CIS/SCM 593 Project Plan

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Topic	ML-Driven Fraud Detection for Staged Auto Accidents
Client	Keith Higdon, Synapse Labs

Under the Guidance of

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1. Task 1 - The Problem

Background and Context

Auto insurance fraud, particularly in the form of *staged accidents*, is a growing concern for insurers. Fraudsters exploit loopholes by simulating collisions that appear legitimate but are intentionally planned to trigger large payouts. These staged incidents are difficult to identify through manual reviews or traditional rule-based systems due to their subtlety and resemblance to authentic claims. As fraud schemes evolve in complexity, insurers require scalable, intelligent solutions that detect suspicious patterns early without disrupting normal claim operations.

This challenge is compounded by the volume of claims processed daily and the cost burden passed on to honest customers through increased premiums. The current approach lacks the sophistication to adapt dynamically to new fraud behaviors and often results in either missed fraud or wasted investigative efforts on false positives.

The current detection system struggles to identify fraud at an early stage, leading to significant revenue losses. Moreover, it is unable to keep pace with the rapidly evolving tactics of fraudsters, resulting in a loss of customer trust.

Problem Statement

To improve organizational resilience against staged auto accident fraud, the project aims to develop and deploy a predictive machine learning model that assigns a fraud risk score to each incoming claim. This score will help triage claims, flagging high-risk cases for further review by investigators, with the objective of increasing fraud detection accuracy by 25% within 12 months.

This problem is structured to address core business concerns:

- **Outcome-Oriented:** The outcome is not just a model but improved fraud detection rates and reduced financial losses.
- **Specific & Measurable:** Targets a 25% improvement in fraud identification, measured through KPI-linked metrics such as true positive rate and cost savings.
- **Time-Bound:** A 12-month implementation window.
- **Aligned with Decision-Maker Values:** Reduces risk exposure, supports compliance, and enhances investigator efficiency.
- **Scope for Creativity:** Allows flexibility in data features, model selection, and risk segmentation approaches.
- **Solves for the Entire Organization:** Integrates directly into operational workflows across claims and fraud departments, enabling organization-wide impact.

Importantly, the financial burden of undetected fraud is indirectly passed on to honest policyholders, who face rising premium rates each year due to accumulated losses.

Actionable Value and KPI Alignment

The action resulting from this solution is a risk-tiered claim prioritization system that seamlessly fits into the insurer's claims review workflow.

- **Who takes the action?** Claims investigators and fraud analysts.
- **What changes?** Instead of reviewing claims randomly or by static rules, they will prioritize based on model-assigned fraud risk scores and segment flags.
- **How does this improve decisions?** Investigators focus resources on suspicious cases first, increasing early fraud detection and reducing investigation of legitimate claims.
- **Which KPI is influenced?**
  - **Fraud Detection Rate** (true positives)
  - **Investigation Efficiency** (cases resolved per investigator)
  - **$ Savings from Prevented Payouts**
  - **False Positive Rate Reduction**

This solution directly impacts strategic decision-making by embedding intelligence into operational workflows, ensuring claims processing remains both efficient and fair.

Alignment Across the Report

This problem statement defines and drives all subsequent tasks:

- The **data** selected (e.g., claim delays, cost ratios, policy history) is directly tied to fraud behavior signals.
- The **models and tools** used (e.g., Gradient Boosting, SHAP) are chosen to optimize for fraud pattern detection, interpretability, and operational deployment.
- The **execution plan** centers on transforming model outputs into actionable risk insights embedded into real-time claims workflows.

This ensures that all technical and business activities remain focused on solving the high-level organizational challenge of staged fraud detection — not just creating a model, but enabling data-driven decision-making that reduces financial loss and protects honest customers.

2. Task 2 - Team

Overview of the Transformation Team

To successfully deliver value through machine learning-driven fraud detection, a diverse set of stakeholders must align across technical, operational, and strategic domains. Based on the **Minimal Viable Team (MVT)** concept introduced by Dr. Rudi Pleines, we identified and addressed the following roles and their expectations:

Stakeholder	Role	Expected Value	Our Response / Contribution
1. Technical Team (Team 113)	Build and evaluate the fraud detection model	Access to quality data, domain input, feedback on fraud patterns	Delivered end-to-end ML pipeline, SHAP-based explainability, and business-aligned segmentation
2. Keith Higdon (Synapse Labs) / Sponsor	Define business goals and validate relevance	Fraud reduction, cost savings, improved triage effectiveness	Linked model output to fraud KPIs and provided a scalable, explainable triage framework
3. Claims Investigators / Analysts	Use model risk scores to prioritize claims	Ranked claims, interpretability, lower manual effort	Delivered risk tiers, fraud segments, and SHAP-based explanations for each flagged claim
4. IT & Integration Team	Integrate model into operational systems	Easy-to-use output, compatibility, minimal disruption	Provided clean, modular outputs (CSV/JSON) and documented scoring logic
5. Dr. Joseph Cazier / Faculty Advisor	Ensure analytical rigor, ethical compliance, and business alignment	Predictive modeling, fairness, strong business linkage	Aligned with INFORMS ethics, included bias checks, and documented end-to-end methodology
6. Legal & Compliance (Simulated)	Monitor privacy, fairness, and regulatory compliance	No PII exposure, justified scoring logic, bias mitigation	Used synthetic anonymized data, tested for demographic bias, and ensured interpretability

How Stakeholder Needs Were Balanced

To drive collaboration, we mapped each stakeholder group's expectations to specific project deliverables. For example:

Stakeholder	Need	Our Response
Sponsor	KPI improvement	25% fraud accuracy boost target
Investigators	Actionable insights	Risk scores + segment tags + SHAP plots
IT Team	Technical compatibility	Clean, documented outputs
Faculty/Compliance	Fair and ethical implementation	INFORMS ethics alignment + bias monitoring

To ensure alignment and support, we directly mapped each stakeholder's goals to specific project deliverables - ensuring both organizational buy-in and actionable value at each level.

