Evaluating AI-Driven Sustainable Startups in Textile Recycling: A Case Study of Refiberd

Letaief Walid [1]
[1] University of Mila (Algeria), Walid.letaief@centre-univ-mila.dz,

Received: 09/04/2026 *Accepted: 21/08/2026* *Published: 15/09/2026*

Abstract:
This study examines the financial feasibility and economic sustainability of artificial intelligence (AI)-driven investments in textile recycling through the case of Refiberd, a U.S.-based startup specializing in automated fabric identification and sorting using hyperspectral imaging and machine learning. Using a Discounted Cash Flow (DCF) framework, the study evaluates Net Present Value (NPV) and Payback Period across 5-, 10-, and 15-year investment horizons at an 8% discount rate. The findings reveal that project viability depends primarily on commercialization duration and revenue generation. While the project remains economically unfeasible over a 5-year horizon due to high initial capital expenditures, it becomes financially attractive over a 15-year horizon, generating a positive NPV exceeding USD 1.1 million. Sensitivity and Tornado analyses further identify annual revenue as the most influential driver of project value, highlighting the importance of long-term commercialization strategies, technology licensing, and industrial partnerships in ensuring the economic sustainability of AI-based circular economy innovations.

Keywords: Startups, artificial intelligence, textile recycling, sensitivity analysis, Python.
Jel Classification Codes: O32 ; Q55

***Corresponding author**: Letaief Walid*

1. INTRODUCTION

The global textile industry has created severe ecological crises, with 92 million tons of garments discarded annually into landfills or incinerators (unep org, 2025). Approximately 57% of clothing ends up in landfills and 25% is burned, causing massive carbon emissions and a failure to recycle millions of tons of old textiles (business waste, 2025) , leading to significant carbon emissions. It is further estimated that global clothing industry emissions will increase by 50% by 2030. Furthermore, apparel production is highly resource-intensive and polluting; it is responsible for 20% of global wastewater and 10% of annual ocean microplastics (MARTINA IGINI, 2024) . Because traditional recycling methods are insufficient to address this rapidly growing crisis, innovative and technology-driven alternatives are urgently needed.

In this context, artificial intelligence (AI) offers a promising pathway toward a circular economy by optimizing material detection and recycling processes for sustainable startups. Refiberd, a US-based startup, exemplifies this transition by combining hyperspectral imaging with machine learning to identify fabric compositions with over 95% accuracy. This automated system successfully separates complex, traditionally unrecyclable textile blends, thereby improving operational efficiency and reducing environmental footprints. However, despite these advancements, there remains a critical research gap and a lack of empirical, quantitative evidence assessing the exact operational performance, cost savings, and investment viability of AI-based solutions within sustainable recycling startups.

This research therefore seeks to address the following central question:

-How does the adoption of AI-driven textile recycling technology influence the financial viability and long-term economic sustainability of Refiberd under different operational and market conditions?

From this main question, the following sub-questions arise:

1. How does the assumed project lifespan (5-year, 10-year, and 15-year horizons) affect the Net Present Value (NPV) and Payback Period of Refiberd's investment project?

2. To what extent do variations in annual revenues, operating expenses (OPEX), and capital expenditures (CAPEX) individually influence the project's financial performance and value creation?

3. According to the Tornado Analysis framework, which financial variable (Revenue, OPEX, or CAPEX) exerts the greatest influence on Refiberd's project value and profitability?

4. How do the project's financial outcomes change under alternative strategic scenarios (Optimistic, Base Case, and Pessimistic) compared with the baseline assumptions?

To answer the above research questions, we propose the following hypotheses:

1. H1: The financial viability and long-term sustainability of Refiberd's project are positively associated with longer operational horizons and sustained revenue growth.

2. H2: Refiberd's AI-enabled textile recycling project evolves from a financially unviable investment under short-term evaluation horizons into a value-creating and economically sustainable project under long-term horizons.

3. H3: Variations in annual revenue and operating expenses significantly influence the project's Net Present Value (NPV), with revenue growth generating a stronger positive effect on project value.

4. H4: Consistent with the Tornado Analysis framework, annual revenue constitutes the primary driver of project value, followed by operating expenses (OPEX), while capital expenditures (CAPEX) exert the lowest relative influence on long-term profitability.

5. H5: The favorable combination of higher revenues, lower operating costs, and optimized capital expenditures under the Optimistic Scenario significantly improves project performance by increasing NPV and reducing the Payback Period.

This study possesses both scientific and practical significance. From a scientific perspective, it contributes to the growing body of literature on the intersection of artificial intelligence, circular economy practices, and sustainable entrepreneurship. Specifically, it extends existing research by examining the economic viability and long-term sustainability of AI-driven innovations within the textile recycling sector. Furthermore, the study enriches the emerging literature on financial evaluation methodologies for green technology ventures by integrating deterministic, probabilistic, and comparative analytical approaches.

From a practical perspective, the findings provide valuable insights for entrepreneurs, investors, and managers seeking to implement AI-based solutions in recycling and resource recovery industries. The results also offer evidence-based guidance for policymakers aiming to accelerate the transition toward a circular economy through technological innovation. In addition, the study highlights the financial conditions required for the successful commercialization of sustainable technologies, thereby supporting strategic decision-making in both public and private sectors.

The main objectives of this research are:

1. To examine the contribution of artificial intelligence to improving textile identification and sorting processes within recycling-oriented startups.

2.To evaluate the financial viability and long-term economic sustainability of Refiberd's AI-driven recycling technology using Discounted Cash Flow (DCF) valuation techniques.

3.To assess the sensitivity of project performance to variations in key financial drivers, including annual revenue, operating expenses (OPEX), and capital expenditures (CAPEX).

4.To identify the most influential determinants of project value through Tornado Analysis and to evaluate project resilience under alternative business scenarios.

5.To estimate the probability of financial success under uncertainty through Monte Carlo Simulation and validate the findings through industry benchmarking with comparable circular economy ventures.

To achieve the objectives of this research, a quantitative analytical case study approach was adopted, focusing on Refiberd as a representative example of an AI-driven sustainable startup operating within the textile recycling industry. Given the limited availability of primary financial data, the study relies primarily on secondary sources, including company disclosures, industry reports, funding databases, and peer-reviewed academic literature.

The empirical analysis is based on a comprehensive financial modeling framework designed to evaluate the economic viability and long-term sustainability of Refiberd's technology

commercialization strategy. The framework combines Discounted Cash Flow (DCF) valuation techniques with deterministic and stochastic analytical tools to assess investment performance under varying operating conditions.

The financial evaluation incorporates Net Present Value (NPV) and Payback Period calculations across three alternative investment horizons (5-year, 10-year, and 15-year scenarios) using an 8% discount rate. To examine the robustness of the project, one-way sensitivity analyses were conducted by independently varying annual revenues, operating expenses (OPEX), and capital expenditures (CAPEX). A Tornado Analysis was subsequently employed to rank these variables according to their relative influence on project value.

