importantly, default risks are very high for consumers buying a car using another form of credit, such as bank loans or money from loan and lease companies, in comparison to buyers using direct contributions, personal savings or financing with a credit card. The automotive industry is experiencing a paradigm shift where the role of the driver is gradually taken over by the vehicle, making the driving task unnecessary. In an era where the vision of accident-free driving appears to be feasible, autonomous vehicles will require a new approach to road safety and expose new safety and security problems. The integration of autonomous and connected vehicles will reshape the automotive domain and the role of intelligence within the vehicle will soon rise to levels comparable to that of a supercomputer. As such, the consideration of safety, security, real-time and dependability will encompass this new type of system of systems and the application layer will play a fundamental role for functionality achievement in low criticality domains. In light of these elements, a novel model-based framework for the risk-driven analysis of the key functional and non-functional properties of in-vehicle applications is proposed and detailed. This probabilistic framework merges different fault and attack trees in a common analysis flow where failure propagates in a conservative way between the architecture and the application models, at worst-constant rate. Finally, the proposed framework is applied to a parking application and its effectiveness is demonstrated at two different stages of the development cycle.

5. Fraud Prevention Strategies

Since the 2013 Global Financial Crisis, the financial services sector has been under increased scrutiny, and numerous multi billion-pound fines are paid every year for various compliance breaches to various geographic regulators. As a result, the integration of these services has been drastically increased, i.e. insurance and credit alongside vehicle finance. This new integration is capable of reduced fraud and eases affordability to enhance vehicle sales to the public. For the providers however, it creates a problem that stretches conventional risk assessments outside the capabilities of existing automated underwriting. This investigation would address that problem by providing a solution that can perform the risk assessments of such multi-service packages. The methods of conventional vehicle loan providers would be compared with the underwriting artificial intelligence. Revelation was provided that potentially a large market is entering this feature. It is expected that multinationals compliance with these regulations would likely adapt the recommended underwriting solution being imposed reliant on due diligence laws. Accessories, insurance, and servicing are typically highly profitable sectors of the automotive industry but are also the most expensive. However, the extensive range of finance providers makes it difficult for any singular service provider to stand out. Hence the payable product is quickly reaching the tipping point of it being supplied for free by the majority of providers, much in the way in-flight entertainment has within the aviation industry. Subsequently vehicle finance provider profit margins have come under increasing pressure; to the point it is offering negative Profit deals. There are £16.7 million AUD per year opportunities that could be seized if a route was developed to introduce this finance-sales integration. As the growing integration of financial and automotive services would potentially play a large market part and trigger the creation of novelty, realistic financing packages.

Fig 5: Fraud Prevention Framework

5.1. Types of Fraud in Automotive Finance

Vehicle financing presents an interesting use case for connected financial services and Industry 4.0 in general of the automotive industry. Risk assessment and fraud detection in this realm is an exceedingly complex and largely unsolved problem. To provide financial services related to automotive industries or vehicles themselves, financial partners will need twice the amount of consumers' and clients' personal or financial data compared to selling simple household or consumer goods, since vehicles and houses are often two most expensive products people buy in their lives. VIN and other vehicle identification serial numbers plus driving and traffic violation records would be involved. This additional information volume and complexity also raises the effectiveness and efficiency demands on the necessary financial and risk assessment models and tools. Additionally, as these vehicles become x-everything connected and are able to and need to make decisions on their own, usually involving finances and financial transactions, it will be a straightforward and almost certain, that some criminal subjects, groups or possible attacks against said vehicles will target such situations and industries at some point. Thus, fraud prediction models also need to be developed and constantly improved.

Fraud approaches can comprise a broad spectrum of attack methods from relatively simple using dealer and retailer connections or their insiders as case in advance-fraud up to very complex denial-of-vehicle (ransomware) DDOS and service attacks. The risk continuously increases along with the amount of vehicle features and functions controlled by financial services or automotive internet-of-things. This paper is aimed to create an encompassing and real-time-risk-aware automotive financial services risk-assessment and fraud-detection model based on an industry 4.0 compliant infrastructure with cloud foundation. Simple fraud but solid black-listing risk assessment models are distributed to the vehicle client and financial service sides. These models are augmented with neural network deep inspection in case of risk or complex financial services.