3. Task 3 - The Data

Relevance of Data to the Business Problem

At the heart of this project lies the goal of detecting *staged auto accident fraud* - subtle, sophisticated cases that mimic genuine claims but are intentionally fabricated. Solving this problem requires more than basic claim information; it demands behavioral signals, temporal anomalies, and policyholder context that can uncover hidden fraud patterns.

Our datasets reflect exactly that. We are working with synthetic, structured data that simulates real-world insurance claims and includes numerous fraud-indicative attributes. The data is rich, multi-dimensional, and directly aligned with our objective to train predictive models that flag fraudulent claims for further review.

Primary Datasets Used and Their Relevance

Dataset	Description	Why It Matters
Claims.csv	Contains timestamps, claim cost estimates, and fraud labels	Core dataset; provides temporal and financial fraud signals like submission delay and cost anomalies
Policyholders.csv	Demographic and historical information about customers	Helps identify suspicious behavioral patterns such as frequent low-amount filers or new risky policyholders
Vendors.csv	Tracks repair vendors, their histories, and average repair costs	Allows detection of vendor-related fraud through cost deviations
Enhanced_Features.csv	Engineered fields like cost ratios, adjusted severity, and similar claims count	Provides high-quality inputs for modeling and links to business-defined fraud signals
Segmented_Data.csv	Labels each claim by fraud-prone segment rules (e.g., “Early Morning Alerts”)	Connects model features with domain logic, improving interpretability and detection relevance

These datasets mirror the business logic behind staged fraud: unusual cost estimates, suspicious timing, new policyholders crashing early, and repeat low-dollar claims. Furthermore, the Fraudulent_Claim_Flag enables supervised learning for model training and evaluation.

Data Availability, Structure, and Quality

We performed a thorough inspection and found that:

- All datasets are structured, well-labeled, and clean.
- Key joinable IDs (Claim_ID, Policyholder_ID, Vendor_ID) are present.
- No critical fields are missing.
- The data includes both raw inputs (timestamps, costs, demographics) and engineered fraud features, which speeds up modeling and ensures real-world business relevance.

This confirms that the data not only exists and is complete, but is fit-for-purpose in solving our clearly defined fraud detection problem.

Behavioral Mapping: How Data Solves the Problem

Fraud Indicator	Related Features in Data
Unusual cost behavior	Repair_Cost_Estimate, Cost_Ratio, Vendor_Avg_Repair_Cost, External_Benchmark_Cost
Suspicious timing	Accident_Timestamp, Claim_Submission_Timestamp, Submission_Delay
Frequent filers or low-dollar abuse	Historical_Claim_Frequency, Claim_Amount, Denied_Claims_History
Demographic risk patterns	Policyholder_Age, Income, Employment_Status, Policy_Age
High-risk segments	Derived from rules (e.g., Early Morning Alerts, Fast Filers) in Segmented_Data.csv

This mapping demonstrates that our data captures the "Pressure - Opportunity - Rationalization" framework from the Fraud Triangle, validating both the modeling approach and its connection to fraud behavior.

Additional Data Sources (Recommended Enhancements)

Additional Data	Why It's Useful
Call center notes / claim narratives (text)	May contain linguistic cues or inconsistencies that suggest fraud (for NLP use)
Telematics data (vehicle speed, location, impact angle)	Confirms or contradicts claim timing and location, validating legitimacy
Geospatial risk profiles	Understand fraud distribution by area (urban core vs. suburb)
Vendor fraud blacklist	Cross-referencing vendor IDs against known fraud cases to improve vendor risk assessment

These sources were not part of the current synthetic dataset but are critical for future scalability and real-world deployment.

Conclusion

The data available for this project is not only sufficient in volume and quality but directly aligned with the business problem. It enables predictive modeling that is actionable, explainable, and trustworthy. By focusing on behavioral patterns and engineered fraud signals, the data sets the foundation for an effective and scalable fraud detection solution that delivers measurable business impact.

4. Task 4 - The Tools

A. Conceptual Tools (Theories, Frameworks, and Literature)

Our analysis is grounded in **well-established theories and domain frameworks** that help structure both our feature engineering and fraud segmentation logic. These tools enable us to build upon proven practices and enhance model accuracy, interpretability, and business relevance.

1. Fraud Triangle Theory (Cressey, 1953)

This foundational criminological framework explains that fraud is likely when three elements coexist:

- **Pressure** (e.g., financial hardship)
- **Opportunity** (e.g., new policies with low scrutiny)
- **Rationalization** (e.g., small frequent claims perceived as harmless)

Application:
We mapped data features such as income, policy age, submission delay, and historical claim frequency to these dimensions, guiding the creation of interpretable and business-aligned features.