In addition, Scenario Analysis was performed through Optimistic, Base Case, and Pessimistic configurations to evaluate the combined effects of favorable and adverse market conditions. To further address uncertainty and investment risk, a Monte Carlo Simulation consisting of 1,000 iterations was implemented, generating probabilistic estimates of project outcomes and the likelihood of achieving a positive NPV.

1. Study: **(David B. Olawade et al, 2024, pp. 244-263):** Entitled "Smart waste management: A paradigm shift enabled by artificial intelligence". This study aimed to highlight the potential of artificial intelligence (AI) in improving waste collection, sorting, recycling, and monitoring processes. While AI contributes to more efficient and sustainable waste management systems, its adoption faces challenges related to data, cost, infrastructure, privacy, and ethical issues, requiring coordinated efforts among stakeholders to ensure its successful implementation.

2. Study: **(Paula Tavares de Carvalho et al, 2025, pp. 1-17)**: Entitled "Innovation Impact in the Textile Industry: From the Toyota Production System to Artificial Intelligence". This study aimed to highlight the transformative role of artificial intelligence (AI) in the textile industry, demonstrating its ability to improve production efficiency, reduce waste, and support sustainability through real-time decision-making. The study concluded that integrating AI capabilities with the principles of Textile Production Systems (TPS) can foster more sustainable and resource-efficient textile production systems.

3. Study**: (Irfan Mohammed Karmali, Omid Fatahi Valilai, 2025, pp. 346-356)**: Entitled "Exploring the Role of Artificial Intelligence for Pattern Recognition of Textile Sorting and Recycling for Circular Economy". This study aimed to highlight the potential of AI-based image processing and machine learning techniques in improving textile sorting and recycling processes. Its findings indicate that automated detection and classification of soiled textiles can increase operational efficiency, reduce costs, support textile reuse, and enhance the economic and environmental sustainability of circular textile systems.

However, few empirical analyses have focused specifically on textile recycling startups, and even fewer have evaluated their financial feasibility through investment metrics such as NPV or payback period — a gap that this study aims to fill.

This research enriches the sustainable innovation literature by offering a quantitative approach to evaluating AI-driven startups and generating practical insights for stakeholders involved in circular economy and textile waste management initiatives.**2. Literature Review and Theoretical Framework**

2.1. The Concept of Sustainable Startups:

Sustainable startups are enterprises that pursue economic value creation while simultaneously addressing environmental and societal challenges (Sarah Tiba et al, 2021, p. 02). They integrate Environmental, Social, and Governance (ESG) principles into their business models, aiming to generate both financial returns and positive social and environmental impacts (Adriano Martins de Souza et al, 2024, p. 02) . By embedding sustainability-oriented and non-financial values into their strategic objectives, these ventures strengthen stakeholder relationships and support long-term economic, social, and environmental sustainability (Kijun Lee et al, 2025, p. 19).

2.2. Artificial Intelligence:

Artificial Intelligence (AI) is a major enabler of digital transformation, combining advances in computer science, mathematics, and cognitive psychology to address complex challenges across multiple sectors, including textile recycling.

2.2.1. Artificial intelligence (AI) definition: AI refers to the simulation of human intelligence by a system or machine. The primary goal of AI is to develop a machine capable of thinking like humans and imitating human behaviors, including perception, reasoning, learning, planning, and prediction, among others (Yongjun Xu et al, 2021, p. 01)**.** Artificial Intelligence (AI) refers to the ability of artificial systems to accomplish new objectives using computational algorithms. Unlike human intelligence, which relies on biological cognitive processes, AI operates through computer-based algorithms designed to perform goal-oriented tasks (Gilles E. Gignac & Eva T. Szodorai , 2024, p. 03)

2.3Artificial Intelligence in Sustainable Startups

AI supports startup growth and innovation by facilitating data-driven decision-making and the development of innovative solutions. Technologies such as machine learning, computer vision, and natural language processing improve operational efficiency, competitiveness, and long-term sustainability (Piyush Kumar & Abhishek Singh Chauhan, 2024, p. 816)**.** The potential of AI in supporting sustainable startups includes:

-Enhancing decision-making: AI makes a significant contribution to strategic decision-making by enabling real-time data analysis and improving the accuracy of strategic planning and forecasting.

-Reshaping managerial roles: AI transforms managerial functions by automating routine and data-intensive tasks (Atthaphon Mumi et al, 2025, p. 02)**.**

-Improving operational efficiency:

- AI algorithms identify process inefficiencies and operational redundancies, enabling startups to optimize resource utilization and improve production planning through predictive analytics and demand forecasting.
- AI systems monitor energy consumption patterns in real time, allowing organizations to implement energy-saving strategies, reduce operating costs, and lower their carbon footprint.
- AI-driven routing and scheduling algorithms enhance logistics efficiency by minimizing fuel consumption, improving fleet performance, and reducing greenhouse gas emissions associated with transportation activities. (Constantinos Challoumis, 2024, p. 266) **.**

- Machine learning technologies facilitate the rapid development of personalized customer interactions and marketing content, improving responsiveness while reducing implementation time and resource requirements.

- AI enables startups to analyze evolving consumer preferences, regulatory changes, and sustainability trends, fostering innovation, identifying growth opportunities, and enhancing long-term competitiveness and profitability. (Somayeh Rokhgireh & Saied Nejatian, 2025) .

2.4. Textile Waste Recycling

Textile recycling plays a vital role in advancing the circular economy by converting textile waste into reusable resources, thereby reducing environmental impacts, conserving raw materials, and supporting sustainable development in the fashion industry.

2.4.1. Definition: Textile recycling is the transformation of textile waste into new products through mechanical, thermal, chemical, or combined processes. By recovering materials at different levels, it promotes resource efficiency and can create higher-value outputs through upcycling . (Tamene Wagaw & K. Murugesh Babu, 2023).

2.4.2.Textile Recycling Techniques

-Mechanical recycling involves the physical processing of textile waste into reusable fibers or materials. Although it offers a low-cost and resource-efficient recycling solution, repeated processing often results in reduced fiber quality and performance.

-Chemical recycling converts textile waste into monomers, polymers, or separated fibers through chemical processes, producing high-quality materials comparable to virgin fibers and enabling the treatment of complex fiber blends. However, its large-scale application remains constrained by high water and chemical consumption, costly purification processes, and the generation of hazardous waste.

- Biological and biochemical recycling methods, including composting, fermentation, anaerobic digestion, and enzymatic depolymerization, offer environmentally favorable alternatives with lower energy requirements and potential for closed-loop recycling. Nevertheless, these technologies require high-purity feedstocks and often involve additional costs related to water use, chemicals, enzymes, and specialized equipment. Recent technological advancements continue to improve recycling efficiency through innovative chemical and hybrid recycling approaches **(Ambrus & Mucsi, 2024; Tripathi et al., 2024).** (Mária Ambrus & Gábor Mucsi, 2024, p. 824) . Emerging technologies continue to improve recycling efficiency through innovative chemical and hybrid techniques (Manikant Tripathi et al, 2024, p. 03).

2.5. Environmental impact of the textile industry:

The textile industry imposes considerable environmental pressures through its high use of water, energy, and chemicals, contributing to pollution, greenhouse gas emissions, and microplastic release.