5.2. AI Techniques for Fraud Detection

Fraud has been a continuing criminal act, and it has been more transparent than the past due to advanced technologies, making it possible to commit the frauds in more sophisticated ways than before, such as mobile telecommunication fraud, computer network breach, etc. Various kinds of fraudulent behavior performed by the offender have been examined widely in the field of accounting, criminology and other academic areas. Frequently, the literature emphasizes explanations about why people commit fraud or the motive behind the crime. The fraudulent method can be well-explained by the fraud triangle, the model describes three critical points related to fraudulent behavior: the incentive/pressure to commit fraud, the opportunity for the fraud to be perpetrated, and the perpetrator's rationalization for why they are committing the fraud. In-depth knowledge of fraudulent activities has drawn the attention of academics and practitioners in recent years, as governments and companies lose a large amount of assets because of fraud, forcing governments to respond more seriously to prevent the perpetuation of fraud. A high frequency of transactions for certain institutions can hide fraudulent transactions. The hidden fraudulent transactions must be eliminated because their risk is very high. One solution to identify these fraudulent transactions from the pool of large, anonymized transactions is by developing a machine learning-based algorithm to minimize risks for automotive industries and financial institutions. Machine learning is a branch of artificial intelligence that allows computers to perform tasks based on training data. Training data can be in the form of any numerical or textual data; garnering the learning process. Deep learning is a subset of machine learning that utilizes artificial neural networks to recognize intricate relationships in data. Currently, many fraud detection systems are built using machine learning and deep learning methods to detect and prevent fraudulent activities. There are a myriad of techniques utilizing both machine learning (ML) and deep learning (DL) used to create models to detect fraudulent behavior from a transactional data set. Parlaying the proliferation of publicly available data since the mid-2010s has allowed academics to experiment and develop various ML and DL models, such as k-nearest neighbors, support vector machines, ensemble classifiers and many more. Despite underlining successes in developing applied ML and DL models for the industry, fraud detection presents several challenges of particular interest: the unbalanced nature of the data and the dynamic nature of fraud itself. In this article, an essay is presented addressing these issues and exploring how such models can be evolved.

Equ 3: Price Elasticity of Demand

$$E_d = \frac{\%\Delta Q}{\%\Delta P}$$

Where:

- E_d = Price elasticity of demand
- ΔQ = Change in quantity demanded
- ΔP = Change in price

6. Case Studies of AI Implementation

Today, a variety of sectors are undergoing massive change as the result of artificial intelligence (AI) implementation. This case study dives into how a customer used an AI digital underwriter to change its digitally connected financial services scene, increase its strengths in capital operation, and test tasks better than its existing methods. The customer can also improve its competitive situation and improve its user profitability. Six months of iteration with the client are presented by taking thoughtful decisions on smart system design. New rules that characterize the automotive e-commerce sector are also provided, benefiting a larger population. For the bank, this benefits the use of bridging, small microcredit, and consumer finance models more wisely.

Intelligent risk control can anticipate transaction risks that may arise during the transaction by using consumer's saved data in advance to decide on remediating. The evaluation of this data can be done with AI. The problematic data is identified, the early warning devices are formed before the risk occurs, and the stage is treated in a timely manner after the risk occurs. Also, in real-time, the risk of occasions is effectively tracked in the case of an event and confirmed as a standard of bank transaction. The difficulty of routine transactions can be warned in advance, inappropriate transactions should not be permitted to pass in real-time systemically, and the bank risk management level can be significantly increased since the AI intervention. At the same time, the bank's loans can be completed under the leadership of AI.

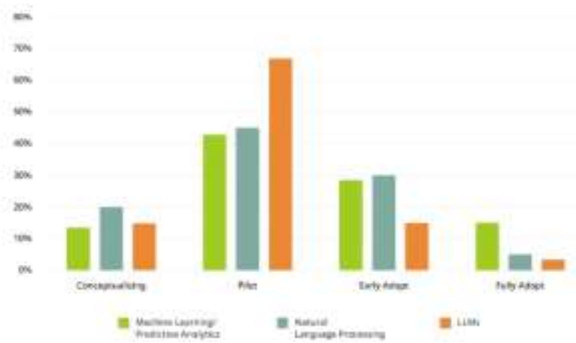

Fig : AI-Enabled Risk Assessment

6.1. Successful AI Integration in Financial Services With fierce competition arising from multiple industries and ever-pressing customer demands, automotive-related companies are pushed to seek new opportunities for growth. One of the most promising ways, along with traditional ones like launching new models, advertising, logistics, etc., is offering connected financial services. Such services not only reduce crash-induced financial risks for car owners, but enable crafting a wide array of unique financial products tailored specifically to drivers' daily behaviour—all based on telematics from the same connected car. This business model relies on the vast amount of behavioral and surveillance data generated by connected cars, meaning customers will gain both financial and non-financial benefits the moment they opt into it. Meanwhile, in the era of burgeoning black-box attacks, addressing customer data security is the top priority.