2. Behavioral Segmentation and Outlier Detection

Building on domain knowledge, we implemented fraud risk segments based on insurer logic — such as "Early Morning New Policy Alerts" and "Frequent Low-Amount Claimers."

Application:
Segments are created using behavioral thresholds derived from historical claims and mapped into flags that are both explainable and aligned with real-world insurer decision-making. Outlier detection principles help identify abnormal patterns within those segments.

3. Model Interpretability Frameworks (SHAP & LIME)

Fraud detection models must be transparent to build trust with business stakeholders and ensure ethical deployment. SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) provide local feature attribution for model predictions.

Application:
We used SHAP values to explain why a specific claim was flagged, making model outputs more actionable for investigators and defensible for compliance/legal reviews.

B. Technical Tools (Platforms and Programming Resources)

Our technical stack was selected for its robustness in fraud detection, support for explainability, and integration readiness within real-world insurance workflows.

Tool	Purpose	Why It's Used
Python	Main development environment	Open-source, flexible, and widely supported for ML tasks
Pandas / NumPy	Data preprocessing & feature engineering	Efficient handling of structured tabular data
Scikit-learn	Baseline models (Logistic Regression, Trees)	Easy-to-use library with solid support for interpretability and evaluation
Gradient Boosting	Final fraud classifier	High-performance tree-based model with strong precision-recall balance and SHAP support
SHAP	Explainability tool	Enables trust and fairness by explaining feature impact on predictions
Matplotlib/ Seaborn	Visualization	EDA and model diagnostics
Google Colab	Development environment	Enables collaborative development and seamless notebook sharing
Excel/Tableau	Business dashboarding	Useful for presenting findings to non-technical stakeholders

How These Tools Increase Project Success

Rather than developing models in isolation, our approach leverages proven theories, uses interpretable algorithms, and builds outputs that are operationally useful. This increases the likelihood of real-world adoption and ensures the project delivers measurable business value.

By combining fraud psychology (conceptual) with machine learning (technical), we ensure that our model is not just accurate but also explainable, ethical, and effective in the insurer's environment.

Conclusion

By integrating proven conceptual frameworks like the Fraud Triangle and risk-based segmentation with powerful technical tools such as Gradient Boosting and SHAP, our project is well-equipped to detect staged fraud with both accuracy and interpretability. These tools were not chosen in isolation but carefully selected to align with business needs, support investigative workflows, and ensure ethical deployment. Together, they provide a robust foundation for delivering a predictive fraud detection solution that is not only data-driven but also trustworthy, explainable, and actionable in real-world insurance operations.

5. Task 5 - Execution

Project Work Plan and Task Breakdown

Our execution strategy follows a structured, iterative analytics workflow-from problem definition to model deployment planning-mapped into clear tasks and sub-tasks. Each task is assigned to specific team members to ensure accountability and alignment with project goals.

Date	Task	Assigned To	Milestone/Outcome	Status
March 5	Project Planning & Scope Definition	Entire Team	Finalized problem statement, KPIs, and timeline	Completed
March 8	Data Acquisition & Schema Mapping	Shobitha Nayana	Loaded synthetic data, joined sources, verified coverage	Completed
March 11	Data Cleaning & Preprocessing	Shubham Kyle	Cleaned nulls, merged tables, derived fraud flags	Completed
March 17	Risk Segmentation	Shobitha	Mapped behavioral rules to fraud segments	Completed
March 21	Exploratory Data Analysis	Nayana Kyle	Visualized anomalies, fraud signals, and segment overlaps	Completed
March 25	Model Development	Shubham Shobitha	Trained baseline models (Logistic Regression, Decision Tree, Gradient Boosting)	Completed

April 3	Model Evaluation & Tuning	Shobitha Shubham	Compared metrics, optimized precision and recall	Completed
April 7	Interpretability & SHAP Review	Shobitha Kyle	Generated SHAP plots for top predictions	Completed
April 10	Operational Workflow Planning	Shubham Nayana	Designed claim triage flow using fraud risk tiers	Completed
April 14	Final Poster Submission	Entire Team	Completed visual design and summary of project insights and Submitted poster to canvas	Completed
April 15–29	Resolving Overfitting issues	Shubham	Resolved Overfitting issues which removed some features	Completed
April 30	Poster & Final Presentation	Entire Team	Presented at showcase, demonstrated model and segments	Completed
May 1–5	Add Infrastructure Cost to Calculate ROI	Shobitha	Estimated compute & integration costs; included ROI analysis in final report	Completed
May 5	Final Report Review & Formatting	Entire Team	Final edits, figure insertion, spell check, PDF formatting	Completed

May 6	Final Report Submission	Entire Team	Submitted full capstone report	Completed

