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Article

Flying Green by Choice: A System Dynamics Forecast of Voluntary SAF Demand Integrating Policy, Market, Demographic, and Behavioral Drivers

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Abstract This conceptual research article proposes a system dynamics-based framework to forecast the voluntary uptake of Sustainable Aviation Fuel (SAF) by air passengers departing from European Union (EU) airports. Unlike existing literature that treats policy and consumer behavior in isolation, the study integrates policy mandates, fuel price dynamics, passenger demographics, and behavioral drivers into a unified conceptual model. The framework emphasizes the role of willingness-to-pay (WTP), segmenting passengers by travel purpose and environmental attitudes. Although no empirical simulation or quantitative calibration is conducted, the model structure is designed to accommodate scenario analysis and uncertainty assessment, incorporating elements such as carbon pricing, SAF-fossil fuel cost differentials, blending mandates (e.g., ReFuelEU), and marketing effectiveness. Four illustrative scenarios (baseline, high policy support, technological breakthrough, and low WTP) are outlined to demonstrate how different assumptions may shape SAF demand trajectories. Model outputs are defined conceptually and include SAF uptake share, absolute demand, CO_2 savings, and abatement cost. This study does not present an empirically calibrated simulation and therefore refrains from producing quantitative forecasts. Its contribution is a rigorously specified conceptual structure intended to guide future parameterization and validation with real-world data; thus, it is intended as a foundation for future empirical research and policy experimentation. The study is offering strategic value for airlines, SAF producers, and regulators aiming to stimulate voluntary contributions to aviation decarbonization. By outlining system interactions and key sensitivities, the study advances a holistic, behaviorally informed approach to modeling voluntary SAF demand.

Keywords sustainable aviation fuel (SAF); voluntary carbon offsets; system dynamics modeling; willingness-to-pay (WTP)

1. Introduction

The passenger aviation sector is a significant and growing contributor to greenhouse gas emissions, with direct emissions from aviation accounting for 3.8–4% of total European Union (EU) greenhouse gas (GHG) emissions in 2022 [1]. By mid-decade, international aviation emissions could triple compared to 2015-levels without technological and operational advancements, as modelled by the International Civil Aviation Organization [2]. This trajectory is mainly driven by growing passenger demand, with a projected growth rate of 52% between 2023 and 2050 within the EU [3]. Decarbonization efforts of the aviation sector are mainly driven by policy-induced initiatives, such as the European Green Deal or the EU emissions trading scheme (EU-ETS), with the overall goal of reducing transport emissions by 90% by mid-century compared to 1990 levels [1]. Despite the call for deep decarbonization of the aviation sector to reach policy-induced targets, there are only minor technological advancements on sustainable aircraft technologies, such as hydrogen or electric, expected in the coming years. Airbus, for example, is working on a hydrogen-powered single-aisle regional aircraft that is expected to enter service on regional routes earliest in 2035 [4]. Current literature also estimates that by 2050, current-generation aircraft (such as Boeing 737 MAX, A320neo Family, Boeing 787, and Airbus A350) will still represent the largest part of the European aircraft fleet [5,6].

Sustainable aviation fuel (SAF) is seen as a pivotal lever in the decarbonization of the aviation sector. Depending on the manufacturing method, SAF can cut aviation lifecycle emissions by up to 80% compared to traditional kerosene [5,6]. Different industry roadmaps, such as IATA's

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"*Fly Net Zero 2050*" roadmap [7], estimate that SAF could deliver an emission reduction of up to 65% by 2050, thereby contributing a majority to mid-century targets and underscoring the importance of scaling SAF uptake. Under the EU's "*Fit for 55*" climate package, the ReFuelEU regulation requires fuel suppliers to blend a specified percentage of SAF into jet fuel uplifted at EU airports—the regulation takes effect in 2025, with at least 2% SAF blended into jet fuel by 2025, rising to 6% by 2030 and 70% by 2050. This ambitious pathway aims to stimulate SAF demand, upscale production capacities, and ultimately reduce aviation's carbon footprint in line with EU-wide emissions targets [8].

Airlines are increasingly aligning with these policy-induced climate targets by integrating SAF into their strategies and operations [9]. Many European airlines have also introduced programs for passengers to contribute to SAF uptake by voluntarily purchasing SAF for a flight. For instance, KLM allows passengers to purchase up to 100% SAF, based on the amount of fuel required per passenger, the destination, and the SAF price at the time of booking [10]. On the consumer side, there is evidence of growing environmental awareness and support for sustainable travel options. Current literature and surveys also found that travelers claim willingness to pay a premium for more sustainable travel options. Notably, the 2023 IATA Global Passenger Survey found that 65% of respondents would be willing to pay a premium to fly on an aircraft powered by SAF [11]. These findings present that a notable segment of passengers is, in theory, open to voluntary climate-related fees. Speaking about passengers' willingness-to-pay for SAF, Reisdorf (2024) [12] found that consumers would accept a surcharge to the base fare of around 10% to fly entirely on SAF, and Rains et al. (2017) [13] found that informing passengers about the use of biofuel on a flight increased their stated willingness-to-pay for the ticket by about 13%. Rains et al. (2017) [13] also suggest that positive emotions connected to "green" flying mediated the effect of paying a premium for SAF.

To date, literature mainly addresses sustainable aviation fuel uptake from either a macro-level policy or a micro-level consumer behavior standpoint with limited overlap [9]. For example, energy and policy studies analyze SAF feasibility, costs, and mandate impacts (e.g., [14–17]), while separate studies in air travel behavior discuss willingness-to-pay and attitudes (e.g., [9,18–21])—but no studies combine these lenses. To our knowledge, no prior research has developed a predictive conceptual model for voluntary SAF purchase demand that simultaneously addresses the economic context (price premiums, fuel cost differentials, and incentives), policy factors (e.g., ReFuel EU SAF blending mandate, EU ETS carbon pricing), behavioral drivers or "mindsets" (passenger environmental attitudes, social norms), and customer-centric strategies (how airlines' communication and service offerings influence customer perceptions). Such an approach would enable both policymakers and airlines to capture the interplay between policy constraints and individual passenger choices and would finally allow for forecasting voluntary SAF uptake volumes. Voluntary SAF uptake refers to an additional payment (premium) made by passengers to replace a specified share of fossil kerosene with SAF.

To address the identified research gap at the nexus of sustainable aviation and consumer behavior, the study at hand aims to integrate perspectives from policy, market prices, demographics, and consumer behavior into a conceptual forecasting model for voluntary SAF purchases within the EU. This conceptual model particularly contributes to sustainable consumer behavior in air transport, a currently underexplored area [9], and builds on emerging research on public acceptance of low-carbon fuels. This research paper aims to answer the research question of "*What are the main behavioral, economic, and policy drivers influencing voluntary Sustainable Aviation Fuel (SAF) purchases by air passengers departing from EU airports, and how can these be integrated into a predictive demand model?*" with practical relevance for both airline managers and policymakers. For airline managers, understanding the likelihood and magnitude of passenger SAF uptake is vital for designing effective SAF programs and customer engagement strategies. Additionally, a forecasting model allows airlines to negotiate offtake agreements in tranches aligned with projected voluntary uptake surges to mitigate price and supply risk. For policymakers and regulators, a scientific understanding of voluntary SAF demand can help the design of complementary measures to boost participation—such as informational campaigns (e.g., campaigns promoting voluntary SAF uptake), green labels, or fiscal incentives for "opt-in" SAF contributions.

Existing SAF models treat voluntary passenger demand as exogenous and seldom account for default (opt-in/opt-out) and price interactions, limiting behavioral realism. We contribute a behaviorally informed system-dynamics model that endogenizes segment-specific WTP and ethical defaults and closes feedback from voluntary demand to supply learning and prices.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature on SAF demand drivers, Section 3 presents the conceptual model framework, and Section 4 discusses implications and limitations, and concludes with directions for future research.

