Lisbon School of Economics & Management
Universidade de Lisboa

MASTER

INNOVATION AND RESEARCH FOR SUSTAINABILITY

MASTER´S FINAL WORK

DISSERTATION

OPTIMIZING SUSTAINABLE AVIATION AND TRANSPORT FUELS: AI-DRIVEN PREDICTIVE UCO MODEL FOR SAF/HVO VALUE CHAINS

YUKA TAKAO

JAN - 2026

MASTER
INNOVATION AND RESEARCH FOR SUSTAINABILITY

MASTER´S FINAL WORK
DISSERTATION

OPTIMIZING SUSTAINABLE AVIATION AND TRANSPORT FUELS:
AI-DRIVEN PREDICTIVE UCO MODEL FOR VALUE CHAINS

YUKA TAKAO

SUPERVISION:
PROF.MARCO FERRAZ, PROF.ANA CASACA
DR.PAULO DIMAS AND DR. DUC HOANG

JAN - 2026

Glossary

AI – Artificial Intelligence.

ATJ – Alcohol to Jet.

CORSIA – Carbon Offsetting and Reduction Scheme for International Aviation.

GB – Gradient Boosting.

GHG – Greenhouse Gas.

HEFA – Hydroprocessed Esters and Fatty Acids.

HVO – Hydrotreated Vegetable Oil.

ICAO – International Civil Aviation Organization.

IEA – International Energy Agency.

IATA – International Air Transport Association.

INE – Instituto Nacional de Estatística.

LCA – Life Cycle Assessment.

MAE – Mean Absolute Error.

MRV – Monitoring, Reporting and Verification.

RED II / RED III – Renewable Energy Directive.

RF – Random Forest.

RMSE – Root Mean Square Error.

SAF – Sustainable Aviation Fuel.

UCO – Used Cooking Oil.

ABSTRACT, KEYWORDS AND JEL CODES

This dissertation explores how Artificial Intelligence (AI) can optimize Sustainable Aviation Fuel (SAF) and Hydrotreated Vegetable Oil (HVO) value chains as alternatives to fossil fuels in aviation and transport. Building on the evolution from the Triple Helix to the Quintuple Helix perspective, it addresses persistent limits in feedstock availability, cost, logistics, and policy coherence. Using a quantitative framework based on open data for feedstock forecasting and logistics optimization, and guided by the PICO and Quintuple Helix models, the dissertation finds that AI primarily serves as a decision-support tool. It improves planning accuracy, integrates technical and policy variables, and reduces uncertainty in supply networks. AI-driven optimization is most effective when part of innovation ecosystems supported by coherent policies, standardized data governance, and cross-sector collaboration.

(PT) Esta dissertação analisa como a Inteligência Artificial (IA) pode otimizar as cadeias de valor dos combustíveis sustentáveis para aviação (SAF) e do óleo vegetal hidrotratado (HVO), alternativas aos combustíveis fósseis na aviação e nos transportes. Partindo da evolução do modelo da Hélice Tríplice para a Hélice Quíntupla, aborda limitações persistentes de matérias-primas, custos, logística e coerência política. Com base numa abordagem quantitativa apoiada em dados públicos e orientada pelos modelos PICO e Hélice Quíntupla, a dissertação conclui que a IA funciona sobretudo como ferramenta de apoio à decisão, melhorando o planeamento e reduzindo a incerteza. A sua eficácia aumenta quando integrada em ecossistemas de inovação sustentados por políticas coerentes e governação de dados padronizada.

KEYWORDS: Sustainable aviation fuel (SAF); Hydrotreated vegetable oil (HVO); Used cooking oil (UCO); AI-driven predictive model; Optimization; Energy and climate policy

JEL CODES: C53, O33, O38, Q42, Q48, Q58

AI DISCLOSURE: This thesis was prepared in accordance with the University's academic integrity guidelines. Artificial intelligence tools were used in a limited and ethically appropriate manner to support language refinement and structural clarity; all research design, analysis and final content remain the sole responsibility of the author.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to all those who have supported me throughout the completion of this project.

First and foremost, I am deeply indebted to my supervisors, Prof. Marco Ferraz, Prof. Ana Casaca, Dr. Paulo Dimas and Dr. Duc Hoang, for their outstanding guidance, valuable advice. Their insightful feedback has greatly shaped the direction on my research and has empowered significantly to my academic growth.

I would like to thank the interviewee, Mr. Tomás Ferreira Duarte, for generously sharing his expertise and perspectives, which enriched the qualitative dimension of this study. I am also thankful to the industry experts who participated in the survey and openly shared their professional experience, helping to anchor the analysis in real-world industry contexts.

I am grateful to all the professors and to my colleagues at ISEG. Sharing this academic path with peers from diverse countries has greatly enriched my learning experience and expanded my perspective on global challenges and remedies. I would like to extend my heartfelt thanks to the members of the Rotary Clubs for providing me with this invaluable opportunity for learning and personal development.

Finally, my deepest gratitude goes to all my family and friends, whose unwavering love and encouragement have accompanied me every step of the way, as well as to my supervisors and colleagues at work for their constant understanding and support. Their presence has given me the strength to persevere and move forward, even in the most challenging times in my life.

January 2026

Yuka Takao

OPTIMIZING SUSTAINABLE AVIATION AND TRANSPORT FUELS:

AI-DRIVEN PREDICTIVE UCO MODEL FOR SAF/HVO VALUE CHAINS

By Yuka Takao

This dissertation investigates how artificial intelligence can support the deployment of sustainable aviation fuel and hydrogenated vegetable oil by improving value-chain decisions for waste-based feedstocks. Focusing on used cooking oil and cross-border supply chains, it develops an interpretable predictive model to explore technical, economic and policy trade-offs. The expert survey and interview findings offer practical insights for policymakers and industry on accelerating low-carbon fuel adoption in aviation and heavy transport.

1. INTRODUCTION

Decarbonising aviation and heavy transport have become a critical component of global climate action as efforts to meet the Paris Agreement's climate goals. At the same time, these sectors remain among the most difficult to decarbonise within global final energy consumption. Transport accounts for approximately 25% of global energy-related CO_2 emissions, with around 70% originating from road transport and roughly 12% from aviation (IEA, 2023). Although road transport dominates in absolute terms, aviation has been one of the fastest-growing sources of emissions over the past two decades, driven largely by the expansion of international travel and the widespread adoption of low-cost air services (IPCC, 2022). Other sectors have progressed more rapidly. Power generation has seen large-scale deployment of renewable energy, while the automotive sector has moved beyond experimentation to the practical rollout of electric vehicles. Aviation, by contrast, faces structural limitations related to aircraft weight, safety requirements, and flight range. These constraints make full electrification technically and economically unfeasible in the short to medium term, leaving the sector dependent on liquid fuels for the foreseeable future.

This dependence explains the growing attention paid to Sustainable Aviation Fuel (SAF) and Hydrotreated Vegetable Oil (HVO). SAF is a jet fuel produced from non-fossil feedstocks such as waste cooking oil, animal fats, agricultural and forestry residues, and fuels derived from municipal solid waste, and is certified as a drop-in fuel compatible with existing aircraft and infrastructure (IEA Bioenergy, 2024). In heavy-duty road transport, HVO performs a comparable function. Hydrotreated vegetable oil (HVO) is a paraffinic diesel-type fuel produced by hydrotreating vegetable oils and waste lipids such as used cooking oil and animal fats, and it can be used in conventional diesel engines either neat or in blends with fossil diesel (IEA AMF, 2013).

At the international level, the International Civil Aviation Organisation (ICAO) and the International Air Transport Association (IATA) have committed to achieving net-zero CO_2 emissions from international aviation by 2050. Both organisations estimate that SAF will need to deliver approximately 50–65% of the emissions reductions required to reach this target (ICAO, 2023; IATA, 2024). Under a net-zero scenario, annual SAF demand is projected to reach around 300 million tonnes by mid-century (ICAO, 2023). Current production, however, remains extremely limited. IATA estimates global SAF output at approximately 0.6 million tonnes in 2023, rising to around 1 million tonnes in 2024 which corresponds to only about 0.3% of global jet fuel supply (IATA, 2024). Despite its strategic importance, SAF therefore remains marginal in volume terms.

Within this global context, a notable development occurred in September 2023, when Portugal's Galp and Japan's Mitsui & Co. announced a joint investment in a production facility at the Sines refinery in Portugal. The project aims to produce approximately 270,000 tonnes per year of HVO and SAF using waste-derived feedstocks, establishing a cross-border value chain linking Europe and Asia (Galp, 2023). Portugal has emerged as a European frontrunner in the energy transition, with renewables supplying about 71% of national electricity consumption in 2024 and some months exceeding 90% (REN). This is well above the EU average of nearly 50%, reflecting extensive deployment of wind, solar and bioenergy within circular-economy policy frameworks (Eurostat, 2026). By contrast, Japan, constrained by limited domestic renewable resources and a comparatively lower renewable share of electricity generation of around 25 %, has pursued a global investment-led strategy under its Green Transformation framework to secure renewable energy value chains, including SAF/HVO (ISEP, 2025). These two countries, although geographically distant, share complementary roles in advancing sustainable transport fuels, from production to innovation ecosystems. This partnership illustrates the potential of international collaboration to accelerate the deployment of renewable fuels using circular feedstocks. However, it also highlights persistent obstacles in digital integration, feedstock logistics, and emissions traceability.

Although SAF/HVO can reduce life-cycle CO_2 emissions by up to 90% compared with conventional fossil fuels (IATA, 2024), current supply satisfies only a small fraction of overall fuel demand. A persistent gap therefore exists between environmental performance and actual availability. This gap reflects a combination of interrelated factors: limited volumes of waste-based feedstocks such as UCO and animal fats, underdeveloped collection systems, high production costs, complex international logistics, and demanding certification and traceability requirements. These challenges are compounded by fragmented policy and regulatory frameworks across regions, as well as limited digitalisation and data integration along the value chain.

As a result, the central challenge facing SAF/HVO today is no longer whether they offer environmental benefits, but how their value chains can be designed and operated under real-world constraints. This includes questions about how costs and risks are distributed across actors, and where value is created and captured in the form of emissions reductions, economic returns, and reputational benefits.

Against this background, this study addresses the tension between the recognised importance of SAF/HVO for long-term decarbonisation and their limited deployment under current market conditions. The analysis focuses on two interconnected bottlenecks within SAF/HVO value chains: constraints on waste-derived feedstocks and the complexity of international supply chains. More specifically, the study compares the availability of waste feedstocks, together with the surrounding policy and regulatory frameworks, across Europe, with a focus on Portugal, and the Asia-Pacific region, particularly Japan, China, and Singapore. It then examines how differences in institutional arrangements and market conditions shape the design and practical relevance of AI-based models for supply forecasting and logistics scenario planning.

Based on this focus, the central research question is formulated as follows:

How can AI-based predictive modelling be used to visualise and optimize feedstock availability and logistics flows, and to what extent can this realistically reduce cost, production volume, and emissions gaps within SAF/HVO value chains?

Recent studies suggest that AI-driven optimisation of feedstock procurement and logistics could help alleviate some of these bottlenecks. Much of the existing literature, however, remains theoretical, with limited empirical work linking AI models to specific regional policy environments or operational projects. To address this limitation, the research adopts three complementary approaches.