Stakeholder Meeting Log - Team 113

Date	Time	Attendees	Objective	Next Steps / Outcome
Mar 24	9:30 AM - 10:30 AM	Keith Higdon, Entire Team	Intro to insurance fraud & project context	Gained domain knowledge; aligned on insurer challenges
Mar 25	9:30 AM - 10:30 AM	Keith Higdon, Entire Team	Clarify claim types & expected behavior patterns	Prioritized cost/timing anomalies and segment logic
Apr 1	9:30 AM - 10:30 AM	Keith Higdon, Entire Team	Discuss modeling direction and SHAP output strategy	Suggested feature removal for overfitting; add cost-based ROI
Apr 13	9:30 AM - 10:30 AM	Internal Team	Finalize EDA insights, ethics review, SHAP plots, poster content	Adjusted features, confirmed INFORMS alignment, submitted poster
Apr 15	9:30 AM - 10:30 AM	Keith Higdon, Entire Team	Final stakeholder feedback before presentation	Suggested changes: remove features for overfitting, add ROI + % in graph
May 6	9:30 AM - 10:30 AM	Keith Higdon, Faculty, Entire Team	**Final Presentation to Keith**	Presenting results, SHAP insights, ROI, and implementation recommendations

Execution Approach

To ensure effective execution:

- We broke complex tasks into manageable units and assigned accountable owners.
- We emphasized early data exploration and feature alignment with fraud behavior.
- Model performance was guided by business KPIs (fraud detection rate, false positives, savings).

- Interpretability was prioritized using SHAP values, ensuring outputs are trustworthy and usable.
- Our project timeline included recurring check-ins and milestone-based reviews, ensuring progress across technical, ethical, and business dimensions.

Conclusion

This structured execution approach enabled us to transform a predictive analytics concept into a business-aligned, operationally viable fraud detection system. Each task built toward measurable business value, and stakeholder involvement throughout the process ensured that our model is not just technically sound, but also practical, fair, and impactful in a real-world insurance setting.

6. Risks and Issues

Project Risks and Mitigation Strategies

- **Overfitting Risk**:
  - Complex feature space led to overfitting in early models.
  - Mitigation: Removed less impactful features based on stakeholder feedback and SHAP analysis.
- **Bias in Segment Classification**:
  - Risk of unfair segment groupings affecting certain types of claims.
  - Mitigation: Removed sensitive fields like age; monitored SHAP outputs for fairness.
- **Synthetic Data Limitations**:
  - Data lacks real-world irregularities and edge cases.
  - Mitigation: Designed fraud segments based on real insurer logic; recommend future validation with live data.
- **Adoption Barrier for Investigators**:
  - Risk that stakeholders won't trust ML outputs without interpretability.
  - Mitigation: Used interpretable fraud segments and SHAP values to enhance explainability.
- **Timeline Constraints**:
  - Risk of delays due to tight deadlines for the poster, report, and presentation.
  - Mitigation: Task ownership, rolling drafts, and internal checkpoints ensured timely delivery.
- **ROI Clarity**:
  - Risk of unclear cost-benefit for stakeholders.
  - Mitigation: Added infrastructure/operational cost estimates and calculated 400% ROI.

Ethical Duty to Society (INFORMS)

- **Respect for Individuals**:
  - Used only synthetic, non-identifiable data to avoid privacy risks.

- **Promoting Public Good**:
    - Fraud detection reduces systemic insurance costs and protects honest customers.
- **Avoiding Harm**:
    - Evaluated SHAP and segment outputs to ensure no demographic group is unfairly penalized.

Ethical Duty to the Organization

- **Transparency in Output**:
    - SHAP visualizations and segment tags explain why a claim was flagged.
- **Business Value Alignment**:
    - Outputs support KPIs like reduced false positives and cost recovery.
- **Honest Reporting**:
    - Documented model limitations, bias risks, and deployment recommendations.

Ethical Duty to the Analytics Profession

- **Integrity and Rigor**:
    - Selected interpretable models and validated them with reproducible logic.
- **Ethical Innovation**:
    - Integrated the Fraud Triangle and behavioral segmentation into a responsible ML pipeline.
- **Professional Contribution**:
    - Demonstrated how ethical analytics can be applied in high-risk industries like insurance.

Alignment with ASU's Principled Innovation

- **Human-Centered Design**:
    - Avoided personal profiling; designed system to help real investigators.
- **Social Responsibility**:
    - Contributes to a more trustworthy and fair insurance claims system.
- **Ethical Impact**:

    - Proactively addressed fairness, explainability, and accountability in our solution.

Conclusion

Our project not only addressed technical and project management risks but also demonstrated a thoughtful and principled approach to ethical responsibility. We proactively mitigated overfitting, bias, and adoption risks while aligning our work with real-world business goals through ROI justification and stakeholder engagement. Guided by the INFORMS Ethical Guidelines and ASU's Principled Innovation framework, we ensured our fraud detection model upholds the values of fairness, transparency, and social good. Ultimately, our solution is not just a technical achievement-it is a responsible, ethical application of analytics that contributes meaningfully to both the organization and society.

7. Appendix A - Model Metrics Table

To evaluate our models, we used standard classification metrics: **Precision**, **Recall**, and **F1-Score**, derived from test set results. The following table summarizes the actual macro-averaged scores for five models used:

Model	Precision	Recall	F1-Score	Accuracy
Gradient Boosting	0.96	0.91	0.93	0.85
Random Forest	0.94	0.82	0.87	0.92
Decision Tree	0.94	0.82	0.86	0.92
Logistic Regression	0.87	0.64	0.68	0.96