2. Literature Review

Understanding the voluntary uptake of SAF by passengers requires a multidisciplinary perspective that integrates insights from policy, economics, behavioral science, and demographics. No existing study integrates all these factors into a single predictive framework. The following review synthesizes literature across these domains to guide the development of a conceptual predictive system dynamic model tailored to flights departing from EU airports. The model outputs will primarily include the uptake share of total kerosene demand (%) and secondary the voluntary SAF demand (kt/year), CO_2 savings (kt/year), and average CO_2 abatement cost (€/tCO_2). The following review aims to identify model input parameters and is structured along four categories: (1) policy and regulation, (2) market prices, (3) passenger demographics, and (4) behavioral drivers. Each category represents a model input. This review aims to highlight both established drivers and emerging trends, thus building the foundation for an empirically grounded modeling framework. In Section 3, model structure and dynamics will be discussed in more detail.

2.1. Policy & Regulation

EU Emissions Mandates & Quotas: Under the ReFuelEU SAF blending mandate, aviation fuel suppliers must blend at least 2% SAF by 2025, 6% by 2030, 34% by 2040, and 70% by 2050 into total fuel supplied to airlines on EU airports [8]. These quotas aim to stimulate SAF demand, create a regulatory floor for SAF demand, and signal long-term policy commitment. Early studies of such mandates suggest they could raise airline costs through higher fuel prices but also drive SAF market growth, which could lower SAF prices in the long-run [22]. SAF blending quotas play a pivotal role in SAF uptake modeling because the mandate's stringency directly influences both the passenger premium for SAF and its market price. For instance, increased SAF demand resulting from higher blending quotas stimulates expansion in production capacity and fosters optimization in production processes, potentially leading to reductions in SAF prices (compare to early HVO adoption under policy, e.g., [23]). Consequently, the premium passengers pay for SAF decreases. Conversely, higher SAF prices induced by blending mandates increase airline operating costs due to elevated fuel expenses, which ultimately translates into higher ticket prices. Blending mandates, by increasing overall fuel costs (and thus ticket prices), may indirectly narrow the apparent price premium for opting into additional SAF. In other words, if all tickets become costlier due to climate policies, an extra few euros for SAF might not seem as steep an add-on (or now within passengers' WTP-limit) relative to the new higher base price.

Carbon Pricing (EU ETS): The inclusion of aviation into the EU emissions trading scheme (ETS), a cap-and-trade scheme, results in airlines incurring a cost for CO_2 emissions and therefore pricing carbon into jet fuel operations. Carbon emissions from SAF are considered to be zero under the ETS [7]. The EU ETS allowance prices have surged, exceeding EUR 90 per ton CO_2 in 2022 [24], which leads to an increasing cost of fossil kerosene and ultimately lowers the price differential between fossil kerosene and SAF. Modeling studies treat carbon price as a key input: a rising ETS price can incentivize airlines or passengers to adopt SAF to avoid carbon costs, whereas a low carbon price diminishes the financial appeal of SAF [24].

Subsidies & Incentives: Incentives from governments are considered critical for bridging the cost gap between SAF and conventional jet fuel. Policies such as production subsidies, tax credits, and grant programs directly reduce SAF prices or de-risk investments in SAF supply chains [25,26]. For instance, the U.S. Inflation Reduction Act introduced substantial tax credits for SAF. Analyses show that these credits will encourage producers to shift their output from diesel toward the jet fuel market. Measures at the EU level—like the use of the Innovation Fund to provide funding for SAF projects or the earmarking of revenues from the Emissions Trading System for clean aviation—also aim to make SAF projects financially viable [24]. In modeling frameworks, these sorts of subsidies are included to examine scenarios in which policy support leads to SAF price reductions and subsequently to higher voluntary uptake by airlines and passengers.

External Shocks: The adoption trajectories of SAF can be significantly impacted by major external events. The COVID-19 pandemic, for instance, caused a drastic decline in air travel demand in 2020, leading to a decline of EU aviation CO_2 emissions by around 60% that year [27]. This decline in demand resulted in temporarily reduced fossil kerosene consumption, which may have delayed airline investment into SAF. Forecasting models must account for such external shocks, as they can alter long-term behavior and policy priorities [28]. Conversely, energy price spikes in 2022 (e.g., during the global oil crisis between 2021 and 2023, see [29]) have made fossil kerosene more expensive and thus narrowed the price gap with SAF in the short term. Such volatility caused by external shocks underscores the importance of policy stability. Long-term climate policies provide consistent incentives for SAF uptake despite fluctuating market conditions. Additionally, external shocks underscore the need for scenario analysis in the proposed model—e.g., a pandemic-like scenario vs an oil crisis scenario—since they can drastically alter short-term uptake and even long-term trends.

Regulatory Environment & Compliance: The Airline's strategic decision to offer SAF for purchase by customers is influenced by the broader regulatory environment [30]. Schemes like CORSIA (the ICAO's offsetting mechanism) and domestic fuel taxes shape the context—for instance, if airlines face stringent emissions caps or taxes, they might more actively promote passenger-supported SAF programs as part of a compliance strategy. Modeling studies should include such external policy factors (e.g., a new tax on jet fuel or a tightening of emissions caps) to examine how they would alter passengers' willingness to purchase SAF or airlines' pricing of SAF options [31]. Overall, policy and regulation provide the boundary conditions in SAF uptake models, defining the "rules of the game" through carbon costs, mandated minimums, and financial incentives that strongly condition voluntary purchase dynamics.

2.2. Market Prices

SAF vs Fossil Jet Fuel Cost: The previous section discussed different policy & regulation frameworks affecting both SAF and fossil jet fuel market prices. A consistent finding is that SAF is currently substantially more expensive than traditional fossil kerosene. Recent estimates put SAF at about 2–5 times the price of fossil kerosene, dependent on feedstock and production pathway [32]. This large cost differential is a fundamental barrier to voluntary uptake and explains why SAF currently comprises less than 1% of fuel use [33]. Such price gaps also pose a risk for airlines to market SAF upgrades to consumers unless the extra cost per ticket is minor or bundled into corporate travel programs. Integrating SAF and fossil fuel price trajectories (based on e.g., technological innovation or higher oil prices) is an essential part of SAF uptake forecasting models. If oil prices remain low, the opportunity cost of using more expensive SAF is greater, thus dampening voluntary adoption. Sensitivity analysis in the literature show that oil prices are a key driver of SAF breakeven costs and hence of predicted SAF demand (e.g., [34]).

Physical Supply Constraints: Even if passengers are willing to pay for SAF, availability is a limiting factor. Current SAF production is still limited, with a share of 0.3% of total jet fuel consumption as of 2024 [35]. Literature points out that the reasons are supply-side barriers such as "feedstock capacity" (e.g., limited sustainable bio-feedstocks that do not compete with food) and insufficient production capacities [36–38]. Some scenario studies predict an aggressive expansion of SAF production (which would lead to around 5.5 million tons of SAF capacity in an optimistic case) while others take a more conservative view that supply remains tight and aligns with the ReFuelEU SAF mandate quota (leading to a SAF capacity of around 2.3 million tons by 2030) [39]. These physical supply constraints must be accounted for in models by constraining the maximum SAF that can be purchased or by linking price to supply (e.g., rising marginal cost as SAF share increases).

Airfare Differences (Short- vs Long-haul): The market context for SAF purchases differs between short- and long-haul flights. Short-haul routes (such as intra-European flights or domestic flights) tend to have lower average base fares and thinner profit margins (e.g., because of low-cost carrier competition), thus meaning a voluntary SAF surcharge might represent a large percentage of the base fare. In contrast, long-haul flights (e.g., Europe to the Americas) tend to have higher base fares, leading to a voluntary SAF surcharge representing a lower percentage of the base fare [40,41]. Hui et al. (2024) [21] note that the willingness-to-pay for green premiums is negatively related to ticket price—more expensive tickets make additional fees, such as a voluntary contribution to SAF, relatively palatable up to a point, whereas adding a slight fee on a cheaper ticket price might deter passengers from purchasing. Thus, passengers' WTP declines as the relative price increase grows. Additionally, airlines compete with alternative modes of transport (e.g., train or bus) on short-haul routes, which could drive passengers away. Models can reflect this issue by segmenting markets, e.g., by applying different uptake rates or price elasticities for short- and long-flights.