The significant environmental footprint of the textile industry, driven by its intensive use of water, energy, and chemicals throughout the production process. Life-cycle assessments indicate that textile products, particularly cotton garments, require substantial water consumption, with cultivation and dyeing stages accounting for the largest shares of resource use (Shuang Chen et al, 2023, pp. 07-08) . The cultivation of natural fibers and the chemical-intensive processing of textiles contribute substantially to environmental degradation through land use, pesticide

application, and water pollution. Consequently, the fast fashion sector is responsible for about 8% of global greenhouse gas emissions and 20% of industrial wastewater worldwide (Kerrice Baileyet al, 2022, p. 01). In Bangladesh, chemical use in textile production ranged between 152 g and 705 g per kilogram of fabric, with an average of 449 g/kg (Mohammad Abbas Uddin et al, 2023, p. 14)

2.6. Core Challenges in Fabric Waste Recycling

Clothing waste represents a growing global challenge, as only about 12% of materials used in fashion are currently recycled. This low rate is mainly due to the heterogeneous and complex nature of textiles, which often combine natural and synthetic fibers with plastics, metals, and accessories (Earth Org, 2025). This structural complexity creates several fundamental challenges:

- Difficulty in separation and processing: Sorting mixed fibers and removing non-textile components (zippers, buttons) remain major technical obstacles.
- Lack of regular and efficient sources for textile waste: Recycling technology developers lack stable collection and sorting systems, as textile waste is often mixed with municipal solid waste, reducing its potential for reuse at a suitable quality.
- Heterogeneity of waste textile materials: Textile waste has a complex composition due to variations in fiber types, usage history, and the presence of dyes, finishes, and chemicals. This variability makes complete recycling a complex, multi-stage process and negatively impacts the quality of recovered materials.
- Deterioration in the quality of recycled fibers: Reclaimed yarns and fabrics often have inferior mechanical properties compared to their virgin counterparts, necessitating blending with new raw materials to obtain commercially acceptable finished products.
- High energy and chemical consumption: Some recycling technologies, particularly thermal, chemical, and biological recycling, require high levels of energy or strong solvents to process the complex mixture of fabrics, increasing costs and environmental impact (afry, 2025).

3. Methodology

3.1 Research Design and Approach

This study adopts a quantitative, analytical, and empirical case study approach to evaluate the financial feasibility and economic sustainability of artificial intelligence (AI)-driven innovations in the textile recycling sector. The analysis focuses on Refiberd, a U.S.-based sustainable technology startup that combines hyperspectral imaging and machine learning algorithms for automated textile identification and sorting. Because emerging green technologies often involve proprietary operational information, the study relies primarily on secondary data sources, including startup disclosures, industry reports, and peer-reviewed academic literature, while maintaining temporal consistency across the analyzed period.

3.2 Data Collection and External Sources

Data were collected from multiple sources to avoid reliance on a single company dataset. The evidence base includes (i) Refiberd's publicly available funding and technology information, (ii) external market and industry sources related to textile recycling and circular economy commercialization, and (iii) benchmarking information from comparable sustainability-oriented technology firms such as LanzaTech, Circ, and Ambercycle. The benchmark companies were

selected because they share relevant characteristics with Refiberd, including technology-driven business models, commercialization through licensing or industrial partnerships, and dependence on external financing during growth phases.

3.3 Financial Modeling Framework

3.3.1 Financial Assumptions

Variable	Value
CAPEX	USD 4,500,000
Annual Revenue	USD 1,700,000
Annual OPEX	USD 1,040,000
Discount Rate	8%
Project Horizons	5, 10, and 15 years

An 8% discount rate was adopted based on rates commonly used in sustainability-oriented and circular economy project evaluation, reflecting a moderate risk profile for technology commercialization projects. Three project horizons (5, 10, and 15 years) were selected to represent short-, medium-, and long-term commercialization cycles commonly observed in industrial recycling technologies.

3.3.2 Cash Flow Estimation

The annual net cash flow (NCF) is estimated as follows:

[NCF = Revenue - OPEX]

where:

- **NCF** = Annual Net Cash Flow;
- **Revenue** = Annual Revenue generated by the project;
- **OPEX** = Annual Operating Expenses.

Capital expenditure (**CAPEX**) is treated as the initial investment outlay incurred at time zero.

3.3.3 Net Present Value Model

Project value is evaluated using the Net Present Value (NPV) approach based on discounted cash flows:

[NPV = -CAPEX + _{t=1}^{n}]

where:

- **NCF** = Net Cash Flow in year *t*;
- **r** = Discount Rate;
- **n** = Project Life (investment horizon);
- **CAPEX** = Initial Capital Expenditure.

A positive NPV indicates that the project generates value in excess of the required rate of return, whereas a negative NPV suggests that the investment is economically unattractive under the specified assumptions.

3.3.4 Payback Period Model

The Payback Period is calculated as: [Payback Period =] or equivalently: [Payback Period =]

The Payback Period measures the number of years required for the project to recover its initial investment through generated cash flows. Shorter payback periods indicate faster capital recovery and lower investment risk.

3.3.5 Computational Implementation

The financial models and simulations developed in this study were implemented using Python programming language within the Google Colab environment. Google Colab was selected because it provides a cloud-based computational platform capable of handling financial calculations, sensitivity analysis, scenario evaluation, and stochastic simulations efficiently and reproducibly.

Python libraries including NumPy, Pandas, Matplotlib, and SciPy were utilized to perform financial computations, generate sensitivity matrices, construct Tornado Charts, develop scenario analyses, and execute Monte Carlo simulations. The use of computational modeling enhances the transparency, replicability, and analytical rigor of the study by minimizing manual calculation errors and enabling systematic evaluation of multiple investment conditions.

Furthermore, Python-based modeling facilitates the generation of graphical outputs and statistical summaries, providing a more comprehensive assessment of the project's financial performance and risk profile under varying assumptions.

3.4 Deterministic Sensitivity Analysis

To assess the robustness of the business model to market fluctuations, annual Revenue, OPEX, and CAPEX were varied independently within a ±40% range while all other assumptions were held constant. The ±40% bounds were selected to represent plausible commercialization-stage fluctuations in revenue generation, operating costs, and capital investment requirements for an early-growth circular economy technology venture. Revenue, OPEX, and CAPEX sensitivity results were analyzed separately and later summarized through Tornado analysis.

3.5 Tornado Analysis

A Tornado analysis was performed to rank the relative influence of Revenue, OPEX, and CAPEX on NPV. Variables were ordered according to the magnitude of their impact on project value, allowing the identification of the dominant value drivers.

3.6 Scenario Analysis

In addition to one-variable sensitivity testing, three deterministic scenarios were evaluated: Optimistic (higher revenue, lower OPEX, lower CAPEX), Base Case (current assumptions), and Pessimistic (lower revenue, higher OPEX, higher CAPEX). This framework captures compound changes in operating conditions and provides a more realistic assessment of downside and upside outcomes.