First, open datasets from sources such as Eurostat, the International Energy Agency (IEA), and ICAO are used to develop feedstock supply and logistics forecasts. Supervised learning models, including Random Forests (RF) and Gradient Boosting (GB), are compared with conventional approaches to assess the added value of AI-based methods. Second, expert surveys and semi-structured interviews are conducted with stakeholders involved in SAF/HVO value chains, including airlines, energy companies, technology providers, and policy authorities. These inputs are used to identify perceived bottlenecks, data limitations, priorities for AI implementation, and assessments of existing regulatory frameworks. Third, policy frameworks for SAF/HVO in the European Union and the Asia-Pacific region are compared to examine how differing regulatory regimes influence investment incentives and interact with AI model design.

This approach leads to three main contributions. First, it brings together waste-derived feedstock availability, policy and regulatory frameworks, and AI-based predictive modelling within a single analytical framework, enabling a more coherent discussion of trade-offs in SAF/HVO value chain design. Second, drawing on expert insights, it identifies practical data and governance challenges that must be addressed for AI tools to be effective beyond experimental settings, with implications for future policy and industrial strategy. Third, by examining the Mitsui & Co.–Galp SAF/HVO project linking Portugal and Japan, the study illustrates how cross-border value chains and innovation ecosystems can emerge between regions with constrained domestic resources and those with strong renewable energy potential.

The following structure is organized into six chapters. Chapter 2 reviews existing literature on SAF/HVO technologies, feedstock constraints, supply and logistics optimisation, AI applications in biofuel systems, regional policy frameworks, and relevant case studies, including the Mitsui & Co.– Galp project. Chapter 3 introduces the conceptual framework and research hypotheses, drawing on the PICO framework (population, intervention, comparison, outcome) and the quintuple helix model of multiple stakeholders' collaboration. Chapter 4 outlines the research methodology, covering AI-based feedstock forecasting, expert surveys and interviews, policy comparison, and case study analysis. Chapter 5 presents and discusses the empirical results, comparing baseline and AI-driven approaches using key performance indicators and integrating policy analysis with the case study findings. Finally, Chapter 6 concludes, discusses policy and managerial implications, and outlines limitations and directions for future research.

2. LITERATURE REVIEW

This chapter reviews academic and policy literature related to the application of AI in the design of SAF/HVO value chains. The discussion focuses on three areas: the technical characteristics and supply chains of SAF/HVO, AI-based forecasting and optimisation in energy and logistics systems, and innovation ecosystems and policy frameworks that support cross-border projects. In this study, an innovation ecosystem is understood as a network in which airlines, fuel suppliers, infrastructure operators, research institutions, governments, investors, and other actors interact, enabling the circulation of capital, knowledge, personnel, and data that supports continuous technological and business innovation. The purpose of this chapter is to clarify the current state of research, identify limitations in the existing literature, and position the present study within that context.

2.1 SAF/HVO Technology, Cost and Feedstock Constraints

Feedstock availability remains one of the most significant barriers to scaling up SAF/HVO. Competing demand for waste-based inputs, combined with regulatory restrictions on feedstocks linked to food markets, places structural limits on supply (EASA, 2022). Cost represents an additional and persistent challenge, with SAF estimated to be between 120% and 700% more expensive than fossil-derived jet fuel, depending on the production pathway. Although SAF can reduce life-cycle greenhouse gas emissions by approximately 27% to 87%, insufficient producer incentives and a persistent mismatch between supply and demand continue to constrain large-scale deployment (IEA, 2023; ICAO, 2023; IATA, 2024). Considering the several production pathways existing for SAF, Hydroprocessed Esters and Fatty Acids (HEFA) is the most established, which involves treating oils such as vegetable oils, waste cooking oil, and animal fats with hydrogen to remove impurities and convert them into hydrocarbons similar to conventional jet fuel. Another pathway, ATJ, first produces alcohol from feedstocks such as sugarcane or maize and then chemically converts this alcohol into jet fuel. A third route, Fischer–Tropsch Synthetic Paraffinic Kerosene (FT-SPK), involves gasifying woody biomass or municipal solid waste and subsequently converting the resulting synthesis gas into kerosene-type fuel through the Fischer–Tropsch process (IEA Bioenergy, 2024).

Although these pathways all produce drop-in fuels compatible with existing aircraft engines, they differ substantially in terms of feedstock requirements, capital intensity, and cost structure per litre. The choice of pathway therefore has significant implications for scalability and economic viability. Analyses by the U.S. Department of Energy (DOE) and IEA Bioenergy highlight that, despite SAF/HVO being technically at the commercialisation stage, market expansion remains constrained. The primary limiting factors are quantitative restrictions on waste- and residue-based feedstocks, regulatory limitations on feedstocks linked to food markets, and insufficient policy support, including the absence of long-term off-take agreements and stable subsidy schemes (DOE, 2024, IEA Bioenergy 2024).

2.2 Optimisation and Forecasting in the Fuel Supply Chain

In the biofuel sector, supply chain efficiency is particularly critical. Feedstock procurement, transportation, and conversion processes must continuously adjust to fluctuations in supply and demand. Previous studies show that logistical delays and uncertainty in feedstock availability have a direct impact on the scalability of SAF/HVO (Goldemberg et al., 2014). In response to these challenges, interest in predictive analytics has grown, driven by its potential to forecast feedstock availability, optimize transport routes, and support real-time supply and demand adjustments.

Martínez-Valencia et al. (2021) emphasise the importance of aligning SAF supply chains with ecological and social co-benefits, arguing for integrated designs that incorporate ecosystem service assessments. Ahmad and Xu (2021) show that aligning the objectives of diverse stakeholders can facilitate SAF adoption. Shehab et al. (2023) identify HEFA, ATJ, and FT-SPK as the most feasible SAF pathways, while noting that unresolved logistical and policy barriers continue to constrain scale up. Recent work on SAF capacity scale-up shows that infrastructure expansion and cost reductions are essential for meeting net-zero aviation targets (Nature Communications, 2025). Taken together, this literature suggests that the primary constraints lie not in technological maturity, but in feedstock availability and value chain design. Building on this insight, the present research does not focus on comparing production technologies or conducting life-cycle assessments as such. Instead, it examines how uncertainty in feedstock supply propagates across the entire SAF/HVO value chain.

From an operational perspective, fuel remains one of the largest cost components for airlines. An examination of TAP Air Portugal's annual cost structure shows that aircraft fuel continues to represent a major share of operating expenses. In FY2024, TAP reported operating revenues of approximately EUR 4.24 billion, while aircraft fuel costs amounted to around EUR 1.05 billion, equivalent to around 25% of operating revenues (TAP Air Portugal, 2025). Although fuel costs declined with earlier years, fuel remained one of the single largest operating cost items, exceeding expenditures on maintenance, traffic-related operations, and airport charges. This cost structure highlights the sensitivity of airline profitability to fuel price increases associated with SAF adoption. Conversely, gains in fuel efficiency, route optimisation, and reductions in SAF and HVO production costs have the potential to deliver substantial economic benefits.

2.3 AI and Open Data in the Energy and Logistics Sectors

In the fields of energy demand forecasting and renewable energy operations, machine learning techniques such as RF and GB have been shown to outperform conventional regression models in predictive accuracy (Sakib et al., 2022). Hosseini et al. (2021) identify several roles for AI in biofuel systems, including raw material yield prediction, process optimisation, and life-cycle emissions monitoring, noting that these tools are particularly effective in systems characterised by non-linear relationships. At the same time, adoption among small and medium-sized enterprises remains limited due to gaps in digitalisation, data infrastructure, and skilled human resources (Trianni and Cagno, 2012).

With respect to data availability, publicly accessible sources such as Eurostat, the IEA, the EIA, and ICAO provide information on energy consumption, emissions, transport activity, population trends, and economic indicators. These datasets can be complemented by satellite and geospatial information from NASA Earthdata, offering insights into land use and spatial patterns (NASA, 2024). Together, these sources form a suitable basis for developing reproducible AI models (Hotmaps Project, 2018). Although such models cannot match the precision of analyses based on detailed corporate datasets, they offer the advantage of transparency, open verification, and comparability across regions.

2.4 Innovation Ecosystems: From the Triple Helix to the Quintuple Helix

The integration of AI into SAF/HVO systems depends not only on technological capability, but also on effective multi-stakeholder collaboration across the innovation ecosystem. A foundational framework for analyzing such collaboration is the Triple Helix model which was developed by Henry Etzkowitz and Loet Leydesdorff (1995). As illustrated in Figure 1, it conceptualizes innovation as the outcome of dynamic interactions between universities, industry, and government.

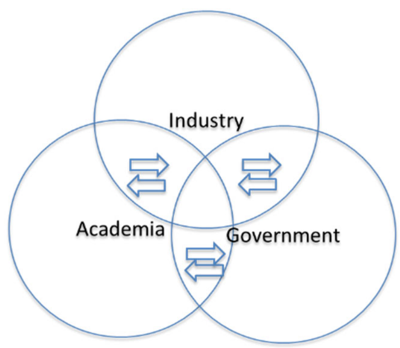
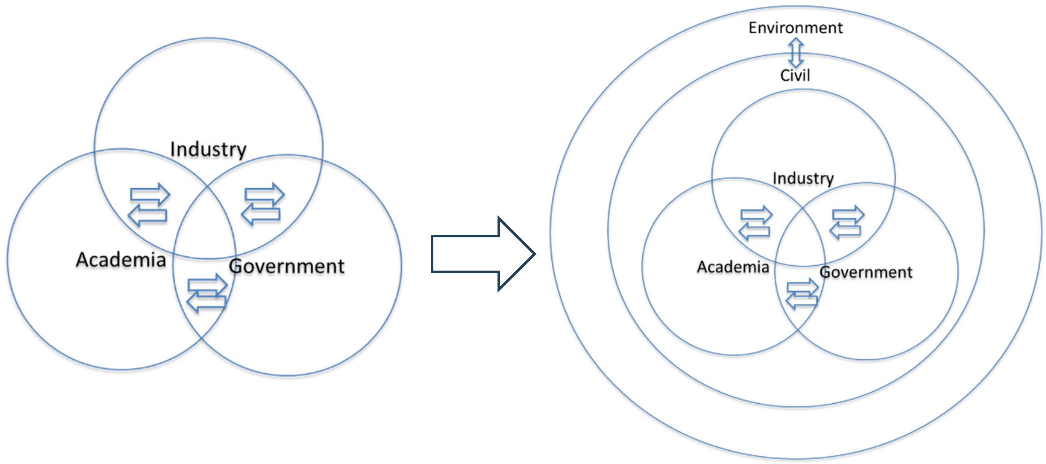


Figure 1 – Triple Helix Model

Source: Own Elaboration

Within this model, universities contribute knowledge creation, industry drives commercialization and implementation, and government shapes regulatory frameworks and provides strategic incentives. The Triple Helix has been widely applied to explain technology development and industrial innovation, particularly in policy-driven sectors.

However, the Triple Helix framework has been criticized for insufficiently accounting for broader societal and environmental dimensions that increasingly shape innovation outcomes. To address these limitations, Elias G. Carayannis and David F. J. Campbell proposed the Quintuple Helix framework, which extends the university–industry–government model by explicitly incorporating civil society including social behavior and the natural environment as endogenous components of the innovation system (Carayannis & Campbell, 2010). As shown in Figure 2, this framework emphasizes that innovation and policy design are not linear processes, but rather dynamic systems shaped by social acceptance, behavioral change, environmental constraints, and sustainability objectives.