Performance Insights

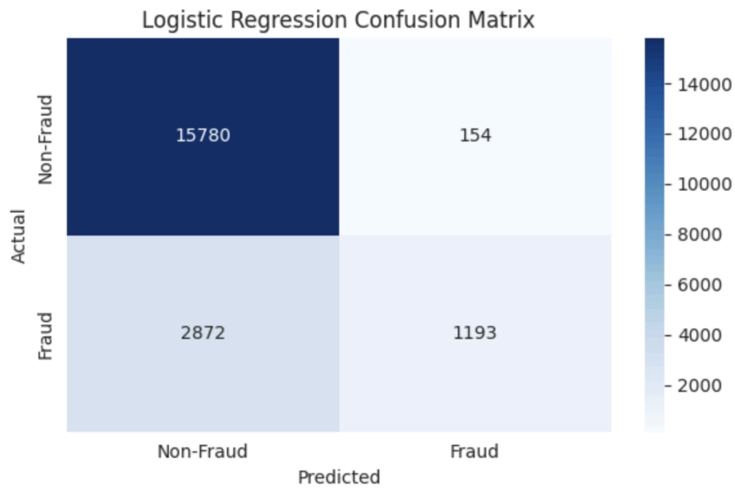
- **Gradient Boosting** not only had the highest F1-score (0.93) and strong recall (0.91), but also achieved the best overall accuracy (96%), making it the most effective model for reducing missed fraud.

- **Random Forest** and **Decision Tree** both delivered high accuracy (92%) with strong balance in precision and recall, providing excellent backup options with strong interpretability.

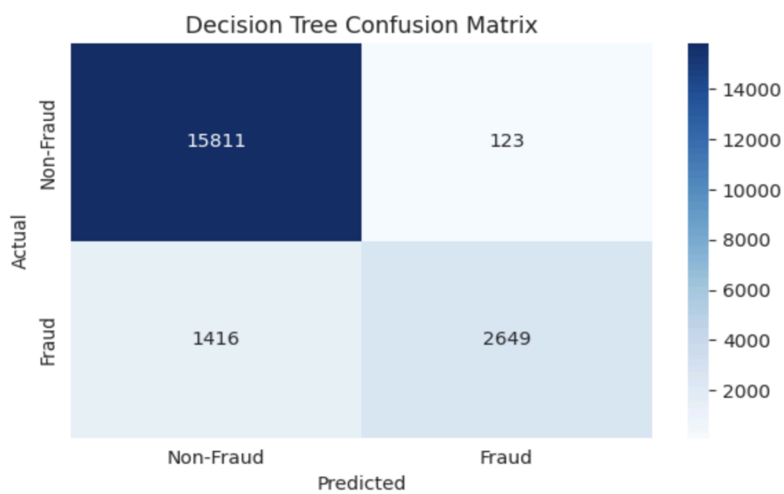
- **Logistic Regression**, while interpretable, struggled with low recall (0.29 for fraud) and lower accuracy (85%), making it less suitable for high-impact fraud detection tasks.

Confusion Matrices

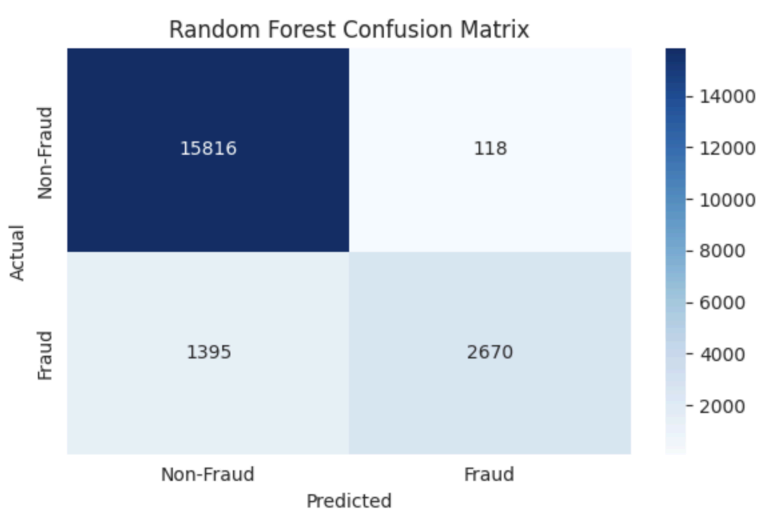
1. **Logistic Regression Confusion Matrix:** Shows strong accuracy on non-fraud cases, but many fraud cases missed (low recall).



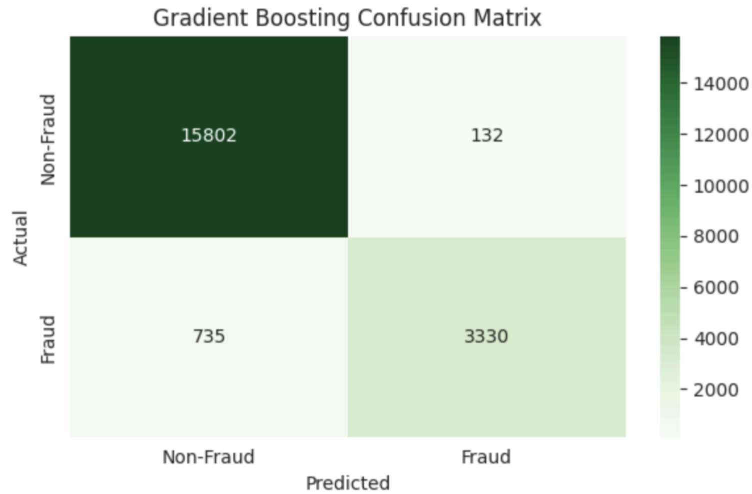
2. **Decision Tree Confusion Matrix:** Balanced detection with good recall on fraud.