2.3. Demographics

Passenger Volume & Growth: Air passenger volumes have been on a growth-trend, which provides a growing pool of potential voluntary SAF purchasers. The global aviation sector is expected to grow to about 12.4 billion passengers carried in 2050, up from 4.6 billion in 2024 [42]. For SAF uptake modeling, both passenger volumes and expected growth are essential input variables, as both influence the absolute potential demand for voluntary SAF. This growth trajectory will be reflected in the model's baseline demand—a larger passenger pool means a higher ceiling for potential SAF uptake.

Leisure vs Business Travel: Survey data suggests that leisure travelers constitute most trips (around 80%), whereas business travelers represent a minor share but spend more per trip (around 20%), dependent on actual route and airline [43]. It seems important to consider this split, as leisure travelers tend to pay out-of-pocket and are price sensitive, whereas business travelers might be more willing to pay for SAF if it helps to meet ESG targets, to offset business travel emissions (scope 3) or if a "green travel" policy is in place [44]. Many European companies and multinationals have started pledging to use SAF for corporate travel, which drives voluntary uptake from the business segment (e.g., [45–47]). Accordingly, models should account for different passengers by travel purpose: higher uptake rates or WTP for business travelers can be assumed based on their higher ability to pay and company support. Conversely, pure leisure markets (e.g., low-cost holiday flights) are likely to exhibit low SAF uptake absent substantial external incentives.

2.4. Behavioral Drivers

Environmental Awareness & Values: A range of sociodemographic variables—particularly age, income, education, and cultural background—have been found to significantly correlate with passengers' pro-environmental values and their willingness to pay for SAF [23,48,49]. Younger travelers tend to exhibit higher environmental awareness and are more likely to act on climate concerns through sustainable consumption, including air travel. The highest willingness to pay "*can be found among young, high-income and highly educated air travelers that are aware of aviation's contribution to climate change and feel personally responsible for their own contribution to it*" ([48], p. 1). Gender effect remains debated in literature: some studies found women to be more likely to support voluntary carbon offsets due to higher environmental risk perception [49,50] while others show no significant difference in voluntary carbon offset support [48]. Besides sociodemographic variables, environmental values—including climate concern, personal responsibility, and alignment with ESG principles—have been shown in multiple behavioral studies to be among the strongest predictors of SAF adoption. Passengers' belief in the environmental harm of flying, combined with internalized moral norm or eco-identity, significantly increases their likelihood to choose SAF over fossil kerosene despite price premiums [51,52]. Modeling studies must operationalize these soft factors by defining probabilistic uptake based on awareness clusters by assigning higher opt-in rates to passengers with strong environmental concern or from specific sociodemographic backgrounds. Environmental awareness might also shift over time, depending on societal movements (e.g., "flygskam" or "flight shame") or natural disasters, for example. In modeling practice, scenario analysis might be helpful to operationalize different awareness levels into an ESG acceptance model. The acceptance model could range from 0 (no environmental awareness) to 1 (full environmental awareness) and cover three different scenarios: high, mid, and low awareness. The level of each scenario can be assessed based on literature, surveys, or (social) media analyses and might vary over time.

Willingness to Pay & Ability to Pay: Many passengers exhibit a positive WTP for sustainable aviation, typically ranging up to 20% of the ticket price. This WTP is heterogeneous, influenced by sociodemographic factors such as higher income levels or age, which correlate with greater WTP for premium services, with younger travelers generally showing a higher WTP for green premiums [21,53]. Strong environmental awareness and belief in the efficacy of climate protection also drive WTP, whereas budget-conscious travelers or those skeptical of environmental initiative often exhibit a near-zero WTP [21,54]. Across recent WTP studies, point estimates vary widely by context and framing. Studies emphasizing default opt-in or integrated checkout placement report higher uptake than voluntary add-ons [55,56]. Evidence also indicates that WTP declines with ticket price (price anchoring), as WTP for SAF is highly sensitive to ticket price increases [57]. Survey-based WTP estimates often overstate what consumers actually pay in real-world settings [58]. This suggests that airlines and policymakers should be cautious when relying on stated WTP to forecast SAF adoption and should consider strategies to bridge the gap between intention and action [21,54]. Importantly, WTP is negatively related to the ticket price, meaning the proportionality of the added cost significantly impacts acceptance [21]. Speaking about the ability to pay (ATP), financial constraints also represent a fundamental barrier, as lower-income travelers may be unable to afford additional costs, regardless of their environmental attitudes. This intertwining of economic factors with attitudinal ones means that macroeconomic conditions also play a significant role: voluntary SAF uptake could improve during periods of economic growth where incomes rise, or corporate budgets absorb costs, but it is likely to worsen during recessions. Both WTP and ATP are crucial factors in forecasting SAF uptake by translating pro-environmental attitudes into actual purchase behavior. For modeling, a single static WTP might be insufficient, and a demand curve or segmented WTP derived from literature is more appropriate (e.g., [12,21]).

Airline Strategies & Marketing: The way airlines market and present SAF purchase options influences voluntary uptake rates. While regulatory and price factors shape the structural conditions for SAF demand, behavioral studies highlight that user interface design and decision architecture play a critical role in shaping consumer behavior [59]. Airlines that integrate SAF purchase options directly into the booking process—particularly through default options, pre-selected contributions, or opt-out structures—tend to see higher uptake compared to airlines that place SAF offerings on separate pages, afterthought add-ons, or indirect platforms (e.g., via QR codes in inflight magazines) [60]. Airlines' strategic marketing decisions, such as bundling SAF contributions with loyalty programs or emphasizing corporate ESG alignment, can turn what is otherwise a costly surcharge into a reputational or emotional value proposition [61]. Modeling studies should account for such variation by incorporating marketing effectiveness as a behavioral multiplier or uptake elasticity factor. This highlights that SAF demand is not only a function of cost and awareness but also of how accessible, credible, and compelling the SAF option appears within the user journey. A large body of behavioral-economics evidence shows that pre-selecting a pro-social option (opt-out) increases take-up relative to opt-in. The most comprehensive meta-analysis of default effects reports a medium average effect across domains, implying sizeable absolute uptake gains versus opt-in baselines [62]. A broader meta-analysis of choice-architecture interventions likewise finds small-to-medium average effects overall with defaults among the more reliable tools [63]. Critically for aviation, an airline field experiment on carbon-offset add-ons showed much higher acceptance under opt-out than opt-in [59]. Recent studies in energy product contexts (e.g., green electricity) confirm robust "green default" effects while noting heterogeneity by region and consumer segment [56,64,65]. Together, this literature supports modeling default framing as an explicit design lever that multiplies uptake conditional on price, rather than folding it implicitly into WTP.

3. Model Structure and Dynamics

While the previous literature review identifies the factors and evidence of model outputs and inputs, the following section discusses how those factors are integrated into a conceptual SAF forecasting model. With model dynamics, we refer to the internal mechanisms and relationships that govern how inputs are transformed into outputs within a simulation or forecasting model. In the context of SAF uptake modeling, they capture the logical, mathematical, and behavioral rules that link external factors—such as policy incentives, fuel prices, and passenger characteristics—to outcomes like voluntary SAF purchases, emissions reductions, or economic costs. While the model is not empirically implemented in this study, its components are described to provide a rigorous foundation for future empirical applications.

3.1. System Dynamics Modelling Approach

A system dynamics approach is adopted due to its suitability for representing interconnected and dynamic relationships across policy, market, demographic, and behavioral factors. The model simulates SAF uptake for flights departing from EU airports from 2024 through 2050 (aligning with policy targets), with annual time steps to capture dynamic targets. Based on the previous literature review, the core structure of the proposed model includes all the discussed categories. Table 1 discusses each input variable and how the variable is used within the model—explicitly or implicitly. The factors "Subsidies & Incentives" and "Regulatory Environment & Compliance" are implicitly included through scenario variations. "Airfare differences" and "Environmental Awareness & Values" are also implicitly modeled via different WTP segments and distributions. External shocks are modeled via Monte Carlo price volatility, and physical supply constraints are modeled indirectly through cumulative production capacity and learning curve limits. Explicit modeling of Airline Strategies & Marketing would require detailed individual airline behavior, passenger interaction data, and potentially an agent-based approach. For the purpose of this model, we consider Airline Strategies & Marketing as being partly embedded within variations of WTP scenarios and business/leisure passenger differentiation. All other input factors are explicitly included in the model.