Triple Helix Quintuple Helix

Figure 2 – Innovation Ecosystem in SAF/HVO Value Chain

Source: Own elaboration

In the context of SAF/HVO, this expanded perspective is particularly relevant. Feedstock availability depends not only on industrial capacity and regulation, but also on civil society factors such as household and restaurant participation in UCO collection schemes, as well as environmental constraints related to resource availability and emissions reduction targets. Public–private partnerships, such as the Mitsui & Co.–Galp SAF pilot project, illustrate how coordination across industry, government, and society, supported by shared data infrastructures and aligned incentives can accelerate progress toward scale-up.

Recent literature reflects growing interest in systemic perspectives, but with important limitations. Shehab et al. (2023) assess the potential of meeting the EU's SAF targets in 2030 and 2050 through pathway analysis, without incorporating AI tools. Martínez-Valencia et al. (2021) review SAF supply chain configurations and call for integrating environmental and social co-benefits, although most models remain relatively static. He et al. (2024) show that machine learning can support smart aviation biofuel systems, but many models rely on highly specific datasets that limit transparency and reproducibility. By contrast, Qu and Kim (2024) highlight how innovation ecosystems shape sustainability transitions, underscoring the importance of institutional coordination and policy alignment.

Against this backdrop, the present study adopts a Quintuple Helix perspective to analyze AI-enabled optimization of SAF/HVO value chains. Using only publicly available data and supervised learning methods such as RF and GB, the study prioritizes transparency and reproducibility while explicitly embedding technological analysis within its policy, societal, and environmental context. This approach offers a middle-range analytical framework that bridges the gap between highly sophisticated, proprietary AI applications and conventional static modelling approaches, and is well suited to policy-oriented analysis of renewable fuel systems.

2.5 Research Gaps

Three key research gaps emerge from the reviewed literature.

First, while substantial work exists on SAF/HVO technologies, costs and life-cycle assessment, few studies analyse waste-derived feedstock potential and international logistics flows using AI models built on publicly available data, as most rely on proprietary datasets or focus on technology pathways rather than supply chain design (IEA Bioenergy, 2024).

Second, although AI applications in energy and logistics are expanding, most studies rely on detailed corporate datasets, and empirical work showing moderately complex, reproducible models built on open sources such as Eurostat and the IEA remains scarce (Sakib et al., 2022). Third, few studies explicitly assess the effectiveness and limits of AI-based predictive modelling across policy contexts such as the EU, Japan and China, while linking these differences to concrete cross-border projects like the Galp–Mitsui & Co. Sines SAF/HVO initiative (Martínez-Valencia et al., 2021; European Commission, 2023).

To address these gaps, this study develops an AI-based predictive model using open data and applies it to the SAF/HVO value chain linking Portugal and Japan, highlighting how feedstock constraints, logistical complexity and policy environments interact in shaping scale-up outcomes. Existing research often treats feedstock availability and logistics as exogenous or technologically fixed, focusing instead on production pathways, manufacturing costs and emissions performance, whereas in practice feedstock collection systems, transport routes and supply stability are strongly shaped by policy design and institutional arrangements. A comparison between Portugal in the EU and the Asia-Pacific region, particularly Japan, Singapore and China show how SAF/HVO value chains are embedded in distinct policy environments.

As an EU member state, Portugal operates under the ReFuelEU Aviation Regulation, which mandates SAF blending in aviation fuel. This legal framework guarantees demand and reduces market uncertainty, encouraging long-term investment in SAF/HVO production capacity (European Commission, 2023). Japan, by contrast, has set ambitious decarbonisation targets, including a 10% SAF utilisation goal by 2030, but relies primarily on policy guidance rather than binding mandates. Implementation therefore depends on voluntary commitments and public-private coordination (Agency for Natural Resources and Energy, 2023).

In Portugal, the collection of UCO is organized through municipalities and specialised operators as part of waste management and circular economy policies. This institutional structure provides a relatively stable feedstock base. In Japan, UCO utilisation is driven mainly by corporate initiatives. A prominent example is the FRY to FLY Project promoted by Japan Airlines (JAL), which collects UCO from households and restaurants for SAF production. While innovative, this approach relies heavily on voluntary participation, which affects supply stability and scalability.

Singapore represents a third policy model. It will become the first country to introduce a dedicated SAF Levy, applied to all departing passenger and cargo flights from 1 October 2026. The levy is calibrated based on the volume of SAF required to meet a 1% blending target and the expected price premium of SAF relative to conventional jet fuel, including certification, blending, and delivery costs (CAAS, 2026). This approach distributes SAF costs between airlines and users through ticket surcharges while providing clear price signals and a phased increase in blending requirements.

China presents a fourth scenario. While pilot projects and research and development activities are advancing, uncertainty surrounding mandatory requirements, export controls, and sustainability certification continues to limit large-scale supply expansion (Reuters, 2024).

These institutional differences are not merely contextual. They directly influence the performance and usefulness of AI-based forecasting and optimisation models. In policy-mature environments such as the EU, blending mandates amplify fluctuations in feedstock demand and logistics intensity, increasing the value of accurate forecasting. In more fluid policy environments, such as Japan and China, AI functions not only as an efficiency tool but also as a means of managing uncertainty and anticipating regulatory change. In cases like Singapore, where price signals are combined with phased obligations, AI models become particularly valuable for forecasting the evolution of demand and cost burdens over time.

From this perspective, the Mitsui & Co.– Galp SAF/HVO collaboration serves as an appropriate demonstration case. The project sits at the intersection of a policy driven European supply environment and a demand oriented Japanese aviation market, while remaining aligned with the ICAO Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA). CORSIA aims to limit growth-related CO_2 emissions from international aviation by combining emissions reductions and offsetting mechanisms. This framework provides a useful analytical reference for examining how policy environments shape feedstock availability, logistics structures, and the performance of AI based forecasting models.

Traditional SAF/HVO value chains are typically designed using historical averages and static assumptions. Policy changes and feedstock variability are treated as external risks, making these systems vulnerable to cost increases and supply disruptions. In contrast, the AI optimized value chain proposed in this study incorporates uncertainty directly into the modelling framework. Differences in policy and institutional settings are explicitly represented through dummy variables, while predictions from RF and GB models are integrated into logistics and production planning.

RF is used to generate stable baseline forecasts due to its robustness to noise. GB complements this by capturing abrupt changes driven by policy shifts, seasonal demand patterns, or logistical disruptions. Together, these models balance predictive accuracy with interpretability, allowing for explicit discussion of the role of policy variables. The resulting framework goes beyond technical efficiency, enabling analysis of the interaction between AI, policy environments, and real-world decision making.

The reviewed literature consistently shows that the main constraints on scaling up SAF/HVO are not technological readiness, but rather feedstock availability, logistics complexity, and policy design. While previous studies provide valuable insights into production pathways, costs, and life-cycle emissions, feedstock supply and logistics are often treated as fixed or external conditions. In practice, however, these elements are shaped by policy frameworks, institutional arrangements, and data availability, and they vary significantly across regions.

At the same time, although AI is increasingly applied to energy and logistics systems, many existing models rely on proprietary corporate data, limiting transparency and reproducibility. This creates a gap between advanced AI research and models that can realistically support policy analysis and decision-making across different regions.

To address these limitations, this study adopts a modelling approach that integrates feedstock availability, logistics uncertainty, and policy context using publicly available data and explainable AI methods. The following chapter presents the conceptual framework and methodology used to examine how AI-based forecasting and optimisation can support SAF/HVO value chain design under real-world constraints.

2.6 Research Question, Hypotheses and PICO frameworks

This study is guided by the following research question: How can AI-based predictive modelling reduce gaps in production scale, cost, and emissions within the SAF/HVO value chains by optimising feedstock availability and logistics flows?

The question is grounded in a systems-level perspective on renewable fuel supply chains. Rather than focusing on end-use combustion or aircraft technology, the analysis concentrates on upstream and midstream stages, specifically feedstock acquisition and logistics. These stages are treated as key leverage points where uncertainty, inefficiency, and policy constraints most strongly affect scalability.

To empirically examine the research question, four hypotheses are proposed.

H1:AI-based predictive models improve the accuracy of feedstock availability forecasts compared to conventional statistical models.

H2:AI-driven optimisation of routing and logistics reduces transport-related costs and emissions across the SAF/HVO value chains.

H3:AI models relying exclusively on publicly available data, including open statistical datasets and satellite-derived information, reduce uncertainty in feedstock potential and transport distances more effectively than conventional statistical approaches.

H4: Organisations operating within structured innovation ecosystems, such as public–private partnerships, achieve more effective AI implementation and higher returns than isolated actors.

The conceptual structure of the study follows the PICO framework.

The Population (P) consists of SAF/HVO producers and logistics operators in Europe and Japan, encompassing organisations of varying size, technological capability, and institutional context. The Intervention (I) is the application of an AI-based predictive model that supports supply chain decision-making through data-driven forecasting and optimisation. The Comparison (C) refers to existing practices based on conventional logistics planning and forecasting methods that rely primarily on historical averages and limited explanatory variables. These approaches are assumed to be insufficiently adaptive to fluctuations in feedstock supply, logistics conditions, and policy environments. The Outcome (O) includes measurable improvements in three areas: (i) reduced cost volatility, (ii) improved accuracy in feedstock procurement forecasting, and (iii) lower life-cycle emissions through optimized routing and scheduling.

This framework provides a structured basis for evaluating the added value of AI-based approaches relative to baseline practices.

3. METHODOLOGY

3.1 Methodological Approach and Data Collection

This is a quantitative study focused on the design and validation of AI-based predictive models. To test the proposed hypotheses, the analysis evaluates whether AI-enhanced models outperform conventional statistical methods in terms of feedstock availability forecasting, emissions reduction, and operational cost optimisation. The study relies exclusively on publicly available datasets to ensure transparency and reproducibility. Data sources include Eurostat, the International Energy Agency (IEA) and the ICAO. These datasets provide information on waste generation, energy use, emissions, population dynamics, transport activity, and spatial characteristics relevant to logistics planning.

Publicly disclosed information on refinery operations associated with Mitsui & Co. and Galp, as well as statistics on UCO, is used where available. In addition, virtual case scenarios are constructed to reflect realistic patterns observed in comparable regions and projects. This approach allows the study to simulate corporate decision-making contexts without relying on proprietary data.

3.2 Comparison of Conventional and AI-Based Models

This section compares the performance of a conventional statistical baseline model with AI-based forecasting models, specifically RF and GB, as shown in Table I.