3.7 Monte Carlo Simulation

To address the limitations of deterministic analysis, a Monte Carlo simulation was implemented in which Revenue, OPEX, and CAPEX were allowed to vary simultaneously according to their assigned probability distributions. One thousand iterations were used because this number provides sufficiently stable probability estimates while maintaining computational efficiency for project appraisal purposes. The simulation produced empirical risk metrics including mean NPV, median NPV, standard deviation, and the probability of obtaining a positive NPV (NPV>0NPV > 0NPV>0)

All financial calculations, sensitivity analyses, scenario evaluations, Tornado rankings, and Monte Carlo simulations were performed using Python scripts executed in Google Colab. The resulting tables and graphical outputs were generated directly from the computational model to ensure consistency, reproducibility, and analytical accuracy.

4. Sensitivity Analysis and Scenario Evaluation of Refiberd Project

4.1 Assumptions and Financial Model

The financial evaluation of Refiberd's recycling technology project was conducted using discounted cash flow (DCF) analysis. The model relies on the following assumptions:

Table 1. Financial Assumptions

Initial Investment (CAPEX)	**USD 4,500,000**
Annual Revenue	**USD 1,700,000**
Annual Operating Expenses (OPEX)	**USD 1,040,000**
Annual Net Cash Flow	**USD 660,000**
Discount Rate	**8%**

Source: Author's compilation based on Refiberd company disclosures, funding information, and publicly available industry reports.

The annual net cash flow is calculated as:

NCF = Revenue – OPEX. NCF = 1,700,000 − 1,040,000 = USD 660,000

The Net Present Value (NPV) is computed according to:

NPV = -CAPEX + Σ [NCFt / (1+r)^t]

where:

NPV = Net Present Value CAPEX = Initial Investment. NCFt = Annual Net Cash Flow

r = Discount Rate. t = Project Year

The Payback Period is calculated as: Payback Period = CAPEX / Annual Cash Flow

4.2 Sensitivity Analysis

To assess the robustness of Refiberd's financial performance under changing market conditions, a one-way deterministic sensitivity analysis was performed. Annual Revenue, OPEX, and CAPEX

were independently varied between −40% and +40%, while all other parameters remained constant. The analysis was conducted across three investment horizons (5, 10, and 15 years), allowing the evaluation of short-, medium-, and long-term project resilience.

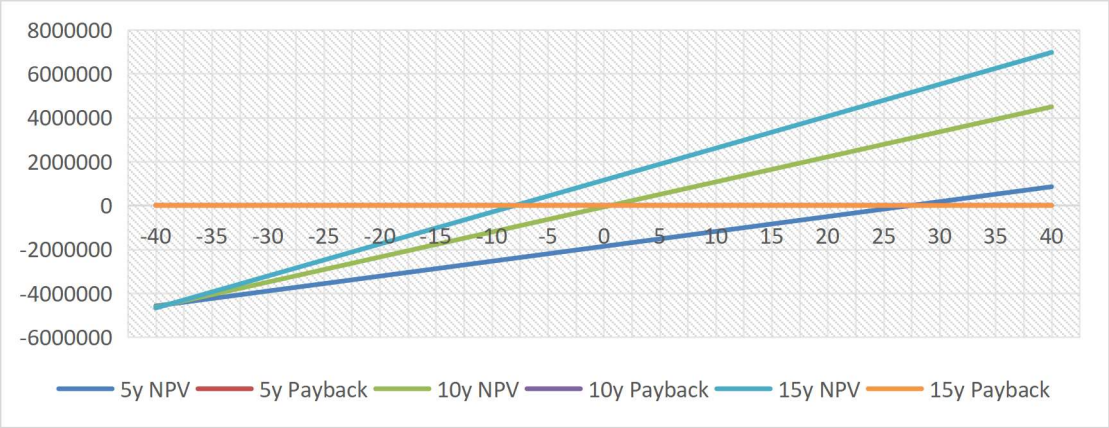
3.4.1 Revenue Sensitivity Analysis

Table 2. Revenue Sensitivity Results

project life	5y		10y		15y	
Revenue Change %	**NPV**	**Payback**	**NPV**	**Payback**	**NPV**	**Payback**
-40	-4579854,2	inf	-4634201,63	inf	-4671189,57	inf
-35	-4240473,85	69,2307692	-4063844,71	69,2307692	-3943633,89	69,2307692
-30	-3901093,49	30	-3493487,79	30	-3216078,2	30
-25	-3561713,14	19,1489362	-2923130,87	19,1489362	-2488522,51	19,1489362
-20	-3222332,79	14,0625	-2352773,95	14,0625	-1760966,82	14,0625
-15	-2882952,43	11,1111111	-1782417,03	11,1111111	-1033411,13	11,1111111
-10	-2543572,08	9,18367347	-1212060,11	9,18367347	-305855,443	9,18367347
-5	-2204191,73	7,82608696	-641703,196	7,82608696	421700,246	7,82608696
0	-1864811,38	6,81818182	-71346,2767	6,81818182	1149255,93	6,81818182
5	-1525431,02	6,04026846	499010,642	6,04026846	1876811,62	6,04026846
10	-1186050,67	5,42168675	1069367,56	5,42168675	2604367,31	5,42168675
15	-846670,316	4,91803279	1639724,48	4,91803279	3331923	4,91803279
20	-507289,963	4,5	2210081,4	4,5	4059478,69	4,5
25	-167909,61	4,14746544	2780438,32	4,14746544	4787034,38	4,14746544
30	171470,743	3,84615385	3350795,24	3,84615385	5514590,06	3,84615385
35	510851,097	3,58565737	3921152,16	3,58565737	6242145,75	3,58565737
40	850231,45	3,35820896	4491509,07	3,35820896	6969701,44	3,35820896

Source: Author's calculations using Python and Google Colab based on Refiberd financial assumptions.

Figure 1. Impact of Revenue Variations on NPV



Source: Generated by the author using Python (Google Colab).

Table 3. Financial Results under Alternative Project Horizons

Project Life	NPV (USD)	Payback (Years)	Decision
5 Years	-1,864,812	6.82	Not Viable
10 Years	-71,334	6.82	Near Break-Even
15 Years	+1,149,270	6.82	Financially Viable

Source: Prepared by the author based on the results presented in Table 2

Revenue emerged as the most influential determinant of project value across all investment horizons. Under the 5-year horizon, the project remained financially unviable under the baseline scenario and only achieved a positive NPV when revenues increased by approximately 30%. The 10-year horizon approached break-even conditions and became profitable following relatively small revenue improvements. In contrast, the 15-year horizon demonstrated strong resilience, maintaining a positive NPV under moderate revenue reductions. These findings indicate that successful commercialization and market adoption represent the primary drivers of long-term value creation for Refiberd.