Table 1. Overview of model inputs and use within the model.

Subsystem	Input Factor	Details
Policy & Regulation	EU Emissions Mandates & Quotas	Included as scenario variables affecting the SAF uptake directly by setting minimum mandated blending levels, influencing the SAF market scale
	Carbon Pricing (EU ETS)	Included through direct impact on the price differential between fossil kerosene and SAF, thus influencing uptake
	Subsidies & Incentives	Represented through scenario variations (e.g., High policy scenario assumes increased subsidies)
	External Shocks	Incorporated implicitly via Monte Carlo price volatility (±10%) reflecting fuel market uncertainty
	Regulatory Environment & Compliance	Reflected implicitly within scenario assumptions (baseline, high policy) as it overlaps significantly with mandates and incentives
Market Dynamics	SAF vs Fossil Jet Fuel Cost	Central input in the model, explicitly modeled using the SAF price premium and fossil fuel base price
	Physical Supply Constraints	Modeled indirectly through cumulative production capacity and learning curve limits, production scalability is captured in learning curve scenario assumptions
	Airfare Differences (Short- vs Long-Haul)	Included implicitly through different WTP segments (business vs leisure), capturing passenger price sensitivity indirectly
Demographics	Passenger Volume & Growth	Explicitly modeled (4.6B in 2024 to 12.4B by 2050), essential for forecasting demand
	Leisure vs Business Travel	Explicitly modeled, distinct passenger segments with differentiated WTP parameters clearly reflected in the uptake calculation
Behavioral Drivers	Environmental Awareness & Values	Implicitly included through WTP parameter distributions and their variations in scenario analysis
	Willingness to Pay & Ability to Pay	Explicitly modeled via probabilistic distributions, central to determining voluntary uptake
	Airline Strategies & Marketing	Airline marketing effects can be seen as partly embedded within variations of WTP scenarios and business/leisure passenger differentiation. If desired, this could be approximated in future model refinements through adjusting WTP distributions based on the assumed effectiveness of airline marketing strategies

3.2. Decision Logic and Model Dynamics

To capture voluntary SAF uptake behavior at the macro level, the model uses a hybrid decision-making structure that integrates price sensitivity, environmental awareness, and social influence—without relying on micro-level agent simulation. A central mechanism is a probabilistic willingness-to-pay distribution across passenger types (e.g., business vs leisure), determining uptake as a share of travelers whose WTP exceeds the current SAF price premium. This threshold-based representation reflects heterogeneity in financial ability and green preferences. Over time, a learning curve reduces SAF production costs as the regulatory mandate share and cumulative uptake grow. This will trigger a feedback loop: lower prices expand adoption, which in turn drives further cost reduction. This dynamic enables S-shaped adoption trajectories common in sustainable innovation diffusion [66]. Social influence is modeled implicitly as WTP shifts for different scenarios and reflects scenario-specific mechanisms through which social influence operates—thus greater visibility or normalization of SAF purchases influencing social norms and WTP over time.

3.3. Scenario Logic

With the model structure established, a range of plausible futures for voluntary SAF uptake are discussed through four illustrative scenarios. Each scenario represents a distinct set of assumptions about the key external drivers identified in the conceptual model. These scenarios form a basis for future empirical modeling and provide qualitative insights into the dynamics of SAF adoption under uncertainty:

Scenario 1: Baseline

- Assumes continuation of current trends: moderate policy ambition, gradual learning-driven SAF cost declines, and stable passenger willingness-to-pay.
- Expected to produce slow uptake, modest emissions reductions, and moderate improvements in cost-effectiveness.

Scenario 2: High Policy Support

- Envisions stronger mandates, higher carbon prices, and SAF subsidies.
- Uptake increases as SAF becomes more affordable and visible; policy action amplifies learning effects and demand.

Scenario 3: Technological Breakthrough

- Assumes rapid cost reductions due to innovation (e.g., in e-fuels or conversion efficiency), independent of major policy changes.
- As SAF prices fall, WTP thresholds are met more easily, accelerating uptake even without strong public subsidies.

Scenario 4: Low Willingness to Pay

- Reflects weaker demand due to economic downturn, climate skepticism, or reduced consumer trust.
- Uptake remains low despite potential supply improvements, highlighting the importance of behavioral and attitudinal drivers.

These scenarios are not intended as predictions but as tools to explore system boundaries and test the conceptual model's sensitivity to driving forces. Each scenario would lead to different trajectories of SAF uptake. Future empirical implementations of this model can use these scenarios to design structured simulation experiments, test policy robustness, and explore "what-if" futures in a transparent and comparative way.

3.4. Dealing with Uncertainty and Sensitivity

While scenarios help to illustrate contrasting "what-if" pathways that combine assumptions about multiple variables, uncertainty analysis aims to understand how uncertainty in inputs (e.g., fuel prices, passenger WTP) translates into uncertainty in model outputs (e.g., SAF uptake). Sensitivity analysis complements this by identifying which parameters most strongly influence model outcomes.

Uncertainty Analysis: given the long-term horizon of the anticipated SAF forecasting model and many unknown parameters, uncertainty analysis is crucial in SAF modelling. Academic studies employ Monte Carlo simulations or probabilistic methods to assess how uncertainties in inputs propagate to outcomes (e.g., [14,67,68]). In modeling voluntary SAF uptake, upstream uncertainties (such as fuel carbon intensity, price, etc.) mean the effective benefit and cost of SAF are uncertain. A robust analysis should sample across these uncertainties: for example, drawing random values for future oil price, carbon price, SAF cost, and passenger WTP from distributions, and then running many simulations to see a spread of outcomes. The literature recommends such analyses to avoid false precision [69,70]. Literature recommends this to avoid false precision—one can report, e.g., a 90% prediction interval for SAF adoption rates in 2030, given the current uncertainty. Some studies also highlight "deep uncertainties" where probabilities can't be easily assigned (e.g., "technological breakthroughs in e-fuels" or "public opinion shifts" as examples) [71,72].

Sensitivity Analysis: Hand-in-hand with uncertainty analysis is sensitivity analysis, which systematically varies one input at a time (or a set of inputs at a time) to see the effect on outputs. Many SAF studies include sensitivity analysis to test their results [73,74]. Common sensitivities are feedstock price, capital cost of biorefineries, carbon credit price, learning rate, and policy incentives. In an SAF context, one might test sensitivity to the fraction of passengers willing to pay or the size of voluntary SAF surcharge. The results of sensitivity analyses often identify which variables the model is most sensitive to, guiding policymakers where to focus. For instance, if the model is highly sensitive to the carbon price, that suggests policy leverage there; if the model is more sensitive to tech cost, that suggests R&D funding importance. In documentation, these analyses may be presented as elasticity values. Xu et al. (2025) [38] note that across studies, policy-related factors (carbon price, blending mandates) and cost factors (oil price, feedstock cost) tend to dominate sensitivities, whereas factors like social variables, while important, are often secondary in quantitative impact. Ultimately, one goal of sensitivity analysis in this domain is to test the robustness of policy conclusions: e.g., "Will a certain policy lead to high SAF adoption under all reasonable assumptions, or only under optimistic ones?"

Together, these approaches would be essential components of a future implementation, helping assess model robustness and policy relevance under uncertainty.

3.5. Model Outputs

The proposed model would generate the following outputs. These outputs are defined conceptually to support future policy-relevant analysis of SAF promotion strategies:

- SAF uptake as a percentage of total kerosene demand.
- Absolute SAF demand (in kilotons per year).
- CO_2 emissions savings (in kilotons per year), based on assumed lifecycle reductions.
- Average CO_2 abatement cost (€ per ton of CO_2 avoided).