Table I

Conventional Statistical Models and AI Predictive Models

Item	Conventional models (regression, ARIMA)	AI models (Random Forest / GBM)
Data structures that can be handled	Few explanatory variables, linear/quasi-linear relationships	Numerous explanatory variables, including non-linear and interaction effects
Prediction accuracy (when variability is high)	Generally limited	High accuracy expected under appropriate learning conditions
Interpretability	High (meaning of coefficients is clear)	Moderate (supplemented by feature importance)
Data requirements	Relatively few	Requires large amounts of high-quality data

Source: Own elaboration

The baseline model represents traditional planning practice and consists of a multiple regression or ARIMA model using a limited set of explanatory variables. These typically include historical feedstock supply volumes, fuel prices, and simple seasonal indicators. By contrast, the AI models predict the same target variables, such as monthly UCO supply or SAF/HVO production volumes, while incorporating a broader and more heterogeneous set of explanatory variables. These include population size, tourism intensity, price levels, international energy price indices, meteorological conditions, waste generation statistics, logistics infrastructure capacity, and biomass potential derived from satellite data. Policy-related variables are also included, such as the introduction of the ReFuelEU Aviation mandate in the European Union and the presence of SAF targets in Japan.

AI is applied as a decision-support tool to reduce uncertainty in feedstock supply and logistics planning. Rather than assuming stable supply conditions or historical average, the models explicitly account for fluctuations driven by seasonality, market competition, and differences in policy and institutional environments. The analytical framework is structured in two stages: forecasting and optimisation.

In the first stage, supervised learning models, RF and GB, are used to forecast monthly feedstock supply volumes, supply variability, and logistics performance indicators. The dependent variable Yrepresents feedstock availability and logistics efficiency, while the explanatory variables Xcapture economic, geographic, and operational factors such as population size, waste generation, transport distance, and demand indicators. Policy and institutional conditions are represented by a set of policy dummy variables P.

The conceptual model is expressed as:

$$Y = f(X, P) + \varepsilon$$

Here, Preflects regional differences in policy design, including binding blending obligations in the European Union, target-based policies in Japan, and higher regulatory uncertainty in China. Incorporating policy variables allows the analysis to distinguish between technological and institutional effects. The error term "ε" captures unavoidable uncertainty arising from unpredictable disturbances such as accidents or operational disruptions in collection systems, which motivates the use of AI-based forecasting to reduce, though not eliminate, misprediction risk in downstream optimisation. Through this structure, the AI models learn how feedstock availability and logistics outcomes respond to combinations of physical variables and policy conditions. Figure 3 demonstrates the AI-optimized SAF/HVO value chain model under heterogeneous policy environments, compared to a traditional model.

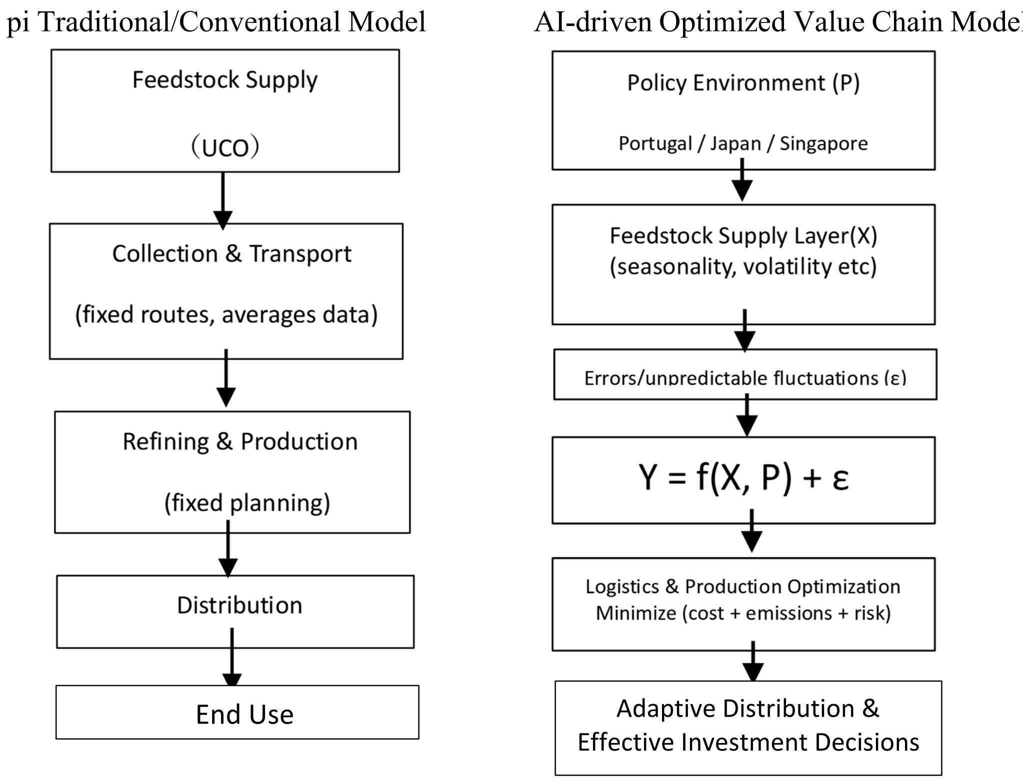


Figure 3 – AI-driven Optimized Value Chain Model for SAF/HVO

Source: Own Elaboration

This enables analysis of how changes in policy environments affect supply stability and logistics performance. Rather than directly reducing costs, AI contributes by reducing uncertainty, improving investment planning, and supporting coordination between policy and operational decisions.

Policy conditions in the European Union, Japan, and Singapore are represented through policy dummy variables that interact with physical and economic variables within the AI forecasting models. The resulting predictions are then used as inputs for an optimisation module that seeks to minimise logistics costs, transport-related emissions, and supply disruption risk.

In the second stage, supply chain optimization is conducted using the forecast outputs from the first stage. Alternative sourcing strategies and logistics routes are evaluated simultaneously in terms of cost, emissions, and supply risk. AI does not autonomously determine decisions. Instead, it provides probabilistic forecasts that allow companies and policymakers to compare feasible options under different policy scenarios.

RF is primarily used to generate stable baseline forecasts due to its robustness to noise. GB complements this by capturing abrupt changes associated with policy shifts, seasonal demand variation, and logistical disruptions. The combined use of both models balances predictive accuracy with interpretability, enabling explicit discussion of how policy variables influence outcomes.

Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and measures related to prediction interval width and reproducibility. Evaluation is conducted not only under stable conditions but also under scenario changes, such as fluctuations in feedstock availability or regulatory requirements. This allows assessment of which modelling approach better reflects real-world constraints faced by SAF/HVO value chains.

3.3 Sampling and Expert Interviews

Market research was conducted using a five-minute expert survey administered via Google Forms to stakeholders involved in SAF/HVO value chains. The target group includes fuel producers, logistics operators, AI developers, and policy-related organisations. The objective to validate modelling assumptions and ensure that the analytical framework reflects practical operational and institutional realities.

Purposive sampling was employed to capture perspectives that differ in company size, and functional role. This approach allows the study to incorporate a range of viewpoints rather than relying on a single stakeholder category. On this survey, participants voluntarily agreed to participate in the study and provided informed consent of their data usage. All the expert inputs were anonymised. The detailed survey results are provided in Appendices A.

To complement the broader expert survey, an online interview was conducted in January 2026 for approximately 40 minutes, to obtain deeper qualitative insights into SAF/HVO policy design from the perspective of the Portuguese government and airline sector. The interviewee is a management consultant with extensive experience in the European airline industry and previously served as an advisor for the Portuguese Minister of Finance. His professional background includes strategic advisory roles for multiple international and national airlines, including TAP Air Portugal and Azores Airlines, with expertise in fleet planning, network optimization, cost management, and airline restructuring linked to state investment decisions.

The discussion focused on current policy frameworks, airline fuel cost structures, incentives for SAF adoption, and the role of data, digitalization, and AI in strategic decision-making. He highlighted that although the Portuguese government holds ownership stakes in the country's two major airlines, its approach to SAF policy remains largely passive, primarily due to cost concerns and limited incentive mechanisms. He argues that more robust data collection, improved policy coordination at the international level, and targeted subsidies would be critical to accelerating SAF adoption.

The interviewee provided informed consent for participation, and data usage complied with the ethical standards of the academic institution. Interview documentation is presented in Appendices B.

3.4 Methodological Limitations

This study has several methodological limitations.

First, the predictive performance of AI models depends strongly on data quality and granularity. Reliance on publicly available datasets and simulated scenarios may limit direct applicability to firm-level operational decision-making. Ensemble learning methods such as RF and GB typically require sufficiently long time series e.g., around 60 months, to support robust learning. In this study, the AI models are therefore applied as simulation tools to explore uncertainty, variability, and extreme scenarios, and to compare decision structures under constrained data conditions. In an ideal operational setting, longer data histories would be required for production-level deployment.

Second, while RF and GB offer robustness and interpretability, they may not fully capture highly complex system dynamics when data are sparse or subject to high noise.

Third, although expert interviews provide valuable contextual insight, the analysis does not rely solely on qualitative input. Findings are cross-checked against quantitative data to reduce subjective bias.

Finally, the empirical focus on SAF/HVO value chains in Europe and Japan limits the generalisability of results to other regions or renewable fuel technologies. The findings should therefore be interpreted as context-specific rather than universally applicable.

4. RESULTS AND ANALYSIS

4.1 Impact on the SAF/HVO Value Chain Using an AI-Driven Model

This chapter examines how AI-based forecasting improves decision-making related to procurement, transport, and inventory allocation within the SAF/HVO value chains. As described, uncertainty in UCO supply is approximated using predictive models based on publicly available data. These forecasts are then incorporated as supply constraints within the optimisation framework.

The training dataset is organized by time "t", defined on a monthly basis. The dependent variable "y_t" represents the volume of UCO collected at time "t".

The baseline model reflects conventional planning practice and assumes that UCO supply is known and constant, based on historical averages. Variations arising from seasonality, tourism, economic conditions, policy changes, and weather are averaged out and not updated dynamically during the planning horizon.

In the AI-driven scenario, UCO supply is forecast using supervised learning models applied to Portugal as a representative case. The explanatory variable vector $X_t$includes population dynamics, tourism activity, seasonal indicators, fuel demand and price signals, policy variables, and meteorological conditions.

The variables are defined as follows:

(1) $y_t =$ UCO supply volume at time t

(2) $X_t = (Pop_t, Tour_t, Season_t, Price_t, Policy_t, Weather_t)$

where Pop_trepresents population size, $Tour_t$tourism indicators such as overnight stays, $Season_t$seasonal dummy variables, $Price_t$fuel demand and price indicators, $Policy_t$policy-related dummy variables, and $Weather_t$meteorological conditions.

The AI-based forecast is represented using GB as an illustrative example:

$$(3) \qquad \hat{y}_t = \sum_{k=1}^{K} f_k\,(X_t)$$

Here, $\hat{y}_t$ the predicted UCO supply, $f_k(\cdot)$represents the k-th decision tree, and K is the number of trees in the ensemble. By combining multiple trees, the model captures non-linear relationships and interactions across explanatory variables.

For comparison, the baseline supply assumption is expressed as the historical average:

$$(4) \qquad \bar{y} = \frac{1}{T}\sum_{t=1}^{T} y_t$$

The forecasted UCO supply is used as an upper bound in the subsequent optimisation model. AI does not directly solve the optimisation problem; instead, it improves the realism of supply constraints by reflecting expected fluctuations.

$$(5) \qquad Supply_t \leq \hat{y}_t$$

Here, $Supply_t$ represents the UCO volume available for procurement at time "t" constrained by the AI forecast.

To operationalise uncertainty in UCO supply, Table II summarises the explanatory variables used for AI model training, together with their empirical motivation and expected relationship to supply variability.