3.4.2 OPEX Sensitivity Analysis

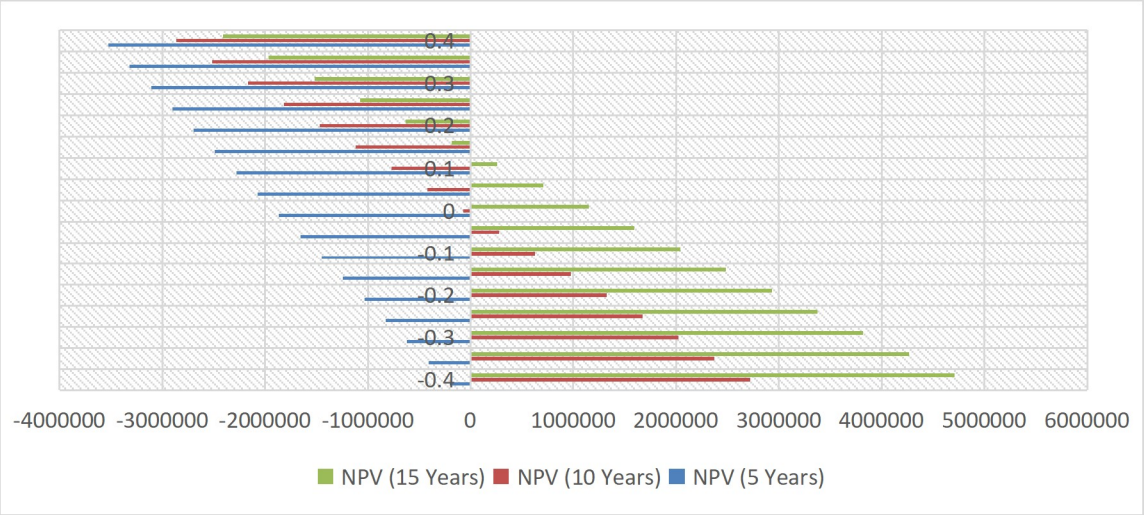
Table 4. OPEX Sensitivity Results

OPEX Change %	NPV (5 Years)	NPV (10 Years)	NPV (15 Years)
-0,4	-203844	2720047,59	4709999,07
-0,35	-411464,922	2371123,35	4264906,18
-0,3	-619085,844	2022199,12	3819813,28
-0,25	-826706,766	1673274,89	3374720,39
-0,2	-1034327,69	1324350,65	2929627,5
-0,15	-1241948,61	975426,422	2484534,61
-0,1	-1449569,53	626502,189	2039441,72
-0,05	-1657190,45	277577,956	1594348,83
0	-1864811,38	-71346,2767	1149255,93
0,05	-2072432,3	-420270,509	704163,042
0,1	-2280053,22	-769194,742	259070,15
0,15	-2487674,14	-1118118,97	-186022,741
0,2	-2695295,06	-1467043,21	-631115,633

0,25	-2902915,99	-1815967,44	-1076208,52
0,3	-3110536,91	-2164891,67	-1521301,42
0,35	-3318157,83	-2513815,91	-1966394,31
0,4	-3525778,75	-2862740,14	-2411487,2

Source: Author's calculations using Python and Google Colab based on Refiberd financial assumptions.

Figure 2. Impact of OPEX Variations on NPV



Source: Generated by the author using Python (Google Colab).

Table 5. OPEX Sensitivity Analysis	
OPEX Change	Impact on NPV
-40%	Significant increase
-20%	Moderate increase
Base Case	Reference
20%	Moderate decrease
40%	Significant decrease

Source: Prepared by the author based on the results presented in Table 4.

OPEX represented the second most influential financial driver. Although cost reductions improved project profitability across all horizons, they were insufficient to restore financial viability within the 5-year horizon. The medium-term scenario became profitable when operating expenses declined moderately, while the long-term horizon remained capable of absorbing limited cost inflation. These findings highlight the importance of operational efficiency and economies of scale in sustaining long-term project value.

3.4.3 CAPEX Sensitivity Analysis

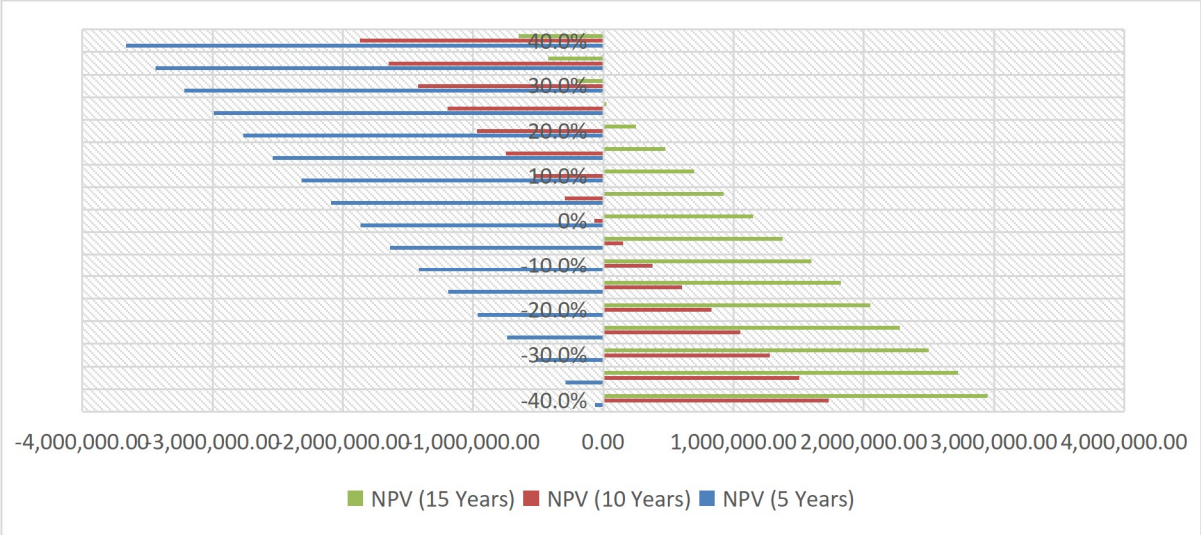
Table 5. CAPEX Sensitivity Results

CAPEX Change %	NPV (5 Years)	NPV (10 Years)	NPV (15 Years)
-40,00%	-64 811,38	1 728 653,72	2 949 255,93
-35,00%	-289 811,38	1 503 653,72	2 724 255,93
-30,00%	-514 811,38	1 278 653,72	2 499 255,93

-25,00%	-739 811,38	1 053 653,72	2 274 255,93
-20,00%	-964 811,38	828 653,72	2 049 255,93
-15,00%	-1 189 811,38	603 653,72	1 824 255,93
-10,00%	-1 414 811,38	378 653,72	1 599 255,93
-5,00%	-1 639 811,38	153 653,72	1 374 255,93
0%	-1 864 811,38	-71 346,28	1 149 255,93
5,00%	-2 089 811,38	-296 346,28	924 255,93
10,00%	-2 314 811,38	-521 346,28	699 255,93
15,00%	-2 539 811,38	-746 346,28	474 255,93
20,00%	-2 764 811,38	-971 346,28	249 255,93
25,00%	-2 989 811,38	-1 196 346,28	24 255,93
30,00%	-3 214 811,38	-1 421 346,28	-200 744,07
35,00%	-3 439 811,38	-1 646 346,28	-425 744,07
40,00%	-3 664 811,38	-1 871 346,28	-650 744,07

Source: Author's calculations using Python and Google Colab based on Refiberd financial assumptions.