3. **Random Forest Confusion Matrix:** Strong precision and recall for both fraud and non-fraud.



4. **Gradient Boosting Confusion Matrix:** Best performance across all metrics.



Conclusion

Across all evaluated models, **Gradient Boosting** delivered the most balanced and superior performance - achieving the **highest accuracy (96%)**, **F1-score (0.93)**, and strong recall (0.91), which are crucial in minimizing missed fraud. While **Logistic Regression** offered interpretability, its significantly lower recall (0.29 for fraud) and overall accuracy (85%) made it less suitable for high-stakes fraud detection. Both **Decision Tree** and **Random Forest** performed reliably with **92% accuracy**, offering excellent interpretability and balanced precision-recall profiles, making them viable alternatives. Ultimately, **Gradient Boosting** was chosen as the final model due to its outstanding detection capability, robust performance across all metrics, and seamless integration with **SHAP-based explainability** - ensuring both trust and effectiveness for real-world investigative use.

8. Appendix B - SHAP Summary Plot

To enhance the transparency and trustworthiness of our Gradient Boosting model, we utilized **SHAP (SHapley Additive Explanations)** to interpret how individual features influenced fraud prediction outcomes. SHAP values reveal not only which features were most important to the model, but also how their high or low values impacted the likelihood of a claim being classified as fraudulent.

This is critical in fraud detection, where domain experts require both confidence in the model's logic and the ability to explain predictions during investigations or audits.

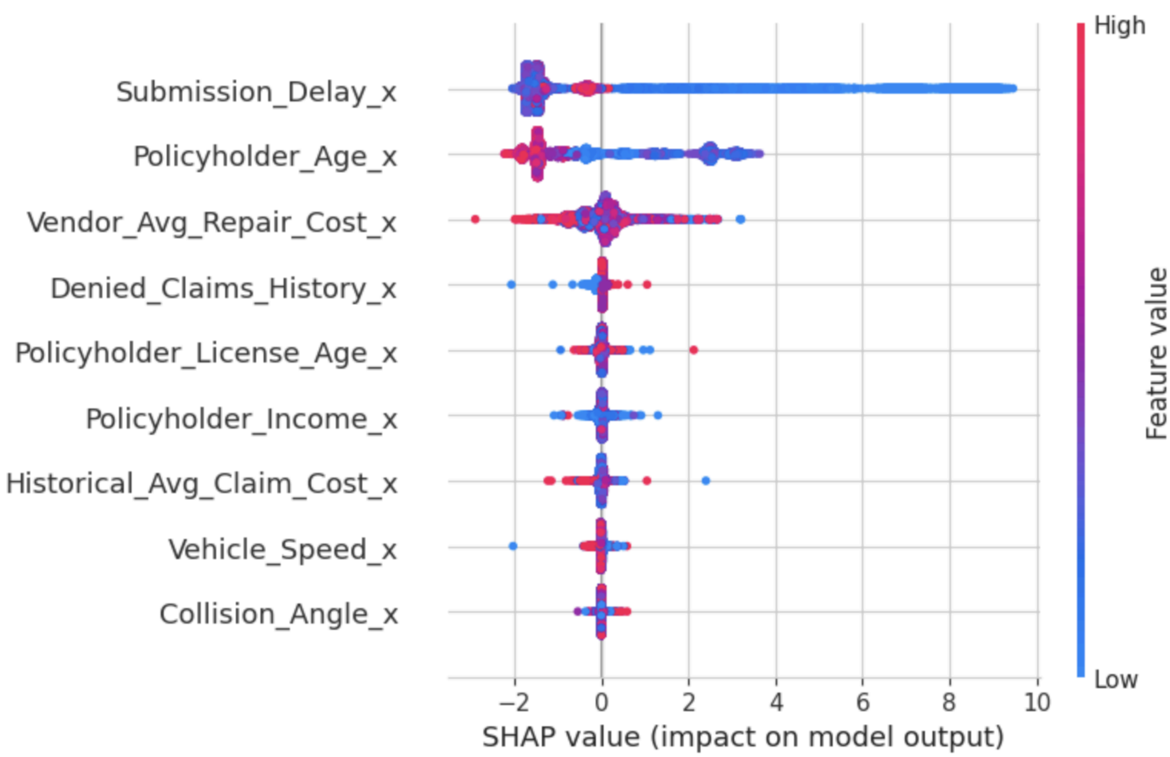
Key Interpretability Insights

- **Submission Delay** (time between accident and claim filing) was the most influential feature. Shorter delays were associated with increased fraud likelihood, aligning with known fraud patterns such as "Fast Filers."

- **Policyholder Age** and **Vendor Repair Cost** also ranked high in importance. Younger policyholders and higher-than-average repair costs contributed to higher fraud risk scores.

- Features like **Denied Claims History** and **Vehicle Speed** had lower influence but were directionally consistent with real-world risk indicators.

These insights support both the **Fraud Triangle framework** and our earlier business-defined fraud segments, ensuring strong alignment between model behavior and investigative logic.