3.6. Model Calibration

Although the present study provides a robust conceptual model for understanding the drivers of voluntary SAF uptake, the next step in the research is an empirical validation of the model and its key parameters. In future work, model parameters—such as price elasticities, WTP distributions, and uptake rates—can be calibrated using real-world data from voluntary SAF programs (e.g., airline opt-in schemes) or literature. Historical adoption patterns, such as corporate SAF procurement trends or public offsetting behaviors, may serve as a basis for behavioral sensitivities. While the availability of SAF uptake data and WTP distribution is currently limited, we believe that additional data will become available when SAF production increases because of EU emissions mandates & quotas.

3.7. Modeling Limitations: Implicit vs Explicit Drivers

While the proposed conceptual model captures a broad range of influences on voluntary SAF uptake, some important drivers—such as airline marketing strategies, external shocks, and environmental awareness—are currently modeled implicitly rather than explicitly. This modeling choice reflects pragmatic and theoretical reasons, including data limitations (the availability of SAF uptake and WTP distribution data is currently limited) and conceptual scope. To improve behavioral and systemic realism, these implicit drivers could be made explicit in future empirical work. For Airline Strategies & Marketing, airline-level decision variables may be included (e.g., share of customers exposed to SAF opt-in messaging) and linked to observed changes in uptake rates. These could be calibrated using A/B test data or surveys [75]. For External Shocks, scenario trees or event-based triggers (e.g., fuel price spikes, pandemics) are suitable to explicitly model abrupt shifts in demand, policy, or costs.

3.8. Summary and Conceptual Overview

This study developed a conceptual system dynamics model designed to forecast voluntary SAF uptake by airline passengers within the EU. The model incorporates key policy, market, demographic, and behavioral inputs to estimate future SAF demand, based on current literature. While the model is not yet empirically implemented, its structure supports scenario analysis, sensitivity testing, and Monte Carlo-based uncertainty assessments to capture plausible system behaviors over time. Figure 1 provides an overview of the model's inputs and their modeling logic. Figure 2 visually maps how inputs influence uptake dynamics and resulting outcomes—both explicit (e.g., fuel prices, mandates, WTP) and implicit (e.g., awareness, compliance strategies).

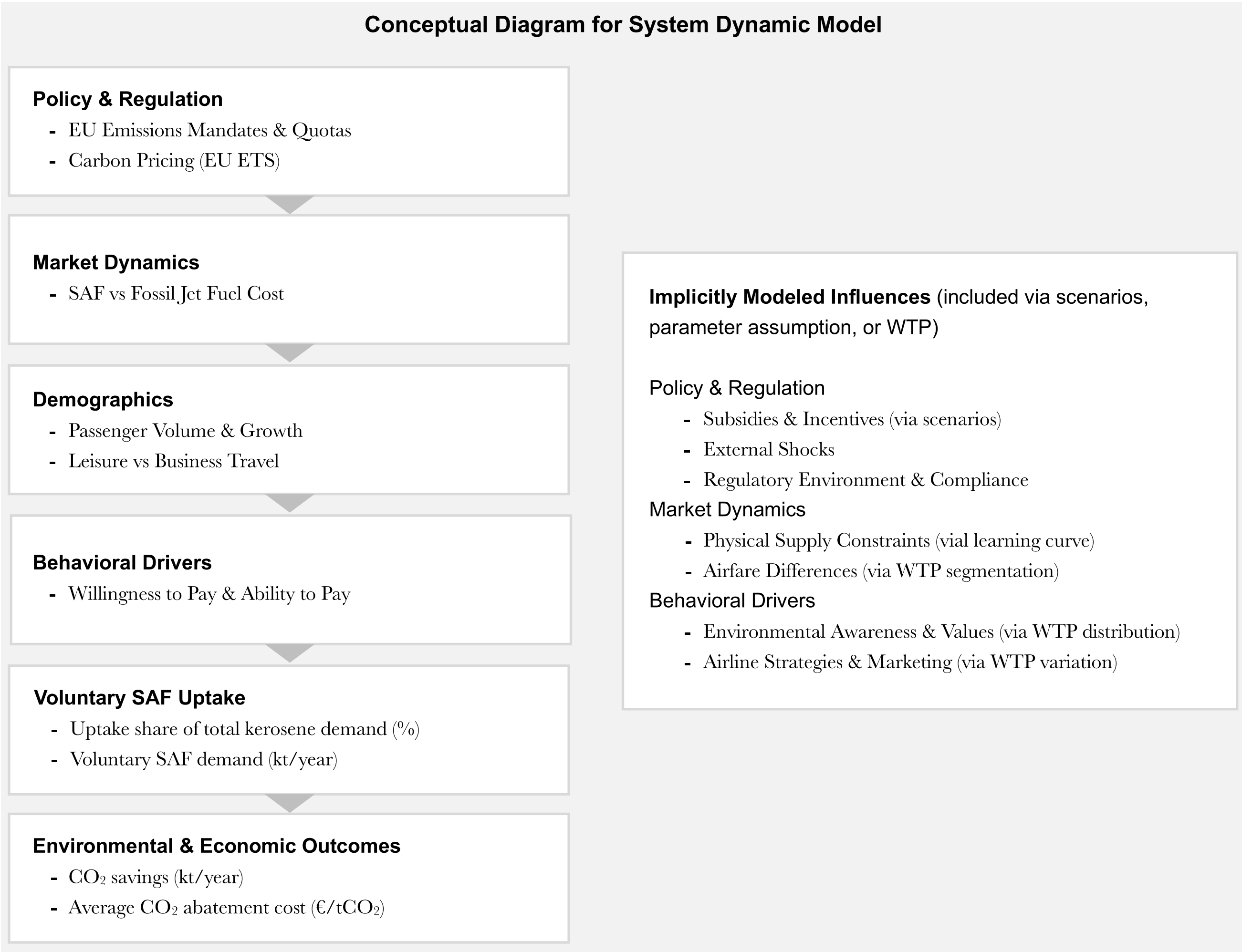

Figure 1. Overview of proposed SAF uptake forecasting model and its implicit and explicit influences.

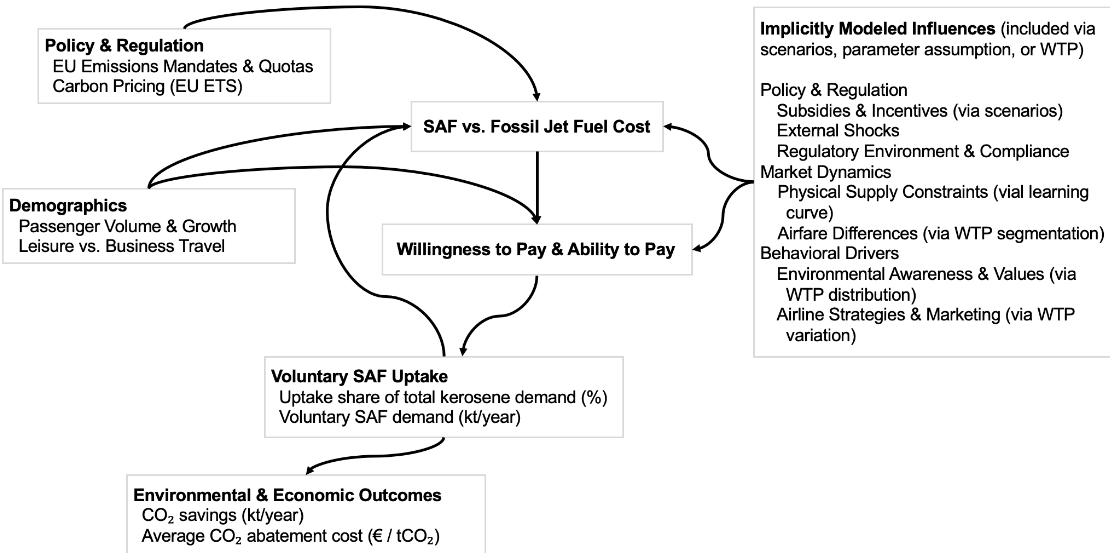

Figure 2. Interdependencies and feedback loops of proposed SAF uptake forecasting model.