Automotive companies are essentially not in the financial industry, which means a risk assessment must be performed when connected financial services are provided. Moreover, the black-box entry's causal discovery process is unknown to its external behavior, causing violence to the debiasing methods, which in varying degrees rely on approximations of the causal structure. In the following study, a model is developed with Shapley additive explanations, so that any black-box, gradient-based machine learning model can be complemented with a more straightforward representation of feature importances. Post hoc explanations approach is employed first and foremost, as the reasons behind a particular prediction are particularly important when the prediction is not the label with the maximum probability. Further, SHAP not only highlights the driving factors behind a specific prediction but also assists in interpreting the global model behavior.

6.2. Lessons Learned from Failures

The automotive industry is currently in a state of upheaval. Sales, production and innovation are being revolutionized by global trends such as connectivity, autonomous driving, sharing and electric vehicles. Global safeguarding of value chains through the provision of connected financial services is moving more into the focus of the industry. This will be particularly important to counteract the massive shift of added value to new mobility players focused on software and platform offerings. In addition, the buildup and operation of new areas such as the analysis of payments in e-vehicles, including the associated real-time risk assessment, increase the complexity of the parties and business relations involved, as well as the structure of the services provided. In the described setting, the paper presents a principled approach on how to systematically derive a transparent representation of the industrial scope. The core of this representation forms a structured view on the involved business processes as well as the derived technical requirements and services provided. It reveals that on one hand, the creation of transparency requires a considerable analytical effort. If applied consistently, however, it helps to identify various opportunities for cooperation and provides the industry partner with a clear understanding of the business challenges and technical requirements of the other.

7. Conclusion

In conclusion, several applications in the automotive industry were demonstrated, providing an extensive overview of how connected financial services can be designed and implemented to benefit different stakeholders in the ecosystem. Retail banking partners can use AI-powered risk assessment to create individual financial products without any acquisition risk. Ford Credit can prevent fraud in applications for car subscription services. Shared mobility partners can develop driver scoring as a value-added service to increase the quality and security of the car sharing service. Starting with the business use case, it was highlighted how connected financial services help different parts of the automotive ecosystem to leverage the value of in-car data. Banking partners, having access to the detailed data set from the car, benefit from the automotive brand reputation and the more personalized risk profile created by the cars. On the other hand, the automotive player is provided with an income share and can indirectly control the fleet age ensuring that better risk-rated cars are connected. How data is collected and processed by the connected financial services was subsequently outlined. The data flow from the car to the car data analytics was detailed, including the car owner’s consent management and the off-line data standardization. Limitations and possible future works were addressed as well. In the concept of connected financial services, the car calculates the risk of fraud based on in-car data and transmits a risk score to the financial institution. However, such a model would fail to prevent fraud if the fraudster decides not to use the car. An extension of the work could be a real-time cloud-based model like the telematics services that process the data in the multi-tenant Ford cloud and generate fraud signals. Additionally, the prior fraud history could be analyzed along with the car information to detect common patterns and anomalies.

7.1. Future Trends

Next, a possible future trend in the automotive domain is addressed, which is connected financial services, focusing on two potential applications: peer-to-peer lending and car insurance. Nowadays, the automotive industry concentrates on connected and autonomous driving and electric vehicles to a great extent. However, another sector with many collaborations, partnerships, and shared knowledge is connected financial services, where car manufacturers offer their customers those and realize partnerships with insurtechs or fintechs. Exemplary applications are peer-to-peer lending or online car insurance. In the former case, cars can be expensive products, so companies offer services where buyers lend money from other people and car manufacturers complete the purchasing of the car. Car insurance is a very sensitive and bureaucratic issue. People are always complaining and always having problems when they need to get indemnity. If the sector is adopted by car manufacturers and insurance companies, customers can simply enter their application; the car provides data related to financial activities and gets 1–2 offers, then the customer picks one and completes the process.

Another potential future trend in the automotive industry is to speed up the commercialization and prototyping process of cars. The automotive sector is now at a very vibrant period. With the help of various institutions and suppliers, unique partnerships, new automobile companies have been founded, and the current automotive companies have changed their long-established strategy and start to focus on electric cars and have future-oriented goals involving self-driving cars and a sharing-oriented system interconnecting cars and other software systems, like smartphones and tablets in our daily life. But these revolutionary changes in the automotive-century relationship also paved the way for lots of uncertainties, such as the commercialization of expensive EV cars, implementations' safe use, uncertain infrastructural requirements of self-driving cars, etc. Car companies have to educate and re-educate their non-skilled and non-engineer employees with these new implementing technologies for the vehicles, which will not be an easy-to-do and cost-effective ongoing process. On the other hand, Turkish automotive start-ups are dreaming of commercializing in two years and already designed some showcase prototypes, but it seems achieving this in a very short time is very difficult due to high certification and cost requirements.

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