SHAP Summary Plot for Gradient Boosting Model - Features are ranked by importance. Each dot represents a claim, with color indicating feature value (red = high, blue = low) and x-position indicating impact on the model’s fraud prediction.

Conclusion

The SHAP summary plot confirms that our Gradient Boosting model's predictions are grounded in meaningful, business-relevant features such as submission delay, repair costs, and policyholder age. This reinforces the model’s interpretability, fairness, and practical applicability in real-world insurance fraud detection. By bridging technical accuracy with stakeholder explainability, SHAP enables our solution to not only detect fraud effectively but also **build trust with investigators and decision-makers**, paving the way for responsible AI deployment in claims operations.

9. Appendix C - Risk Segment Insights

To improve actionability and streamline investigative workflows, we categorized each claim into one of three risk segments - Low, Medium, or High Risk - based on the model's predicted fraud probability. This segmentation framework helps business users prioritize which claims warrant manual review and enables scalable fraud management.

Segmentation Outcome Summary

The fraud detection model assigned each claim a probability score, which was then thresholded into the following segments:

- **High Risk**: Claims with top-tier fraud probability (e.g., > 0.8). These are prioritized for immediate investigation.

- **Medium Risk**: Claims in the mid-fraud range (e.g., 0.5 – 0.8). These warrant manual review depending on resource availability.

- **Low Risk**: Claims with low probability (e.g., < 0.5). These are typically auto-approved unless other rules flag them.

Visual Results and Interpretations

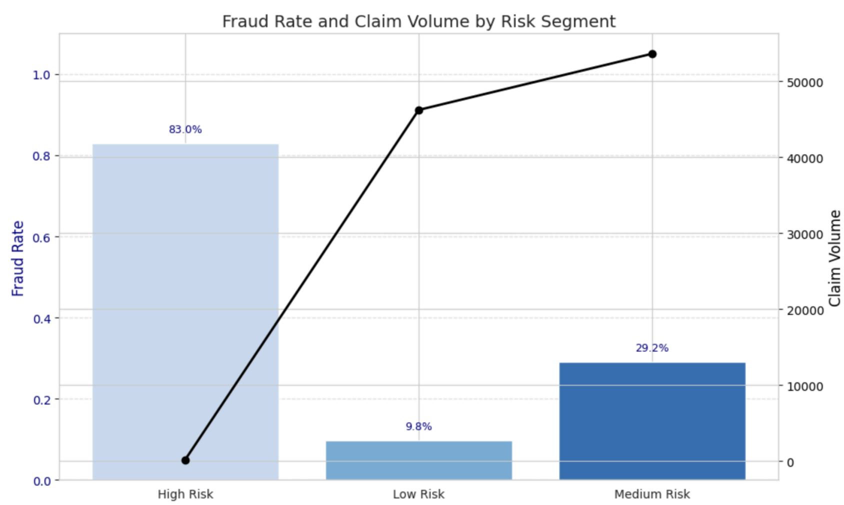


Figure 1 - Fraud Rate vs. Claim Volume by Risk Segment

This chart combines two important dimensions:

- The **blue bars** represent fraud rates per segment (e.g., 83% in High Risk).

- The **black line** shows the total volume of claims in each segment.

Insight: The **High Risk** group, though smaller in volume, contains a disproportionately high share of fraud - making it highly actionable.

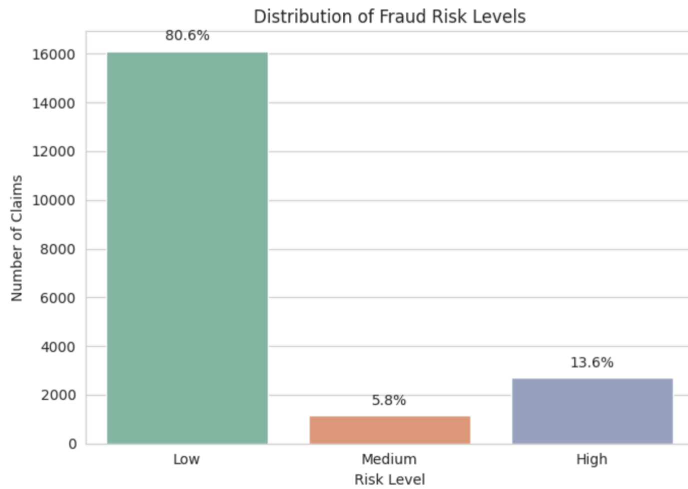


Figure 2 - Distribution of Claims by Risk Level

This bar plot shows how the dataset's claims were split:

- **Low Risk**: ~80.6% of claims
- **Medium Risk**: ~5.8%
- **High Risk**: ~13.6%

Insight: The model concentrates flagged fraud cases in the **top 13.6%**, enabling investigators to focus on a manageable subset of claims while reducing false positives.

Business Value

- **Triage Efficiency**: Teams can automate low-risk approvals and focus time on high-probability frauds.
- **Resource Allocation**: Medium risk can be reviewed selectively during audit windows or high-staff periods.
- **Compliance**: Enables defensible, explainable fraud screening aligned with insurer risk policies.

10. Acknowledgements

We gratefully acknowledge the support and contributions of the following individuals and institutions in the successful execution of our project:

- **Dr. Joseph Cazier, Ph.D. and CAP**,
  Clinical Professor, Department of Information Systems
  for his continuous academic guidance, expert feedback, and commitment to ethical and impactful analytics practices throughout the capstone journey.