4. Discussion, Implication, and Conclusion

In this final section, we reflect on the broader significance of our conceptual model—examining its policy and managerial implications, acknowledging its current limitations, and outlining directions for future research before drawing our concluding insights.

4.1. Policy and Managerial Implications

For policymakers, the model highlights that voluntary SAF uptake is shaped not only by price, but also by behavioral dynamics—especially defaults, framing, and perceived credibility. This suggests the need for a portfolio approach combining price instruments (e.g., subsidies, carbon pricing) with non-price interventions. While financial incentives reduce the SAF premium, their effectiveness depends on the baseline WTP distribution across traveler segments. For instance, even modest premiums may deter large portions of the leisure market unless paired with low-friction defaults or social norm cues. Behavioral levers such as green labeling, transparent opt-out options, and credible communications can thus complement economic tools, especially when fiscal or regulatory space is constrained. The model also enables policy experimentation, allowing governments to simulate how voluntary demand responds to different combinations of instruments, market conditions, or credibility shocks.

For airlines, the model supports the strategic design of voluntary SAF offers, differentiated by traveler type. Business travelers—who tend to have higher ability to pay and ESG sensitivity—may respond to reputational framing, integrated reporting, or B2B climate commitments. In contrast, price-sensitive leisure travelers are more responsive to opt-out defaults, embedded add-ons, or social proof cues at checkout. Airlines can use these insights to position SAF contributions not only as an environmental compliance tool, but as a loyalty- and brand-building asset, reinforcing customer trust and identity. Moreover, the model allows for phased implementation strategies, aligning offer rollouts with projected demand growth and SAF supply availability. This helps airlines avoid underinvestment in marketing channels or premature contracting with SAF providers.

For SAF producers and fuel industry stakeholders, the model estimates the potential scale of voluntary SAF demand, which—when combined with mandated demand—can drive early production ramp-up. The demand curves can inform decisions on capacity investment, risk-sharing instruments, and pricing strategies. Importantly, voluntary uptake is highly sensitive to behavioral design and policy context, which affects the pace at which producers move down the cost curve. This highlights the need for early coordination between fuel suppliers, regulators, and airlines to avoid demand–supply mismatches and to accelerate learning-driven cost reductions.

4.2. Limitations of the Current Framework and Future Research Directions

As a conceptual model, it lacks empirical calibration, and its value lies in structuring hypotheses and framing behavioral dynamics, not in producing numeric forecasts. Key behavioral variables, such as WTP, are operationalized through assumed segments or distributions, not yet validated through observed or measured data. External shocks (e.g., pandemics, economic crises, political events) are not explicitly modeled but are acknowledged as future enhancements via scenario input variation. The scenario logic applied in this study combines parameter uncertainty (e.g., WTP elasticity, default effectiveness, policy crowding) with plausible trajectories for policy and cost drivers (e.g., SAF learning rates, carbon pricing). Future empirical work should focus on refining these assumptions by estimating segment-specific WTP under realistic framing, experimentally testing price interactions, and tracking policy salience effects over time. Such data would enable more precise parameterization of the adoption and behavior sub-models and reduce reliance on literature-calibrated priors. Longitudinal or revealed-preference data on actual SAF opt-in behavior (e.g., from airline pilots or booking portals) could further strengthen model realism.

While the model is designed with modularity in mind, implementation in a simulation environment (e.g., Vensim, Stella) is needed to fully explore dynamic feedback behavior over time.

A logical next step is empirical testing and calibration of the model using survey-based or experimental data:

- Discrete choice experiments (DCEs) or contingent valuation surveys could generate WTP data across demographic groups. When available, data from the literature can also be used.

- Behavioral interventions (e.g., default SAF options, social norm prompts) could be trialed in lab or field settings to further develop behavioral drivers.

The model could be implemented in system dynamics software (e.g., Vensim, Stella) to conduct simulations, run Monte Carlo uncertainty analysis, and explore sensitivity to policy levers. Future extensions may incorporate agent-based modeling components, especially for simulating peer influence or corporate travel manager decisions or life-cycle climate metrics, allowing integration of SAF emissions performance by feedstock or technology type.

4.3. Conclusion

This paper introduces a conceptual system dynamics model that integrates behavioral, economic, and market drivers of SAF uptake among EU air passengers. Unlike previous publications that focus narrowly on cost or regulatory mandates, this model places WTP and behavioral segmentation at the center of voluntary demand forecasting. The model's structure allows both quantitative and qualitative forecasting and scenario building, which is especially useful in early policy design stages. While not quantitatively implemented, the model provides a valuable tool for theoretical reasoning, qualitative scenario development, and early-stage policy exploration. By integrating implicit (e.g., values, awareness) and explicit (e.g., carbon taxes, ticket price) drivers, the model aims to reflect real-world complexities while remaining flexible for empirical enhancement. The proposed conceptual framework is expandable and modular, as additional variables (e.g., airline branding, climate sentiment indices) can be added in future versions.

In conclusion, the framework serves as a foundation for future empirical modeling, simulation, and real-world policy design, ensuring that voluntary SAF demand becomes a strategic pillar of sustainable aviation transitions.

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Data Availability

No new data were created or analyzed in this work. Data sharing is not applicable to this article.

Author Contributions

Stephan Soklaridis: Writing – original draft, Conceptualization, Project administration. Andrea Reisdorf: Writing – review & editing, Validation. Sebastian Kummer: Writing – review & editing, Supervision, Validation.

Conflicts of Interest

The authors have no conflict of interest to declare.

References

1. European Commission. (2025). *Reducing emissions from aviation—European Commission*. https://climate.ec.europa.eu/eu-action/transport-decarbonisation/reducing-emissions-aviation_en (accessed 13 June 2025).
2. ICAO. (25 May 2025). *Trends in Emissions that affect Climate Change*. ICAO. https://www.icao.int/environmental-protection/Pages/ClimateChange_Trends.aspx (accessed 13 June 2025).
3. Medina, R. (2024). *EUROCONTROL Aviation Long-Term Outlook: Flights and CO2 emissions forecast 2024 – 2050*.
4. Airbus. (25 March 2025). *Airbus showcases hydrogen aircraft technologies during its 2025 Airbus Summit*. https://www.airbus.com/en/newsroom/press-releases/2025-03-airbus-showcases-hydrogen-aircraft-technologies-during-its-2025 (accessed 13 June 2025).
5. Clean Sky 2 Joint Undertaking. (2022). Towards Climate Neutral Aviation. An independent study on the socioeconomic impact of the European Union's Clean Sky 2 Programme. With assistance of Roland Berger, Oxford Economics. *CleanAviation Joint Undertaking*.
6. Rau, A., Stumpf, E., & Gelhausen, M. (2024). Modelling the impact of introducing first-generation narrowbody hydrogen aircraft on the passenger air transportation network in Europe. *Journal of the Air Transport Research Society*, *3*, 100029. https://doi.org/10.1016/j.jatrs.2024.100029
7. McCausland, R. (2024). *Net zero 2050: Sustainable aviation fuels*.