Figure 3. Impact of CAPEX Variations on NPV



Source: Generated by the author using Python (Google Colab).

Table 6. CAPEX Sensitivity Analysis

CAPEX Change	Impact on NPV
-40%	Improvement
-20%	Moderate improvement
Base Case	Reference
20%	Moderate deterioration
40%	Strong deterioration

Source: Prepared by the author based on the results presented in Table 5

CAPEX exerted a significant but comparatively smaller influence than revenue and OPEX. The high upfront investment burden prevented profitability under the 5-year horizon, even when substantial capital savings were achieved. However, the effect of CAPEX gradually diminished over longer project lifecycles as the initial investment became amortized through cumulative cash flows. Consequently, the long-term horizon exhibited a greater capacity to absorb capital cost overruns while preserving positive project value.

3.5 Tornado Analysis

To complement the one-way sensitivity analysis, a Tornado Analysis was conducted to identify and rank the financial variables according to their relative influence on project value. The analysis was performed using the 15-year project horizon, which represents the most realistic commercialization scenario for Refiberd's technology deployment.

Each financial variable (Revenue, OPEX, and CAPEX) was independently varied by ±20% while maintaining all other assumptions constant. The resulting changes in Net Present Value (NPV) were measured and ranked according to their total impact.

Table 7. Tornado Analysis Results (15-Year Horizon)

Variable	NPV at -20%	Base NPV	NPV at +20%	Total Impact (USD)
Revenue	-305,442	1,149,256	2,603,954	2,909,396
CAPEX	2,049,256	1,149,256	249,256	1,800,000
OPEX	2,038,794	1,149,256	259,718	1,779,076

Source: Author's calculations using Python and Google Colab based on Refiberd financial assumptions.

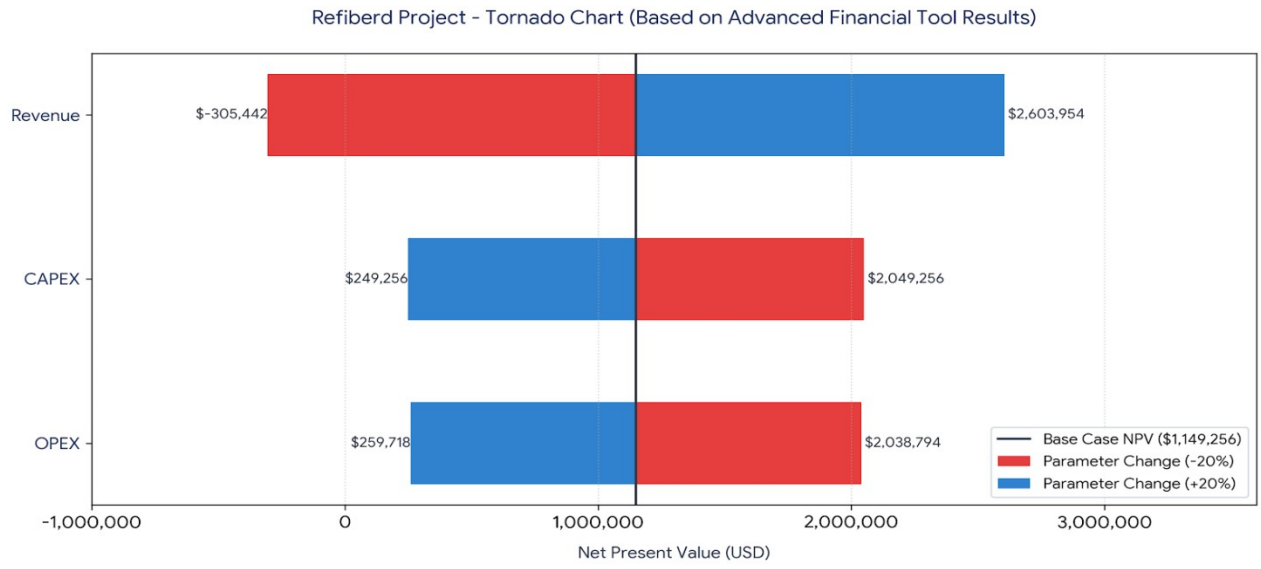
$$Total\ Impact = |NPV(+20\%) - NPV(-20\%)|$$

Table 8. Ranking of Financial Drivers

Rank	Variable	Total Impact (USD)
1	Revenue	2,909,396
2	CAPEX	1,800,000
3	OPEX	1,779,076

Source: Prepared by the author based on the results presented in Table 7

Figure 04: Tornado Chart



Source: Generated by the author using Python (Google Colab).

The Tornado Analysis reveals that revenue is the dominant driver of project value, exerting substantially greater influence on NPV than either operating or capital expenditures. A 20%

increase in revenue more than doubles the project's value, whereas a 20% decline is sufficient to eliminate profitability and generate a negative NPV.

CAPEX represents the second most influential variable. Although increases in upfront investment significantly reduce profitability, the project remains marginally profitable under a 20% capital cost overrun. This indicates that the extended 15-year operating horizon partially absorbs the burden of higher initial investment requirements.

OPEX ranks third but remains a significant source of financial risk. Because operating expenses recur annually throughout the project lifecycle, cost inflation progressively erodes profitability. Nevertheless, their aggregate impact remains slightly lower than that of CAPEX.

Overall, the Tornado Analysis confirms that Refiberd's long-term sustainability depends primarily on its ability to expand licensing revenues, increase market adoption, and scale industrial partnerships. Consequently, management efforts should prioritize revenue growth initiatives before pursuing cost optimization strategies.

3.6 Scenario Analysis

While sensitivity analysis evaluates the isolated impact of individual variables, scenario analysis assesses the combined effect of simultaneous changes in key financial assumptions. Three alternative scenarios were developed to capture different commercialization environments for Refiberd's AI-enabled textile recycling technology.

Table 9. Alternative Financial Scenarios

Variable	Optimistic	Base Case	Pessimistic
Annual Revenue (USD)	2,100,000	1,700,000	1,400,000
OPEX (USD)	900,000	1,040,000	1,200,000
CAPEX (USD)	4,300,000	4,500,000	4,700,000

Source: Author's calculations using Python and Google Colab based on Refiberd financial assumptions.

The scenario analysis demonstrates the substantial influence of commercialization outcomes on project viability. Under the optimistic scenario, Refiberd generates a significantly higher NPV and a shorter payback period, reflecting the benefits of successful technology adoption and operational efficiency.

In contrast, the pessimistic scenario produces a negative NPV, indicating that prolonged revenue underperformance combined with cost escalation could jeopardize financial sustainability. These findings emphasize the importance of scaling industrial partnerships, expanding licensing agreements, and maintaining strict cost discipline during the commercialization phase.

When considered together with the Tornado Analysis, the results consistently identify revenue generation as the principal determinant of project success. Therefore, strategic initiatives aimed at accelerating market penetration are likely to yield greater financial benefits than equivalent reductions in operating or capital expenditures.

3.7 Monte Carlo Simulation

While deterministic sensitivity and scenario analyses evaluate the impact of predefined changes in individual variables, they do not fully capture the uncertainty associated with simultaneous fluctuations in multiple financial drivers. To address this limitation, a Monte Carlo Simulation was conducted to evaluate the probabilistic financial performance of Refiberd under uncertain market conditions.