Table II

Training variables features and expected relationship to supply

Symbol	Variable	Primary Source	Intuitive Relationship Impact on UCO Supply
Pop_t	Population size	Eurostat Municipal Regional Statistics	The larger the population, the greater the potential for increased eating out and home cooking, creating a larger foundation for UCO generation
Tour_t	Tourism activity (overnight stays, visitors)	Eurostat City Statistics	Increased tourism leads to ↑ demand for eating out →Potential for increased UCO generation and collection volumes

Season_t	Seasonal dummy	Calendar	UCO generation fluctuates cyclically during summer/peak seasons
Price_t	Fuel demand and price indicators	IEA (fuel demand/price related)	Changes in fuel prices and demand may alter recovery and diversion incentives
Policy_t	Policy Dummy (Mandates, Targets)	EU Regulations	Strengthened demand and certification requirements may advance the organisation of collection and supply
Weather_t	Weather (temperature, precipitation)	Meteorological data (public meteorological agencies)	Exogenous factors potentially affecting collection operations and consumer behaviour

Source: Own elaboration

As shown in Table II, UCO supply is shaped by interacting demographic, economic, policy, and environmental factors. Population and tourism establish the structural baseline for waste oil generation, while seasonal effects capture cyclical fluctuations in consumption and collection. Price signals and policy variables reflect economic and regulatory incentives, and weather conditions represent exogenous shocks affecting both behaviour and collection operations. These interacting drivers cannot be captured by baseline models based on historical averages, which smooth out seasonal peaks and policy-driven shifts. By contrast, the AI-based model exploits the variable structure in Table II to learn non-linear relationships and interaction effects, allowing forecasts to adjust dynamically to changing conditions.

The relevance of these variables is evident in Portugal, where a large share of technically recoverable UCO remains uncollected, particularly at household level, as shown by monthly UCO supply data of Lisbon for 2015–2023 (9 years). Population density, tourism intensity and local policy interventions therefore play a decisive role in explaining gaps between potential and realised supply. The sharp increase in UCO collection observed in Lisbon following targeted municipal initiatives illustrates how policy and infrastructure can rapidly alter outcomes. Data from the Portuguese Environment Agency (APA) indicate that domestic cooking oil consumption in 2015 was approximately 77,000 tonnes, of which around 58,000 tonnes were technically recoverable as UCO, yet only about 23,000 tonnes were collected and recycled, with the remainder often disposed of via sewage systems (APA, 2015; ECOX, 2024). The data also reveal structural imbalances in UCO generation and recovery: approximately 69% of UCO generation originates from the HoReCa sector, 25% from households and 6% from industry, while collection rates differ markedly, with household recovery at about 1.6% compared with roughly 46% in HoReCa, indicating substantial untapped household feedstock potential. Based on these data, Portugal's per-capita collected UCO in 2015 is estimated at 2.22 kg per person per year (23,000,000 kg divided by a population of 10,370,267; Eurostat, 2015), a static estimate that becomes variable once an effective population including tourists and other non-residents is considered. At the municipal scale, Lisbon provides evidence that targeted policies can rapidly increase collection volumes: from January to July 2024, UCO collection rose by 37.8% compared with the same period a year earlier (Lisbon City Council, 2023), illustrating the impact of local infrastructure and policy amid rising population and tourism.

Because the AI model explicitly incorporates the drivers listed in Table II, it is expected to reduce both average errors and extreme misestimations relative to baseline approaches. Forecast performance is therefore evaluated using MAE and RMSE, which together capture overall accuracy and sensitivity to large deviations that are critical for avoiding supply shortages in downstream optimisation.

$$(6) \quad MAE = \frac{1}{N}\sum_{t=1}^{N} | y_t - \hat{y}_t |$$

$$(7) \quad RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2}$$

MAE captures average deviation, while RMSE places greater weight on large forecasting errors, making it particularly relevant for identifying supply shortage risks.

Traditional baseline forecasting approaches, such as historical averages or simple trend extrapolation, generate point estimates that implicitly assume stable and predictable supply conditions. While such methods may perform adequately in low-variability environments, they fail to capture the inherent uncertainty and dispersion observed in waste-based feedstock supply. In practice, relying on a single deterministic forecast increases the risk of systematic underestimation or overestimation, particularly during periods of seasonal fluctuation, policy changes, or logistical disruptions. Figure 4 compares forecasting outcomes under traditional baseline and AI-driven approaches.

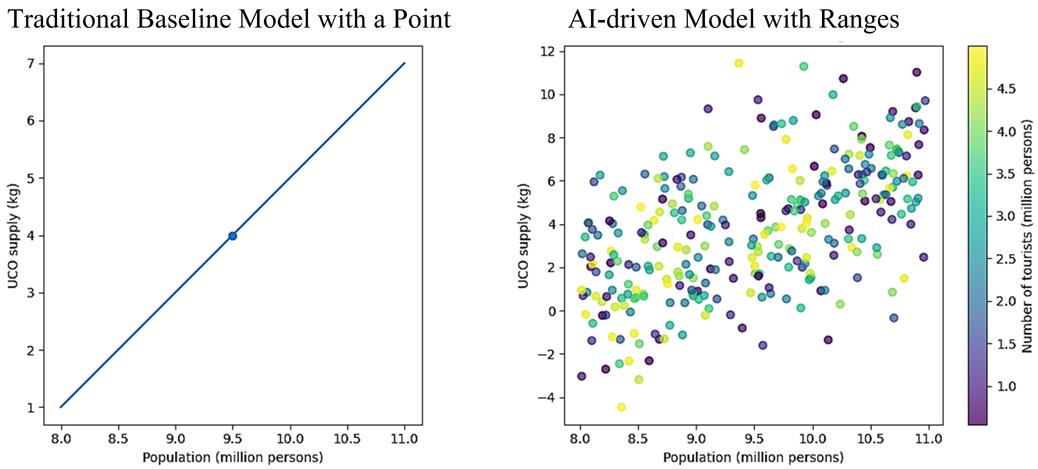


Figure 4 –Comparison between a Traditional Model and an AI-driven Model

Source: Own elaboration

As illustrated, the AI-driven forecasting model does not merely produce a single expected value but learns the underlying distribution of observed outcomes across multiple dimensions, including seasonality, regional variation, and interaction effects among explanatory variables. This enables the model to generate forecasts that reflect a plausible range of outcomes rather than a fixed-point estimate. As a result, prediction errors are reduced not only on average, as reflected in lower MAE values, but also in terms of extreme deviations, which is captured by improvements in RMSE.

From a decision-making perspective, forecasting uncertainty is as important as forecasting accuracy. Supply planning based on point estimates implicitly treats forecast errors as negligible, whereas AI-based range-aware forecasts allow uncertainty to be incorporated directly into operational constraints. In this study, predicted supply ranges are integrated into the optimisation framework as dynamic supply constraints, ensuring that collection and logistics decisions remain feasible even under adverse realisations of feedstock availability. In the case of UCO collection, overestimating available volumes may lead to inefficient routing, underutilised vehicles, and unnecessary emissions, while underestimating supply can result in missed collection opportunities and higher marginal sourcing costs. By minimising large forecasting errors and explicitly accounting for uncertainty, the AI-driven approach supports more robust route optimisation, balancing cost, emissions, and shortage risk more effectively than traditional baseline models. Figure 5 illustrates the integration of AI forecasting into the optimisation framework used in this study.

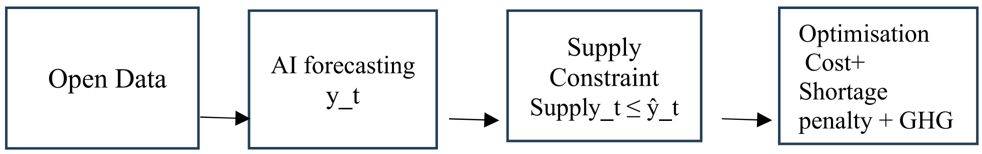


Figure 5 – AI Forecasting Integrated into Supply Constraint and Optimization

Source: Own elaboration

Open data sources are first processed through the AI forecasting model to estimate future feedstock availability. These forecasts are then translated into supply constraints that reflect both expected values and uncertainty bounds. Finally, the optimisation model determines collection and logistics decisions by minimising total system costs, including transport costs, shortage penalties, and associated greenhouse gas emissions.

The objective of the Key Performance Indicator (KPI) analysis is not to produce firm-specific optimisation outcomes, but to illustrate how improved forecasting alters decision structures within the SAF/HVO value chains. The optimisation framework and objective functions are held constant, with only the method of supply constraint specification differing between scenarios. KPI are selected to reflect economic viability, operational stability, and environmental performance. These include total cost, out-of-stock frequency, greenhouse gas intensity, and supply stability.

The results indicate that AI-based forecasting reduces emergency sourcing, improves logistics planning, and leads to measurable improvements across KPIs when compared with historical average planning. While models using proprietary corporate data would likely achieve higher precision, the findings demonstrate that meaningful insights can be derived using open data combined with robust modelling techniques. Also, the results confirm that AI contributes primarily by reducing uncertainty rather than directly lowering costs. Traditional planning approaches tend to generate higher costs and emissions due to supply shortages and reactive logistics adjustments. AI-enhanced processes, by contrast, enable proactive planning, route optimisation, and emissions reductions. Beyond technical efficiency, the analysis highlights the importance of innovation ecosystems. Public–private partnerships and coordinated policy environments enhance the effectiveness and scalability of AI tools in SAF/HVO systems. Scenario simulations further illustrate how AI models respond to feedstock shortages, policy interventions, and carbon pricing, supporting both operational and strategic decision-making.

To assess the operational implications of improved forecasting, selected KPIs are used to compare baseline planning with an AI-driven scenario under an identical optimisation structure and objective function. Table III reports relative changes in key performance indicators. Values are averages of estimates from three large language model–based assistants (Perplexity, ChatGPT and Gemini).

Table III

KPI Comparison: Baseline versus AI-Driven Scenarios

KPI	Definition	Baseline (Conventional)	AI-driven (Forecast-Updated)
Total Cost	Procurement + Transport + Inventory +	Baseline	−5% to −10%
Stockout Rate	Percentage of Unmet Demand	Standard	−10% to −30%
GHG intensity	Emissions per unit supplied	Baseline	−1% to −5%
Supply stability	Number of stockouts	Standard	−10% to −25%

Source: Own elaboration

The baseline reflects historical-average planning, while the AI-driven scenario incorporates forecast-updated supply constraints to capture variability, with AI applied as a simulation tool to explore extreme scenarios. Across all KPIs, the AI-driven scenario outperforms the baseline. Total costs decline by approximately 5–10%, driven by reduced emergency sourcing and more efficient routing. Stockout frequency falls markedly, indicating improved operational stability, while greenhouse gas intensity decreases modestly due to fewer reactive logistics adjustments. These improvements stem primarily from reduced forecasting uncertainty rather than direct cost optimisation. By narrowing the gap between expected and realised supply, the AI-driven approach enables proactive planning that remains feasible under a wider range of conditions, whereas baseline planning based on fixed averages is more prone to shortages and reactive responses.