8. European Commission. (2025). *ReFuelEU Aviation—European Commission*. https://transport.ec.europa.eu/transport-modes/air/environment/refueleu-aviation_en (accessed 13 June 2025).
9. Xu, B., Ahmad, S., Charles, V., & Xuan, J. (2022). Sustainable commercial aviation: What determines air travellers' willingness to pay more for sustainable aviation fuel? *Journal of Cleaner Production*, *374*, 133990. https://doi.org/10.1016/j.jclepro.2022.133990
10. KLM. (2025). *SAF: Alternative aviation fuel - KLM*. SAF: Alternative Aviation Fuel - KLM Austria. https://www.klm.at/en/information/sustainability/saf (accessed 13 June 2025).
11. IATA. (2024). *ReFuelEU Aviation Handbook*.
12. Reisdorf, A. (2024). *The Influence of SAF on International Aviation Competition*.
13. Rains, T., Winter, S. R., Rice, S., Milner, M. N., Bledsaw, Z., & Anania, E. C. (2017). Biofuel and commercial aviation: Will consumers pay more for it? *International Journal of Sustainable Aviation*, *3*(3), 217. https://doi.org/10.1504/IJSA.2017.086846
14. Ahire, J. P., Bergman, R., Runge, T., Mousavi-Avval, S. H., Bhattacharyya, D., Brown, T., et al. (2024). Techno-economic and environmental impacts assessments of sustainable aviation fuel production from forest residues. *Sustainable Energy & Fuels*, *8*(19), 4602–4616. https://doi.org/10.1039/D4SE00749B
15. Braun, M., Grimme, W., & Oesingmann, K. (2024). Pathway to net zero: Reviewing sustainable aviation fuels, environmental impacts and pricing. *Journal of Air Transport Management*, *117*, 102580. https://doi.org/10.1016/j.jairtraman.2024.102580
16. Shahriar, M. F., & Khanal, A. (2022). The current techno-economic, environmental, policy status and perspectives of sustainable aviation fuel (SAF). *Fuel*, *325*, 124905. https://doi.org/10.1016/j.fuel.2022.124905
17. Watson, M. J., Machado, P. G., Da Silva, A. V., Saltar, Y., Ribeiro, C. O., Nascimento, C. A. O., et al. (2024). Sustainable aviation fuel technologies, costs, emissions, policies, and markets: A critical review. *Journal of Cleaner Production*, *449*, 141472. https://doi.org/10.1016/j.jclepro.2024.141472
18. Ahmad, S., Xu, B., Greening, P., & Ouenniche, J. (2020). *Public Attitude Towards Aviation Bio-Fuels: A Pilot Study Findings*. https://doi.org/10.46855/energy-proceedings-6464
19. Chiambaretto, P., Laurent, S., Schmalz, U., Fu, M., Rouyre, A., Bildstein, C., et al. (2024). Are consumers willing to pay more for green innovations? Insights from the air transport industry. *Technovation*, *137*, 103079. https://doi.org/10.1016/j.technovation.2024.103079
20. Hong, S.-A., & Huh, S.-Y. (2025). *Assessing the Market Viability of Sustainable Aviation Fuel: Consumer Acceptance and Willingness to Pay*. https://doi.org/10.2139/ssrn.5262656
21. Hui, T. H., Itani, N., & O'Connell, J. F. (2024). Examining Air Travellers' Willingness to Pay for Non-voluntary Environment-related Fees: The Case of SAF Surcharge and Carbon Taxes. *Highlights of Sustainability*, *3*(1), 61–75. https://doi.org/10.54175/hsustain3010005
22. Chen, R., Yang, H., Wang, K., & Jiang, C. (2024). Impacts of a sustainable aviation fuel mandate on airline competition—Full-service carrier vs. Low-cost carrier. *Transportation Research Part B: Methodological*, *190*, 103098. https://doi.org/10.1016/j.trb.2024.103098
23. Marcuta, L., Cazacu, M., & Marcuta, A. (2023). Study on the development of the biofuel market and their future in sustainable production. *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development*, *23*(3), 565–571.
24. Grimme, W. (2023). The Introduction of Sustainable Aviation Fuels—A Discussion of Challenges, Options and Alternatives. *Aerospace*, *10*(3), 218. https://doi.org/10.3390/aerospace10030218
25. Breen, M., Carton, J. G., & Efthymiou, M. (2025). Sustainable Aviation Fuel (SAF) Supply. In C. McNally, P. Carroll, B. Martinez-Pastor, B. Ghosh, M. Efthymiou, & N. Valantasis-Kanellos (Eds.), *Transport Transitions: Advancing Sustainable and Inclusive Mobility* (pp. 646–651). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-89444-2_94
26. Malina, R., Abate, M. A., Schlumberger, C. E., & Navarro Pineda, F. (2022). *The Role of Sustainable Aviation Fuels in Decarbonizing Air Transport*. Washington, DC: World Bank. https://doi.org/10.1596/38171
27. Eurocontrol. (26 January 2021). *EUROCONTROL Data Snapshot on CO2 emissions from flights in 2020*. https://www.eurocontrol.int/publication/eurocontrol-data-snapshot-co2-emissions-flights-2020 (accessed 13 June 2025).
28. Lipsmeyer, C. S., Philips, A. Q., Rutherford, A., & Whitten, G. D. (2024). Bad times keep us together: Policy priorities and economic shocks. *Social Science Quarterly*, *105*(4), 934–947. https://doi.org/10.1111/ssqu.13382
29. World Economic Forum. (23 May 2022). *Davos 2022: The world's first energy crisis and how to fix it*. https://www.weforum.org/stories/2022/05/first-global-energy-crisis-how-to-fix-davos-2022 (accessed 13 June 2025).
30. Rutherford, D. (2021). *Potential tankering under an EU sustainable aviation fuels mandate*.
31. Mayeres, I., Peduzzi, E., Alder, M., Baier, F., Buchtal, K., Chatterjee, S., et al. (2025). Assessing Policies for the Uptake of Sustainable Aviation Fuels Using the Impact Monitor Framework. *Engineering Proceedings*, *90*(1), 95. https://doi.org/10.3390/engproc2025090095
32. Zhou, Y., Searle, S., & Pavlenko, N. (2022). *Current and future cost of e-kerosene in the United States and Europe*.
33. EASA. (2025). *SAF Market*. https://www.easa.europa.eu/en/domains/environment/eaer/sustainable-aviation-fuels/saf-market (accessed 13 June 2025).