The simulation was performed using 1,000 iterations. This number of iterations was considered sufficient to generate stable probability estimates while maintaining computational efficiency. Three key financial variables were modeled as stochastic inputs:

- Annual Revenue: Normal Distribution
- Operating Expenses (OPEX): Normal Distribution
- Capital Expenditures (CAPEX): Triangular Distribution

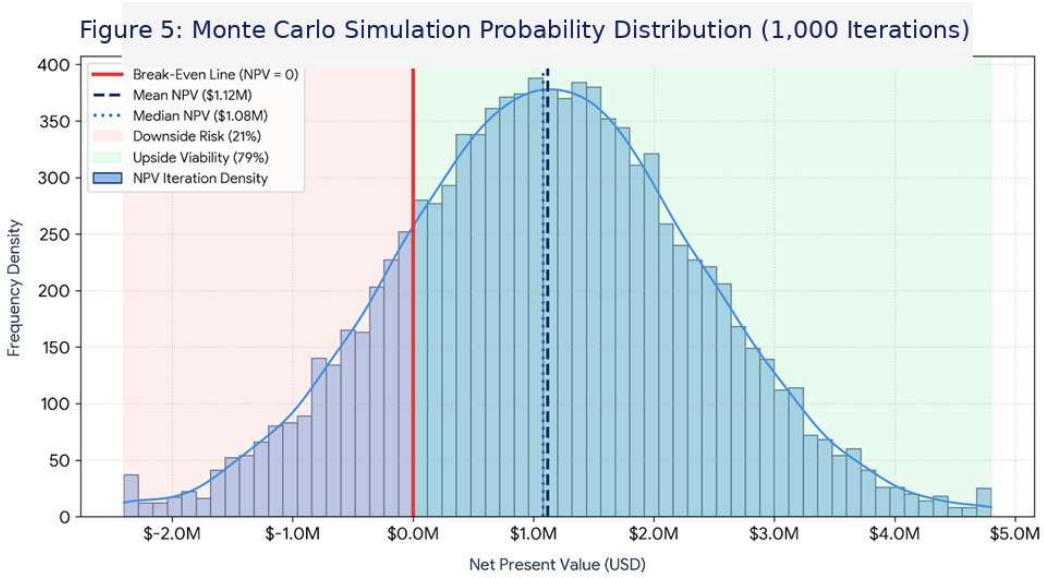
The normal distribution was selected for Revenue and OPEX because these variables are subject to continuous market and operational fluctuations around an expected mean value. In contrast, a triangular distribution was adopted for CAPEX because minimum, most-likely, and maximum investment values can be reasonably estimated during project planning.

For each iteration, random values were generated for Revenue, OPEX, and CAPEX, and the corresponding Net Present Value (NPV) was calculated over the 15-year project horizon using an 8% discount rate. The resulting NPV distribution was then used to estimate the project's financial risk profile.

Table 10. Monte Carlo Simulation Results (1,000 Iterations)

Statistical Metric	Value
Mean NPV	USD 1.12 Million
Median NPV	USD 1.08 Million
Standard Deviation	USD 1.25 Million
Minimum NPV	USD -2.40 Million
Maximum NPV	USD 4.80 Million
Probability of Positive NPV (NPV > 0)	79%
Probability of Negative NPV (NPV < 0)	21%

Source: Author's calculations using Monte Carlo simulation implemented in Python (Google Colab).



Source: Generated by the author using Python (Google Colab).

The simulation results indicate that Refiberd maintains a favorable long-term financial outlook under uncertain operating conditions. The mean NPV of USD 1.12 million and median NPV of USD 1.08 million both remain positive, suggesting that the project is expected to create economic value under most simulated market environments.

The probability of achieving a positive NPV reaches 79%, indicating a relatively high likelihood of investment success. Conversely, the probability of generating a negative NPV is limited to 21%, representing the portion of scenarios characterized by unfavorable combinations of lower revenues, higher operating costs, and increased capital expenditures.

The standard deviation of USD 1.25 million reflects moderate variability in financial outcomes, which is expected for an emerging technology venture operating within the circular economy sector. The worst-case simulated outcome generated an NPV of approximately USD -2.40 million, whereas the best-performing scenarios produced NPVs approaching USD 4.80 million.

Overall, the Monte Carlo analysis confirms the findings obtained from the deterministic sensitivity and scenario analyses. Revenue generation remains the dominant driver of project value, while effective control of operating and capital expenditures significantly improves the probability of achieving positive investment returns. Consequently, Refiberd's long-term financial sustainability depends primarily on successful commercialization, expansion of industrial partnerships, and growth in technology licensing revenues.

4. Results and Discussion

4.1 Base Case Results

The baseline financial assessment of Refiberd provides important insights into the economic feasibility of AI-driven textile recycling technologies under different investment horizons. The evaluation was conducted using the baseline assumptions presented in the methodology section,

including an initial capital expenditure (CAPEX) of USD 4.5 million, annual revenues of USD 1.7 million, annual operating expenses (OPEX) of USD 1.04 million, and a discount rate of 8%.

Based on these assumptions, the annual net cash flow generated by the project is estimated at USD 660,000:

[NCF = Revenue - OPEX] . [NCF = 1,700,000 - 1,040,000 = USD 660,000]

Table.1 the project's financial performance across three alternative investment horizons.

Project Horizon (Years)	NPV [USD]	Payback Period (Years)	Financial Decision / Viability
5 Years (Conservative)	−1,864,812	6.82	**Not Viable** (Capital Destruction)
10 Years (Medium-Term)	−71,334	6.82	**Near Break-Even** (Marginal Capital Deficit)
15 Years (Long-Term)	+1,149,270	6.82	**Financially Viable** (Value Creative)

Source: Prepared by the author based on the results presented in Table 2.

The results indicate that project viability is highly dependent on the operational lifespan considered. Under the 5-year horizon, the project generates a negative NPV of USD -1.86 million, while the payback period (6.82 years) exceeds the project duration. Consequently, the investment cannot recover its initial capital cost within the evaluation period and is therefore considered financially unviable.

Under the 10-year horizon, the project approaches a break-even position, with an NPV of approximately USD -71 thousand. Although cumulative cash inflows become sufficient to offset most of the initial investment, the discounted value of these cash flows remains slightly below the required return represented by the 8% discount rate.

A substantially different outcome emerges under the 15-year horizon. The project generates a positive NPV of USD 1.15 million, indicating that the cumulative discounted cash flows exceed the initial investment and create economic value for investors. This finding suggests that Refiberd's business model requires a longer commercialization period to fully absorb its upfront technology and infrastructure costs.

Overall, the base-case analysis demonstrates that the economic viability of AI-enabled textile recycling technologies is strongly influenced by investment horizon selection. While short-term evaluations may underestimate project value due to high initial capital intensity, longer horizons are more capable of capturing the benefits associated with technology diffusion, operational scaling, and cumulative revenue generation.