4.2 Case Study Findings

The collaboration between Mitsui & Co. (Japan) and Galp (Portugal) is among the most strategically significant cross-border initiatives currently underway in SAF. Aviation accounts for approximately 2–3% of global energy-related CO_2 emissions, and air transport demand is projected to continue growing over the coming decades (IEA, 2023). Against this backdrop, both Japan and Portugal position SAF as a core element of aviation decarbonisation, despite differences in domestic constraints and policy instruments. This case is examined not primarily as an industrial project, but as an empirical reference point that aligns closely with the AI-based predictive modelling framework developed in this thesis. It provides a realistic setting for analysing how feedstock uncertainty, logistics complexity, and policy regimes jointly shape SAF/HVO value chain performance.

In feedstock procurement, the emphasis is on second-generation waste-derived inputs, mainly UCO and animal fats. According to official estimates, the European Union collects approximately 4 million tonnes of UCO annually, while animal fats amount to about 3 million tonnes per year (IEA Bioenergy, 2022). These feedstocks are eligible under the EU Renewable Energy Directive (RED II) and CORSIA sustainability standards, but they are characterised by seasonality, regional variability, and price volatility.

Production is concentrated at Galp's Sines refinery on Portugal's Atlantic coast. Sines is expected to become one of Europe's largest single-site SAF/HVO facilities, with maritime logistics enabling efficient distribution within Europe and potential exports to Asia. The project operates under a layered regulatory environment. At the European level, ReFuelEU Aviation provides demand certainty through binding blending obligations. In Japan, SAF targets are pursued largely through public–private coordination rather than strict legal enforcement. Internationally, both countries operate within the ICAO CORSIA framework, which standardises life-cycle emissions accounting and supports cross-border SAF trade.

Logistically, feedstock is sourced from restaurants, food processing facilities, and waste management operators across Southern and Northern Europe. Short distance transport is mainly via road approximately 100–500 km, while longer distance supply from Northern Europe and France often relies on maritime transport to the Port of Sines. These logistics chains are exposed to uncertainty related to seasonality, port congestion, fuel price volatility, and weather disruptions, which makes them a suitable context for AI-based forecasting and optimisation.

The Mitsui & Co.–Galp case provides a real-world setting with characteristics closely aligned to the objectives of this thesis. Feedstock availability and logistics demand show non-linear behaviour shaped by policy requirements, tourism cycles, and cross-border transport conditions. Under these conditions, RF can provide robust baseline forecasts even when data are noisy, while GB is better suited to capturing abrupt shifts caused by seasonal events or policy changes. By linking physical variables such as feedstock quantities, transport distance, and transport mode with policy-related dummy variables, the case study enables analysis of how institutional environments influence forecasting performance and optimisation outcomes. The partnership therefore functions both as an instructive industrial example and as an empirical foundation for testing the hypotheses introduced earlier. At a broader level, the pilot illustrates how European production capacity and Japanese demand and investment capacity can be combined into a cross-border SAF supply hub. It is sufficiently large and variable to support AI analysis, while also aligning with EU regulatory frameworks, ICAO CORSIA requirements, and Japan's decarbonisation strategy. This supports the argument that AI-driven optimisation becomes most valuable when it is embedded within a coherent and reasonably stable policy environment.

Finally, regulations and incentive designs do not operate only as external constraints. In this thesis, they are treated as institutional mechanisms that shape market formation, influence supply structures, and affect investment decisions.

4.3 Empirical Evidence from Industry Surveys on SAF/HVO Bottlenecks

To complement the quantitative modelling based on publicly available data, this dissertation conducted a targeted survey of stakeholders in the SAF/HVO value chains. The survey covered three main groups in international contexts: energy companies, aviation-related operators, and technology and engineering professionals. A total of 22 responses were collected via Google form, with 83.3% from the energy sector and 16.7% from the airline and aviation sector.

The survey aimed to identify perceived bottlenecks in scaling SAF/HVO and to assess expectations about the role of digitalization and artificial intelligence. The results show strong convergence across stakeholder groups regarding the main structural constraints. As shown in Figure 6, feedstock supply limitations were identified as the most critical barrier by 81.0% of respondents, followed by high production costs (66.7%). Regulatory and institutional uncertainty was cited by 38.1%, while logistical constraints were mentioned by 9.5%. Technical immaturity and limited market demand were each identified by 14.3%, indicating that upstream and cost-related factors dominate perceived barriers to scale u

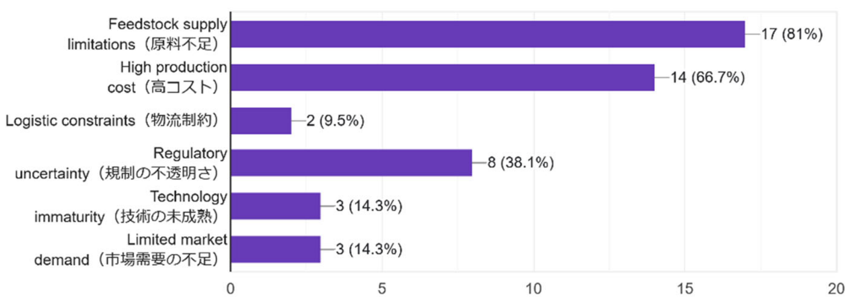


Figure 6 – Survey Results for Bottlenecks in SAF/HVO

Source: Own elaboration based on survey

At the operational level, these constraints were reported to have clear business impacts. Increased production costs were cited by 61.9% of respondents, while 47.6% reported greater uncertainty in business planning and 28.6% identified limitations in production capacity. These results indicate that feedstock and cost pressures directly constrain scale-up potential and reduce the market availability of SAF/HVO. Several respondents also described a reinforcing relationship between feedstock supply volatility and cost premiums, undermining overall supply-chain stability.

Analysis of feedstock constraints points to multiple interacting drivers rather than a single dominant cause. Import dependency was identified by 31.8% of respondents, while variability in feedstock quality accounted for 13.6%. Additional concerns included limited collection infrastructure, seasonal variability, competition with other industries for waste-based feedstocks and exposure to price volatility. Together, these findings indicate that feedstock supply challenges are systemic, reflecting the interaction of physical availability, infrastructure development, international trade structures, and price mechanisms. This supports the use of AI-based forecasting approaches that incorporate multiple explanatory variables rather than relying solely on historical averages.

Regarding technical constraints, respondents emphasized scaling challenges rather than technological immaturity. Refining capacity scale-up was identified as the most significant technological barrier by 42.9%, followed by digitalization gaps (28.6%). This suggests that while major SAF pathways have reached commercial readiness, large-scale deployment remains constrained by capital intensity, infrastructure capacity, and data integration requirements.

Looking ahead, perceptions of digitalization and AI were largely positive. Approximately 50% of respondents rated AI and digitalization as highly important, identifying priority application areas such as feedstock supply forecasting (33.3%) and logistics optimization (28.6%). At the same time, persistent barriers to adoption were reported, including limited availability of structured datasets (42.9%), poor data standardization (23.8%), and restricted cross-company data sharing. These findings indicate that effective AI implementation depends not only on technological capability, but also on appropriate data governance frameworks and coordinated stakeholder engagement.

From a policy perspective, respondents expressed mixed assessments. While 42.9% characterized current regulations as a strong driver, 19.0% viewed them as a strong barrier of SAF/HVO adoption. Among existing frameworks, ReFuelEU was identified by 61.9% of respondents as the most influential policy instrument, underscoring its central role in shaping international SAF markets. Overall, the survey results empirically support the core premise of this study that policy environments systematically shape behavior and investment incentives within SAF/HVO value chains, thereby validating the inclusion of policy-related variables in AI-based forecasting and optimization models.

Figure 7 presents a ranked summary of the key constraints and enabling factors affecting SAF/HVO scale-up, based on the share of respondents identifying each factor as significant.

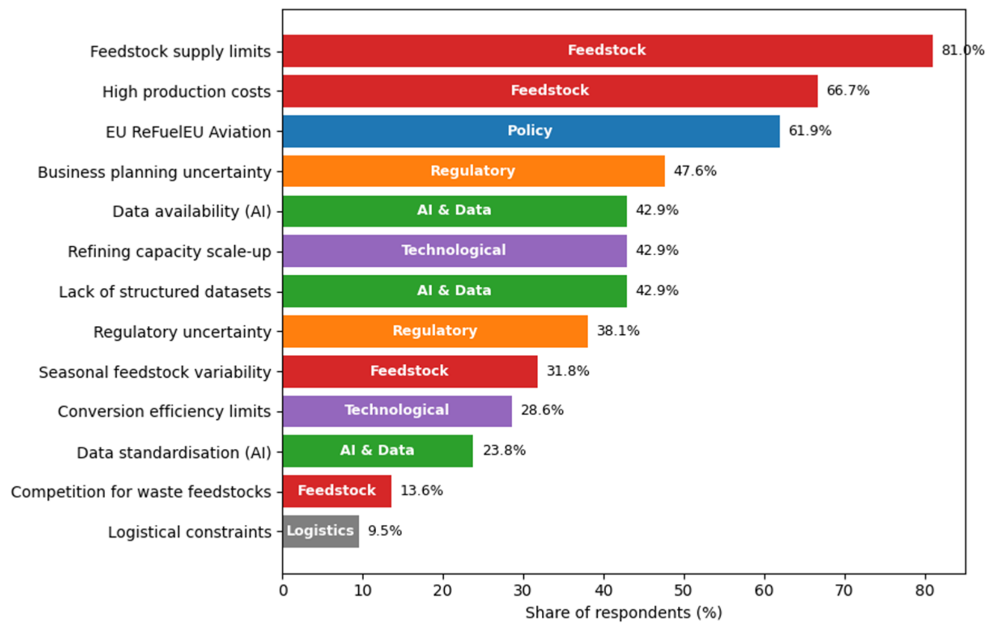


Figure 7 Summary of Constraints and Enablers for SAF/HVO Scale-up (N=22)

Source: Own elaboration

5. DISCUSSION

5.1 Key Contributions

This chapter interprets the results in relation to existing literature and the objectives established earlier. A central expectation is that AI-based predictive models, particularly ensemble methods such as RF and GB, outperform conventional statistical methods in forecasting feedstock availability and supporting logistics planning. This aligns with findings by Liao et al. (2021), which highlight the suitability of ensemble approaches for dynamic, non-linear energy supply systems.

A key contribution of this study is the adaptation of these methods to SAF/HVO value chains under realistic data limitations. Conventional approaches often rely on static assumptions that respond poorly to sudden shifts in feedstock availability, weather conditions, port disruptions, or policy changes. Martínez-Valencia et al. (2021) noted that static frameworks can constrain planning flexibility. In contrast, the framework developed here treats uncertainty as an explicit modelling condition, rather than an external risk.

5.2 Operational and Data-Related Implications

The results indicate that improved forecasting can support reductions in logistics costs and associated emissions when integrated into optimization-based planning. However, this study does not quantify the magnitude of such reductions, as doing so would require proprietary operational data and full system integration to translate AI-enabled capabilities into measurable operational outcomes, which are outside the scope of this work. In practice, AI does not replace operational decision-making but improves the quality of planning inputs and supports more robust comparisons across feasible options under changing policy and market conditions. Its primary contribution therefore lies in enhancing planning robustness and decision quality under uncertainty. At the same time, AI performance depends critically on data availability, consistency, and governance. Incomplete or fragmented datasets can reduce generalization performance and introduce systematic bias in real operational settings, indicating that effective AI deployment should not be framed as a purely technical challenge. Instead, it requires coordination across stakeholders, including standardized data practices, governance frameworks, and incentives for data sharing.