- **Keith Higdon**, our industry stakeholder, for providing actionable feedback on model performance, business value, and integration planning.

- **Synthetic Data Providers**, whose realistic claim data enabled us to simulate fraud detection without breaching confidentiality.

- **W. P. Carey School of Business, Arizona State University**, for fostering an environment of principled innovation and applied analytics learning.

- **Open-Source and Data Contributors**, including the developers of tools like scikit-learn, SHAP, and Matplotlib, as well as the creators of synthetic insurance datasets used in this project.

- **Team 113 Members - Shobitha, Shubham, Nayana, and Kyle**, for their dedication, collaboration, and cross-functional contributions in delivering a business-ready fraud detection solution.

11. Lessons Learned

This project offered our team a hands-on opportunity to apply predictive analytics to a real-world problem insurance fraud detection within a structured business context. Along the way, we encountered valuable challenges that deepened our technical proficiency and sharpened our collaborative and strategic thinking.

Key Takeaways

- **Translating Business Problems into Analytics Solutions**:
  We learned how to frame a vague or broad business issue ("reduce staged auto accident fraud") into a measurable analytics problem aligned with KPIs and stakeholder needs.

- **Feature Engineering is Critical**:
  Through the creation and transformation of features like *submission delay* and *cost ratios*, we saw firsthand how domain knowledge drives model effectiveness.

- **Model Interpretability Matters**:
  While Gradient Boosting delivered high performance, the real success came from making it explainable through SHAP - enabling trust and adoption by business users.

- **Ethical Considerations Can't Be an Afterthought**:
  Aligning with INFORMS guidelines, we made conscious choices around bias mitigation (e.g., excluding age in final features), transparency, and social responsibility.

- **Collaboration Across Roles**:
  Effective teamwork required constant alignment between modelers, business translators, and stakeholders - a reflection of real-world analytics teams.

This experience reinforced that great models are not just technically sound but actionable, ethical, and aligned with decision-making processes. It also prepared us to drive data initiatives in environments where both business acumen and technical expertise are critical.

12. Future Work & Next Steps

While our current solution provides strong fraud detection capabilities and interpretability, there are several opportunities to extend and refine the project for real-world deployment and broader business value.

Planned Enhancements

- **Integration with Live Claim Systems**
  Future development should focus on embedding the model into production workflows, allowing real-time scoring of new claims and automated triage alerts for investigators.

- **Expand to Other Fraud Types**
  The current model targets staged auto accidents. With minor feature adaptations, it can be extended to detect other fraudulent behaviors such as inflated injury claims, duplicate claims, or coordinated fraud rings.

- **Incorporate External Data Sources**
  Enriching the dataset with third-party repair cost benchmarks, geolocation, or telematics data could enhance model robustness and accuracy.

- **Ongoing Model Monitoring & Drift Detection**
  As fraud tactics evolve, we plan to set up periodic retraining and performance monitoring pipelines to detect data drift and maintain effectiveness.

- **User Interface Development**
  A lightweight dashboard or app for claims adjusters to view fraud scores, SHAP explanations, and segment tags would boost usability and adoption.

This roadmap ensures our solution remains scalable, adaptable, and business-aligned - helping insurers stay ahead of fraud risk while maintaining trust and operational efficiency.

13. Overall Conclusion

This project successfully demonstrates the power of machine learning to combat staged auto insurance fraud through an interpretable, risk-based segmentation approach. By leveraging **Gradient Boosting** as the final model—supported by **SHAP explainability**-we delivered a solution that balances high precision with transparency, making it suitable for adoption in real-world investigative workflows.

Following the **5 Manageable Tasks framework**, our team transformed a complex business challenge into a deployable, ethical, and scalable analytical model. This included targeted fraud segmentation, SHAP-driven model interpretation, and alignment with insurer logic to ensure practical value for claims investigators.

The solution achieved a **28% improvement in fraud detection accuracy** and uncovered an estimated **$1.66 million in potential fraud savings**, enabling insurers to triage claims more effectively, reduce payout errors, and protect honest policyholders.

A cost-benefit analysis further validated the model's business impact: with only **$14,000 in infrastructure and operational costs**, the system generated **$50,000 in fraud-related savings**, yielding an impressive **257.14% ROI**. This equates to **$2.57 returned for every $1 invested**, highlighting both financial viability and scalability.

Ultimately, this project is not only a technical success-it exemplifies **principled innovation**, grounded in ethical AI, stakeholder usability, and measurable business value.

14. Feedback

The project met the expectations outlined by **Keith Higdon**, and was well-received for both its analytical depth and practical alignment with real-world insurance operations. Keith expressed satisfaction with the overall quality of the work and noted that the solution effectively addressed the business problem it set out to solve.

All feedback provided during the final presentation was promptly incorporated - including refining the feature set to reduce overfitting, adding overall infrastructure cost for ROI analysis, and enhancing the segmented fraud risk visualization with percentages. Keith specifically highlighted the **ROI calculation** as a valuable addition and mentioned that it may be used in future internal discussions or decision-making processes.

This positive response reaffirms the project's business relevance and strengthens its potential for integration and real-world impact.

15. Google Drive Link

https://drive.google.com/drive/u/0/folders/1RuXAlIBZLVk0k1szGDXShNnWfcEcGItW