34. Sharma, B. P., Yu, T. E., English, B. C., & Boyer, C. N. (2021). Economic Analysis of Developing a Sustainable Aviation Fuel Supply Chain Incorporating with Carbon Credits: A Case Study of the Memphis International Airport. *Frontiers in Energy Research*, *9*, 775389. https://doi.org/10.3389/fenrg.2021.775389
35. IATA. (2024). *Disappointingly Slow Growth in SAF Production*. https://www.iata.org/en/pressroom/2024-releases/2024-12-10-03 (accessed 13 June 2025).
36. Ahmad, S., & 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
37. Kousoulidou, M., & Lonza, L. (2016). Biofuels in aviation: Fuel demand and CO2 emissions evolution in Europe toward 2030. *Transportation Research Part D: Transport and Environment*, *46*, 166–181. https://doi.org/10.1016/j.trd.2016.03.018
38. Xu, Y., Zhang, Y., Deng, X., Lee, S.-Y., Wang, K., & Li, L. (2025). Bibliometric analysis and literature review on sustainable aviation fuel (SAF): Economic and management perspective. *Transport Policy*, *162*, 296–312. https://doi.org/10.1016/j.tranpol.2024.11.014
39. EASA. (2023). *EASA Report – State of the EU SAF Market in 2023*.
40. Morrell, P. S. (2021). *Airline Finance* (5th ed.). Routledge. https://doi.org/10.4324/9781003038191
41. Renold, M., Kuljanin, J., & Kalić, M. (2019). The comparison of financial performance of airlines with different business model operated in long-haul market. *Transportation Research Procedia*, *43*, 178–187. https://doi.org/10.1016/j.trpro.2019.12.032
42. ICAO. (2024). *ICAO unveils 2026-2050 Strategic Plan: "Safe Skies, Sustainable Future"*. https://www.icao.int/Newsroom/Pages/ICAO-unveils-20262050-Strategic-PlanSafe-SkiesSustainable-Future.aspx (accessed 13 June 2025).
43. RSB. (2022). *SAF Sustainability Guidance for Airports: A summary of the Sustainable Airports Platform outputs in 2022*.
44. Santos, K., & Delina, L. (2021). Soaring sustainably: Promoting the uptake of sustainable aviation fuels during and post-pandemic. *Energy Research & Social Science*, *77*, 102074. https://doi.org/10.1016/j.erss.2021.102074
45. AMEX. (2024). *SAF FAQs*.
46. Surgenor, C. (4 April 2025). Microsoft backs SAF for Scope 3 business travel emissions in agreements with IAG and FEG. *GreenAir News*. https://www.greenairnews.com/?p=7044 (accessed 13 June 2025).
47. Wenzel, E. (9 May 2024). Corporations buy into sustainable fuel certificates to address air travel emissions. *Trellis*. https://trellis.net/article/corporations-buy-sustainable-fuel-certificates-address-air-travel-emissions (accessed 13 June 2025).
48. Cordes, H., Baumeister, S., & Käyrä, M. (2023). Factors influencing the willingness to pay for aviation voluntary carbon offsets: A literature review. *European Journal of Tourism Research*, *36*, 3602. https://doi.org/10.54055/ejtr.v36i.2741
49. Moser, S., & Kleinhückelkotten, S. (2018). Good Intents, but Low Impacts: Diverging Importance of Motivational and Socioeconomic Determinants Explaining Pro-Environmental Behavior, Energy Use, and Carbon Footprint. *Environment and Behavior*, *50*(6), 626–656. https://doi.org/10.1177/0013916517710685
50. Eger, C., Munar, A. M., & Hsu, C. H. C. (Eds.). (2023). *Gender and tourism sustainability*. Routledge.
51. Chen, F.-Y. (2013). The intention and determining factors for airline passengers' participation in carbon offset schemes. *Journal of Air Transport Management*, *29*, 17–22. https://doi.org/10.1016/j.jairtraman.2013.01.001
52. De Groot, J. I. M., & Steg, L. (2009). Mean or green: Which values can promote stable pro-environmental behavior? *Conservation Letters*, *2*(2), 61–66. https://doi.org/10.1111/j.1755-263X.2009.00048.x
53. Yraola Iii, S. D., & Mendiola, A. A. (2024). The Theory of Planned Behavior and Its Influences on Willingness-To-Pay for Green Air Travel: A Values Orientation Perspective. *Journal of Management for Global Sustainability*, *12*(1). https://doi.org/10.13185/2244-6893.1226
54. Dioba, A., Kroker, V., Dewitte, S., & Lange, F. (2024). Barriers to Pro-Environmental Behavior Change: A Review of Qualitative Research. *Sustainability*, *16*(20), 8776. https://doi.org/10.3390/su16208776
55. Ebeling, F., & Lotz, S. (2015). Domestic uptake of green energy promoted by opt-out tariffs. *Nature Climate Change*, *5*(9), 868–871. https://doi.org/10.1038/nclimate2681
56. Kaiser, M., Bernauer, M., Sunstein, C. R., & Reisch, L. A. (2020). The power of green defaults: The impact of regional variation of opt-out tariffs on green energy demand in Germany. *Ecological Economics*, *174*, 106685. https://doi.org/10.1016/j.ecolecon.2020.106685
57. Rice, C., Ragbir, N. K., Rice, S., & Barcia, G. (2020). Willingness to pay for sustainable aviation depends on ticket price, greenhouse gas reductions and gender. *Technology in Society*, *60*, 101224. https://doi.org/10.1016/j.techsoc.2019.101224
58. Berger, S., Kilchenmann, A., Lenz, O., & Schlöder, F. (2022). Willingness-to-pay for carbon dioxide offsets: Field evidence on revealed preferences in the aviation industry. *Global Environmental Change*, *73*, 102470. https://doi.org/10.1016/j.gloenvcha.2022.102470
59. Araña, J. E., & León, C. J. (2013). Can Defaults Save the Climate? Evidence from a Field Experiment on Carbon Offsetting Programs. *Environmental and Resource Economics*, *54*(4), 613–626. https://doi.org/10.1007/s10640-012-9615-x
60. Mello, F. P. D. (2024). Voluntary carbon offset programs in aviation: A systematic literature review. *Transport Policy*, *147*, 158–168. https://doi.org/10.1016/j.tranpol.2023.12.023

61. Yunyoung, Y. K., & Wooje, C. (2024). The Effect of Airline's ESG Management on Corporate Reputation, Corporate Image, and Relationship Continuance Intention. *Global Business Finance Review*, *29*(5), 146–159. https://doi.org/10.17549/gbfr.2024.29.5.146
62. Jachimowicz, J. M., Duncan, S., Weber, E. U., & Johnson, E. J. (2019). When and why defaults influence decisions: A meta-analysis of default effects. *Behavioural Public Policy*, *3*(02), 159–186. https://doi.org/10.1017/bpp.2018.43
63. Mertens, S., Herberz, M., Hahnel, U. J. J., & Brosch, T. (2022). The effectiveness of nudging: A meta-analysis of choice architecture interventions across behavioral domains. *Proceedings of the National Academy of Sciences*, *119*(1), e2107346118. https://doi.org/10.1073/pnas.2107346118
64. Agarwal, A., Canfield, C., & Fikru, M. G. (2024). Role of greener default options on consumer preferences for renewable energy procurement. *Renewable Energy*, *221*, 119802. https://doi.org/10.1016/j.renene.2023.119802
65. Ghesla, C., Grieder, M., & Schubert, R. (2020). Nudging the poor and the rich – A field study on the distributional effects of green electricity defaults. *Energy Economics*, *86*, 104616. https://doi.org/10.1016/j.eneco.2019.104616
66. Christodoulos, C., Michalakelis, C., & Varoutas, D. (2011). On the combination of exponential smoothing and diffusion forecasts: An application to broadband diffusion in the OECD area. *Technological Forecasting and Social Change*, *78*(1), 163–170. https://doi.org/10.1016/j.techfore.2010.08.007
67. Al-Duais, F. S., & Al-Sharpi, R. S. (2023). A unique Markov chain Monte Carlo method for forecasting wind power utilizing time series model. *Alexandria Engineering Journal*, *74*, 51–63. https://doi.org/10.1016/j.aej.2023.05.019
68. Whiteside, J. D., II, PE. (2008). A Practical Application of Monte Carlo Simulation in Forecasting. *AACE International Transactions*.
69. Duque, L.-F., O'Connell, E., & O'Donnell, G. (2023). A Monte Carlo simulation and sensitivity analysis framework demonstrating the advantages of probabilistic forecasting over deterministic forecasting in terms of flood warning reliability. *Journal of Hydrology*, *619*, 129340. https://doi.org/10.1016/j.jhydrol.2023.129340
70. Papadopoulos, C. E., & Yeung, H. (2001). Uncertainty estimation and Monte Carlo simulation method. *Flow Measurement and Instrumentation*, *12*(4), 291–298. https://doi.org/10.1016/S0955-5986(01)00015-2
71. Oh, J.-H., Oldani, A., Solecki, A., & Lee, T. (2024). Learning to predict sustainable aviation fuel properties: A deep uncertainty quantification viewpoint. *Fuel*, *356*, 129508. https://doi.org/10.1016/j.fuel.2023.129508
72. Yang, F., & Yao, Y. (2025). Sustainable aviation fuel pathways: Emissions, costs and uncertainty. *Resources, Conservation and Recycling*, *215*, 108124. https://doi.org/10.1016/j.resconrec.2025.108124
73. Borgonovo, E., & Plischke, E. (2016). Sensitivity analysis: A review of recent advances. *European Journal of Operational Research*, *248*(3), 869–887. https://doi.org/10.1016/j.ejor.2015.06.032
74. Lopez, M., Leon, S., Kwakernaak, S., Silva, V., Posada, J., & Alvarez, O. (2024). Sustainable Aviation Fuel Production Optimization in Colombia: An In-depth Sensitivity Analysis. *Chemical Engineering Transactions*, *109*, 337–342. https://doi.org/10.3303/CET24109057
75. Kohavi, R., & Longbotham, R. (2023). Online Controlled Experiments and A/B Tests. In D. Phung, G. I. Webb, & C. Sammut (Eds.), *Encyclopedia of Machine Learning and Data Science* (pp. 1–13). Springer US. https://doi.org/10.1007/978-1-4899-7502-7_891-2