5.3 Innovation Ecosystems and Multi-Helix Perspectives

This observation connects to the concept of an innovation ecosystem. Effective AI integration is rarely a purely technical challenge. It requires the support of what scholars describe as an innovation ecosystem a network of actors, including companies, public institutions, and research organizations, working together to develop and deploy new technologies. Public–private partnerships, such as the Mitsui & Co.–Galp project, illustrate how shared investment, data coordination, and aligned objectives create favourable conditions for technology adoption. This supports Etzkowitz's Triple Helix model, which emphasises the role of collaboration between academia, industry, and government in enabling innovation. In SAF/HVO systems, these relationships appear especially relevant because market formation depends heavily on policy, infrastructure coordination, and long-term investment planning.

The interview evidence reinforces this interpretation. In an interview, fuel costs were described as the largest component of third-party costs, while the ability of airlines to absorb SAF price premiums was considered limited (Duarte, 2026). He also noted that airline operational data are often well organized, whereas upstream feedstock data, including UCO collection, remain fragmented and difficult to integrate into AI systems. This aligns with the methodological constraints of this thesis and supports the conclusion that stronger data governance and institutional design are prerequisites for scaling AI tools.

Finally, this study also aligns with the broader perspective of the Quintuple Helix, which extends the Triple Helix by explicitly incorporating civil society and the natural environment. In the specific case of UCO recovery, supply depends not only on policy design and industrial capacity, but also on collection behaviour in households and restaurants, community participation in collection systems, and social acceptance of circular-economy practices. The AI-based scenario framework presented here offers a way to examine how these layered factors interact and shape realistic supply potential over time.

6. CONCLUSION AND RECOMMENDATIONS

6.1 Summary of Key Findings

This study examined how AI, particularly predictive modelling, can support more efficient and resilient value chains for SAF/HVO. While these fuels offer significant potential to reduce emissions in aviation and heavy-duty transport, scale-up remains constrained by feedstock limitations, high costs, and supply chain inefficiencies. The modelling framework tested whether supervised learning methods can improve forecasts of UCO supply and support logistics optimisation under uncertainty. The analysis was complemented by the Quintuple Helix perspective to capture how technology interacts with policy, institutions, society, and environmental constraints.

The findings suggest that AI contributes most effectively by reducing uncertainty and improving planning quality. When forecasting outputs are integrated into optimisation, decision-makers can better anticipate supply shortages, compare sourcing options, and evaluate logistics trade-offs across policy scenarios. In the short term, AI-based models provide value as decision-support and simulation tools for analysing uncertainty under current data constraints, in the long term, their potential increases as data infrastructures mature. However, AI tools are not self-sufficient, and their practical usefulness depends on data quality, digital infrastructure, and governance mechanisms that enable consistent monitoring and information sharing.

6.2 Recommendations

Based on the results, three policy recommendations follow. First, standardised data and transparency are essential for AI-enabled optimisation. Policy authorities should strengthen digital infrastructure and data platforms that support standardised reporting for SAF/HVO, including feedstock origin, transport routes, energy inputs, and emissions factors, while protecting commercial confidentiality. Frameworks that link carbon intensity metrics to incentives, including life-cycle assessment-based compliance systems, increase the value of consistent data.

Second, innovation ecosystems and public–private partnerships should be strengthened. Cross-border projects such as Mitsui & Co.–Galp demonstrate that coordinated data sharing and risk-sharing mechanisms can reduce institutional uncertainty and support investment. For small and medium-sized enterprises, targeted support through clusters and collaborative programmes can enable access to digital infrastructure and analytical capabilities that are difficult to develop individually.

Third, regulatory design and AI deployment should be treated as complementary. Practitioners often view regulation as both a driver and a barrier. Policy authorities should combine blending obligations and price-based incentives with digital Monitoring, Reporting and Verification (MRV) approaches that reduce compliance costs while improving transparency and credibility.

6.3 Limitations

This study has several limitations. The AI models rely primarily on open datasets and simulated scenarios rather than proprietary operational data; therefore, the results should be interpreted as proof of concept rather than firm-level predictions. While quantifying the economic and emissions impacts of AI across the SAF/HVO value chains remains an important requirement, such quantification would require detailed open operational data and full system integration and is outside the scope of this study.

In addition, the expert survey was designed to identify qualitative patterns rather than support statistical inference, which limits generalisability. The policy comparison also relies mainly on publicly available sources and may not fully capture ongoing institutional or regulatory changes in real time.

6.4 Future Research

Future research could extend this work in four directions: (1) validation using real operational data through collaboration with firms, airports, and port authorities; (2) more advanced optimisation frameworks incorporating deep learning and reinforcement learning where appropriate; (3) comparative modelling across multiple renewable fuel pathways, including Power-to-Liquid; and (4) longitudinal studies tracking how policy maturity and AI capability evolve together over time.

In summary, AI has meaningful potential to improve SAF/HVO value chain resilience and decision quality. Whether this potential translates into large-scale impact depends less on algorithms alone and more on the surrounding ecosystem: data governance, institutional coordination, and credible, stable policy frameworks.

REFERENCES

Agência Portuguesa do Ambiente (APA) (2015). *Relatório sobre óleos alimentares usados em Portugal.* Lisbon: APA. Available at: https://apambiente.pt/sites/default/files/_Residuos/FluxosEspecificosResiduos/OAU/Relatorio/Relatorio_%20Gestao%20OAU-2018_19_20_set2022.pdf (Accessed: 10 January 2026).

Ahmad, S. and Xu, B. (2021) 'A cognitive mapping approach to analyse stakeholders' perspectives on sustainable aviation fuels', *Transportation Research Part D: Transport and Environment*, 100, 103076. https://doi.org/10.1016/j.trd.2021.103076

Carayannis, E.G. and Campbell, D.F.J. (2010). Triple Helix, Quadruple Helix and Quintuple Helix and how do knowledge, innovation and the environment relate to each other? *International Journal of Social Ecology and Sustainable Development*, 1(1), pp. 41–69. https://www.igi-global.com/article/triple-helix-quadruple-helix-quintuple/41959

Carayannis, E.G., Barth, T.D. and Campbell, D.F.J. (2012). The Quintuple Helix innovation model: Global warming as a challenge and driver for innovation. *Journal of Innovation and Entrepreneurship*, 1(2), pp. 1–12. https://www.econstor.eu/bitstream/10419/78609/1/723733201.pdf

Civil Aviation Authority of Singapore (CAAS) (2025). New SAF levy to apply from 1 April 2026 for flights departing from 1 October 2026. Singapore: CAAS. Available at: https://www.caas.gov.sg/who-we-are/newsroom/Detail/new-SAF-levy-to-apply-from-1-apr-2026-for-flights-departing-from-1-oct-2026 (Accessed: 10 January 2026).

Duarte, T.F. (2026). Personal interview, January 2026.

European Aviation Safety Agency (EASA) (2022). *Sustainability criteria for aviation fuels.* Cologne: EASA. Available at: https://www.easa.europa.eu (Accessed: 01 November 2025).

European Commission (2023). *ReFuelEU Aviation Regulation.* Brussels: European Commission. Available at: https://transport.ec.europa.eu (Accessed: 01 November 2025).

Eurostat (2024). Population on 1 January by age and sex. Luxembourg: Statistical Office of the European Union. Available at: https://ec.europa.eu/eurostat/databrowser/view/demo_pjan/default/table (Accessed: 05 January 2026).

Eurostat (2026). Electricity production capacities by main fuel groups and shares of renewable electricity in the EU. Luxembourg: Statistical Office of the European Union. Available at: https://ec.europa.eu/eurostat (Accessed: 05 January 2026).

Galp (2026). HVO Galp project. Available at: https://www.galp.com/corp/en/about-us/what-we-do/industrial-and-midstream/hvo (Accessed: 01 May 2025).

Goldemberg, J., Coelho, S.T. and Guardabassi, P. (2014). The sustainability of ethanol production from sugarcane. *Energy Policy*, 65, pp. 92–102.

He, X., Wang, N., Li, Y. and Zhang, J. (2024) 'Smart aviation biofuel energy system coupling with machine learning technology', *Renewable and Sustainable Energy Reviews*, 189, 113914.

Hosseini, S.E., Wahid, M.A. and Ganjehkaviri, A. (2021). Applications of artificial intelligence in bioenergy systems. *Renewable and Sustainable Energy Reviews*, 150, 111456.

Hotmaps Project (2018). *Hotmaps toolbox: Open data and modelling framework for heating and cooling demand.* Brussels: European Commission, Horizon 2020 Programme. Available at: https://www.hotmaps-project.eu/ (Accessed: 01 May 2025).

IEA Advanced Motor Fuels (AMF) (2013) *Synthesis, characterization and use of hydrotreated oils and fats for engine operation (Annex 45).* IEA-AMF. Available at: https://iea-amf.org/app/webroot/files/file/Annex%20Reports/AMF_Annex_45.pdf (Accessed: 01 October 2025).

IEA Bioenergy (2022). *Availability of waste lipids for biofuel production.* Paris: IEA Bioenergy. Available at: https://www.ieabioenergy.com (Accessed: 01 October 2025).

Institute for Sustainable Energy Policies (ISEP) (2025). *Renewable energy data and statistics in Japan.* Tokyo: ISEP. Available at: https://www.isep.or.jp/en/ (Accessed: 01 October 2025).

International Air Transport Association (IATA) (2024). *Net zero roadmap for aviation.* Montreal: IATA.

International Civil Aviation Organization (ICAO) (2023). *Sustainable aviation fuel guide.* Montreal: ICAO.

International Energy Agency (IEA) (2023). *World energy outlook 2023.* Paris: IEA.

Japan Airlines (JAL) (2022). Fry to Fly sustainable aviation fuel initiative. Tokyo: Japan Airlines Co., Ltd. Available at: https://www.jal.com/en/sustainability/environment/ (Accessed: 01 May 2025).

Liao, M., Aghbashlo, M., Shamshirband, S., Tabatabaei, M. and Lam, S. (2021) 'Applications of artificial intelligence-based modelling for bioenergy systems: A review', *GCB Bioenergy*, 13(4), pp. 608–647.

Martínez-Valencia, L., García-Pérez, M. and Wolcott, M. (2021) 'Supply chain configuration of sustainable aviation fuel: Review, challenges, and pathways for including environmental and social benefits', *Renewable and Sustainable Energy Reviews*, 152, 111654.

Martulli, A., Brandt, K., Allroggen, F. and Malina, R. (2025) 'The potential scale-up of sustainable aviation fuels production capacity to meet global and EU policy targets', *Nature Communications*, 16, 11619. Available at: https://www.nature.com/articles/s41467-025-66686-9 (Accessed: 1 October 2025)

Mitsui & Co., Ltd. (2026). Hydrotreated vegetable oil and SAF production in Portugal. Available at: https://www.mitsui.com/solution/en/solutions/lowc-fuel/560 (Accessed: 05 May 2025).

NASA (2024). *NASA Earthdata: Earth observation data for land, atmosphere and oceans.* Washington, DC: National Aeronautics and Space Administration. Available at: https://earthdata.nasa.gov/ (Accessed: 01 May 2025).

Qu, J. and Kim, Y. (2024). Innovation ecosystems and sustainability transitions. *Technological Forecasting and Social Change*, 197, 122874.

REN – Redes Energéticas Nacionais (2025) 'Portugal achieves 71% renewable electricity in 2024'. Available at: https://www.ren.pt/ (Accessed: 02 January 2026).

Sakib, M., Sarker, M.N.I., Alam, M.S. and others (2025) 'An ensemble deep learning framework for energy demand forecasting using genetic algorithm-based feature selection', *PLOS ONE*, 20(1), e0310465.

Shehab, A., Abdelwahab, M. and Elgowainy, A. (2023) 'Analysis of the potential of meeting the EU's sustainable aviation fuel targets in 2030 and 2050', *Sustainability, 15(9266), pp. 1–20.*

TAP Air Portugal (2025). *TAP Annual report 2024.* Lisbon: TAP Air Portugal. Available at: https://www.tapairportugal.com/en/investors/financial-information

(Accessed: 22 January 2026).

Trianni, A. and Cagno, E. (2012) 'Dealing with barriers to energy efficiency and SMEs: Some empirical evidences', *Energy*, 37(1), pp. 494–504.

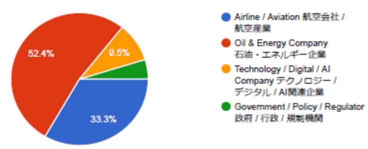
U.S. Department of Energy (DOE) (2024). *Sustainable aviation fuel grand challenge: Roadmap to build a domestic SAF industry.* Washington, DC: U.S. Department of Energy. Available at: https://www.energy.gov/eere/bioenergy/sustainable-aviation-fuel-grand-challenge (Accessed: 01 May 2025).

APPENDICES

This appendices A presents the survey result by experts from 2025 to 2026.

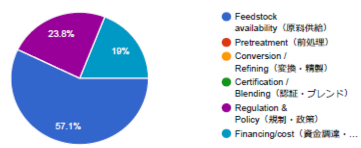
Q1. Which sector best represents your professional background?
(Please select one.)
あなたのご専門分野・所属業種を教えてください。
（もっとも近いものを1つお選びください）

21 responses



Q2. Where in the SAF/HVO value chain does the main pressure point occur?
SAF/HVO バリューチェーンの中で、最も圧力がかかっている部分はどこですか？

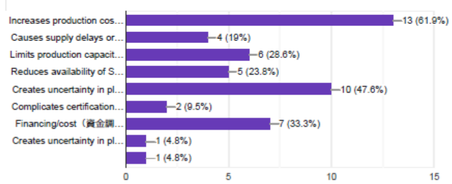
21 responses



Q3. How does this bottleneck affect your company's operations?

このボトルネックは貴社の事業にどのような影響を与えていますか？
（Multiple selections allowed / 複数選択可能）

21 responses

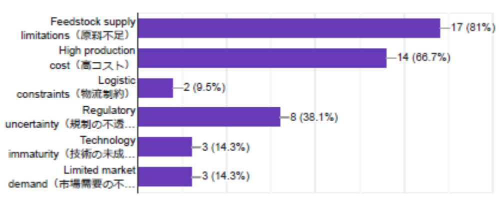


Q4. What is the primary constraint limiting SAF/HVO scale-up?

SAF/HVO の拡大量化を妨げている主な制約は何ですか？

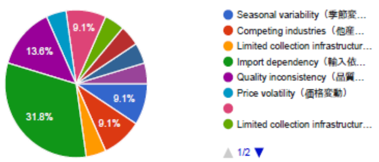
(Multiple choice / 複数選択可能)

21 responses



Q5. What is the main factor causing feedstock limitations?
原料供給が制約されている主な要因は何ですか？

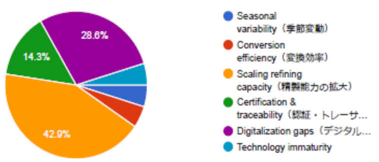
22 responses



Q6. Which technological barrier has the largest impact on development?

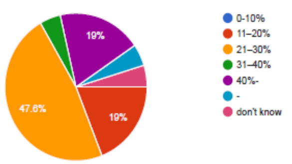
SAF/HVO の開発に最も影響を与えている技術的障壁はどれですか？

21 responses



Q7. How much do current constraints increase overall SAF/HVO cost?
現在存在する制約によって SAF/HVO の総コストはどの程度上昇しますか？

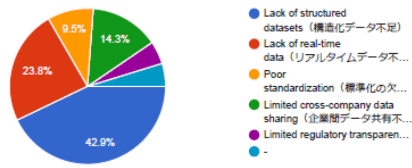
21 responses



Q8 Key data gaps limiting AI modeling?

AIモデル構築を妨げている主なデータギャップは何ですか？

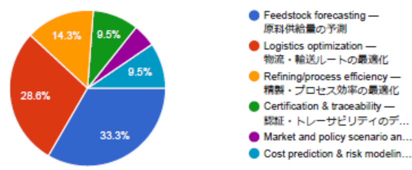
21 responses



Q9. In which area can AI have the biggest impact?

AIが最も効果を発揮できる分野はどこですか？

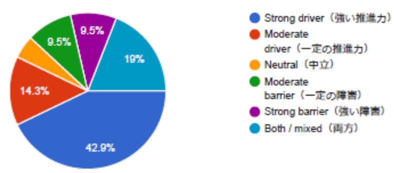
21 responses



Q10. Are current regulations a driver or barrier?

現在の規制は推進力ですか、障害ですか？

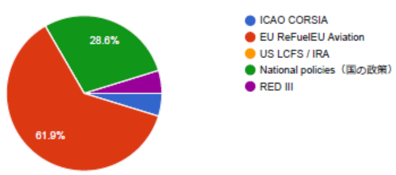
21 responses

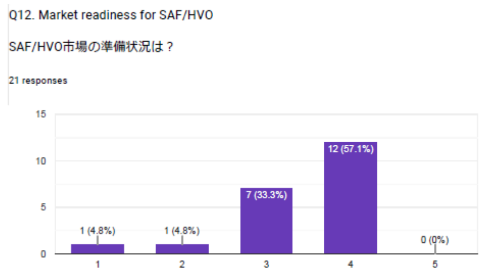


Q11. Regulation affecting operations the most?

最も影響が大きい規制はどれですか？

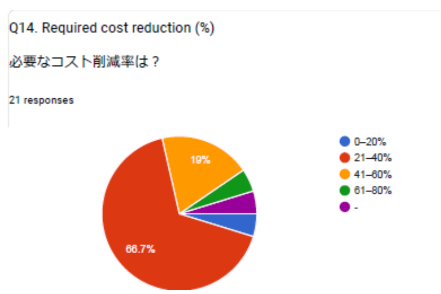
21 responses

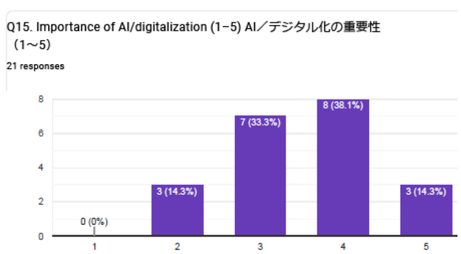


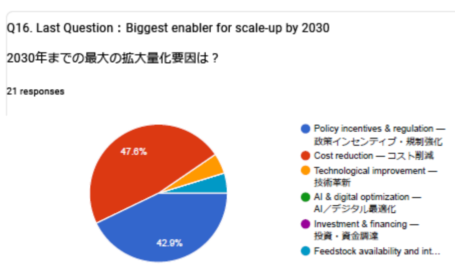


Q13: Policy Changes to Accelerate Adoption

-Suggested changes include standardized certification and increasing SAF requirements.
-Tax incentives for SAF usage were also mentioned.
-Greater openness to different feedstock types is needed.







APPENDICES B– EXPERT INTERVIEW RECORD SUMMARY ……….. 49

This appendices B presents a summary of the expert interview conducted on 21 January 2026.

Speaker 1: Interviewer, Yuka Takao Speaker 2: Interviewee, Tomas Ferreira Duarte

Introduction and Participant Backgrounds (0:00)

Speaker 1 asks for permission to record and use the interview for thesis and requests the interviewee's name and position. Speaker 2 agrees and introduces themselves as a management consultant and details his experience in the airline industry, including work with BCG and various airlines across Europe and the Middle East. His background as a private pilot and his knowledge of aircraft mechanics and dynamics.

Expertise (2:10)

Speaker 1 confirms Speaker 2's extensive experience with airlines and his role as a former advisor for airline-related matters. Speaker 2 offers a more generic perspective on the use of SAF and the role of executives and decision-makers in airlines.

Portuguese Government's Policy on SAF (3:52)

Speaker 1 asks about the current priorities of the Portuguese government regarding SAF/HVO in the aviation and transport sectors. Speaker 2 explains that the Portuguese state, as the owner of the two biggest airlines, has the power to enforce SAF use but is generally passive in sustainability matters. He notes that the government follows European Commission guidelines rather than setting its own trends in sustainability.

Challenges and Cost Considerations (8:34)

Speaker 2 discusses the financial implications of SAF use, noting that it increases costs without a clear increase in revenues. He explains that the government is focused on selling the airlines for the most profitable deal possible, which reduces the incentive to enforce SAF use. He highlights that fuel costs are a significant portion of airline expenses, and increasing SAF use would significantly impact the bottom line. He notes that the government is not keen to increase costs without clear revenue benefits, especially with the airlines undergoing privatization.

Sustainability and Fleet Modernization (14:49)

Speaker 2 explains that the CO2 emissions of air travel depend on the aircraft model, with newer aircraft being more fuel-efficient and emitting less CO2. He notes that the government's focus on selling the airlines reduces the immediate interest in enforcing SAF use. He suggests that the government's strategy should prioritize data collection to inform policies on aviation sustainability.

Digitalization and AI in Aviation (17:46)

Speaker 1 shifts conversation to digitalization and AI, asking about data availability and the role of AI in supporting policy design and decision-making. Speaker 2 explains that data was not a main driver of policy in the past, but the new government has a strong digitalization and innovation agenda. He notes that data collection on aviation operations is limited, and there is a need to reinforce data collection to inform policies. He suggests that better data collection could drive policy and positive discrimination of more modern equipment use, reducing overall emissions.

Potential Solutions and Taxation (24:06)

Speaker 1 asks about the potential role of a SAF tax as an example in Singapore to subsidize SAF use. Speaker 2 explains that subsidies are important for the initial adoption of green technologies, but a tax on passenger tickets needs to be carefully implemented. He notes that the efficiency of air travel is a complex metric, and a fixed tax per passenger might not be fair. He suggests that the government could subsidize SAF directly through an environmental fund, which already supports various projects to reduce carbon emissions.

International Collaboration and Innovation (32:37)

Speaker 1 asks about the importance of international collaboration in SAF deployment.

Speaker 2 emphasizes the need for coordinated policy at the European Union level to ensure a common approach. He highlights the importance of industrial players collaborating to develop more advanced and affordable SAF technologies. He expresses positivity about the collaboration between Galp and Mitsui, noting the innovation and technical quality of Galp.

Speaker 1 thanks Speaker 2 for his insights.