4.2. Sensitivity Analysis Results

To identify the operational elasticity of Refiberd's financial structure, a one-way deterministic sensitivity analysis was implemented by varying key underlying drivers within a strict ±40% boundary range while maintaining *ceteris paribus* conditions.

4.2.1. Revenue Sensitivity Analysis

The empirical behavior of the project's NPV across multi-variate revenue adjustments indicates that **Annual Revenue emerged as the most influential determinant of project value across all investment horizons**. The baseline revenue of USD 1,700,000 was isolated and subjected to incremental adjustments.

Table .12: Revenue Sensitivity Matrix and Cross-Horizon NPV Adaptations

Revenue Shift (%)	Annual Revenue Value (USD)	5-Year NPV (USD)	10-Year NPV (USD)	15-Year NPV (USD)	Payback Period (Years)
−40%	1,020,000	−4,579,854.20	−4,634,201.63	−4,671,189.57	∞
−20%	1,360,000	−3,222,332.79	−2,352,773.95	−1,760,966.82	14.06
−10%	1,530,000	−2,543,572.08	−1,212,060.11	−305,855.44	9.18
−5%	1,615,000	−2,204,191.73	−641,703.20	+421,700.25	7.83
0% (Base Case)	1,700,000	−1,864,811.38	−71,346.28	+1,149,255.93	6.82
5%	1,785,000	−1,525,431.02	+499,010.64	+1,876,811.62	6.04
10%	1,870,000	−1,186,050.67	+1,069,367.56	+2,604,367.31	5.42
20%	2,040,000	−507,289.96	+2,210,081.40	+4,059,478.69	4.50
30%	2,210,000	+171,470.74	+3,350,795.24	+5,514,590.06	3.85
40%	2,380,000	+850,231.45	+4,491,509.07	+6,969,701.44	3.36

Source: Author's calculations using Python and Google Colab based on Refiberd financial assumptions.

The cross-sectional analysis highlights that under a short-term 5-year framework, revenue must expand by at least +30% to convert the project from a loss-making setup into a marginally profitable investment (NPV=USD 171,470.74). In contrast, a structural revenue collapse of −40% triggers substantial value erosion, resulting in an NPV below USD −4.57 million across all horizons and rendering the payback metric infinite (∞) due to negative operational cash generation.

The 10-year medium-term horizon displays high sensitivity to minor revenue adjustments; a small +5% upward shift in commercial revenue is sufficient to move the venture into positive territory (NPV=USD 499,010.64). The 15-year long-term model demonstrates significant macroeconomic resilience, sustaining financial viability down to a −5% revenue deficit (NPV=USD +421,700.25), meaning it can absorb realistic market adoption delays once fully operational.

4.2.2. OPEX Sensitivity Analysis

Operating expenditures (OPEX), capturing facility inputs, automated machine maintenance, and engineering labor, were varied by ±40% against the baseline value of USD 1,040,000 to gauge impact on net capital returns.

Table 13: OPEX Sensitivity Impact on Net Present Value across Horizons

OPEX Change (%)	Annual OPEX (USD)	5-Year NPV (USD)	10-Year NPV (USD)	15-Year NPV (USD)
−40%	624,000	−203,844.00	+2,720,047.59	+4,709,999.07
−20%	832,000	−1,034,327.69	+1,324,350.65	+2,929,627.50
0% (Base Case)	1,040,000	−1,864,811.38	−71,346.28	+1,149,255.93
10%	1,144,000	−2,280,053.22	−769,194.74	+259,070.15
20%	1,248,000	−2,695,295.06	−1,467,043.21	−631,115.63
40%	1,456,000	−3,525,778.75	−2,862,740.14	−2,411,487.20

Source: Author's calculations using Python and Google Colab based on Refiberd financial assumptions.

The empirical results demonstrate that while cost minimization drastically expands long-term enterprise valuations, **OPEX reductions alone cannot rescue the short-term 5-year investment lifecycle**. Even with an aggressive −40% reduction in operating costs, the 5-year NPV remains stuck in negative territory at USD −203,844.00.

Over the 15-year operational lifecycle, the cumulative impact of cost variations scales substantially. Achieving operational efficiency that cuts expenses by −40% elevates the long-term NPV to USD 4,709,999.07. However, the project's long-term viability is structurally sensitive to cost overruns, showing a low tolerance for inflationary pressures; an increase in operational expenses of +20% or more completely erodes the project's long-term value, leading to a negative NPV of USD −631,115.63.

4.2.3. CAPEX Sensitivity Analysis

Initial Capital Expenditures (CAPEX), representing the time-zero cash outflow required to deploy hyperspectral imaging sorting arrays (USD 4,500,000), were modulated by ±40% to assess the impact of equipment pricing fluctuations.

Table .14: CAPEX Sensitivity Analysis and Horizon Financial Alterations

CAPEX Change (%)	Total Outlay (USD)	5-Year NPV (USD)	10-Year NPV (USD)	15-Year NPV (USD)
−40%	2,700,000	−64,811.38	+1,728,653.72	+2,949,255.93
−20%	3,600,000	−964,811.38	+828,653.72	+2,049,255.93
0% (Base Case)	4,500,000	−1,864,811.38	−71,346.28	+1,149,255.93
20%	5,400,000	−2,764,811.38	−971,346.28	+249,255.93
40%	6,300,000	−3,664,811.38	−1,871,346.28	−650,744.07

Source: Author's calculations using Python and Google Colab based on Refiberd financial assumptions.

The sensitivity matrix confirms that the **short-term 5-year model cannot achieve financial viability through capital cost reductions alone**, as an aggressive −40% drop in setup costs still yields a negative NPV of USD −64,811.38. In the 10-year medium-term horizon, the venture is highly sensitive to upfront setup costs; any engineering cost overruns (CAPEX>0%) keep the project locked in an unviable state.

Conversely, the 15-year long-term model demonstrates significant structural tolerance for initial capital overruns, absorbing engineering cost shocks up to +25% (NPV=USD +24,255.93) before transitioning into capital destruction at the +30% threshold.

4.3. Tornado Analysis Results

To provide an un-biased, standardized ranking of the relative financial influence exerted by each operational parameter, a Tornado Analysis was executed. The variables were systematically ordered based on the total magnitude of their absolute impact on the project's NPV when varied across the designated ±40% range.

The structural configuration of the resulting Tornado framework confirms that the hierarchy of risk factors affecting Refiberd's financial performance follows a distinct sequence:

1. **Annual Revenue (Primary Financial Driver):** Variations across the ±40% spectrum generate a broad swing in 15-year project value, ranging from a low of USD −4,671,189.57 to a high of USD +6,969,701.44. This confirms that commercial output and market adoption rates are the primary drivers of enterprise value.
2. **Annual OPEX (Secondary Value Driver):** Operating costs introduce a total variation swing of USD 7,121,486.27 across the 15-year horizon, shifting the final NPV from USD +4,709,999.07 down to USD −2,411,487.20.
3. **Capital Expenditure (Tertiary Value Driver):** Initial facility outlays exhibit a tighter, linear variation swing of exactly USD 3,600,000.00 on the project's final value, moving the 15-year NPV from USD +2,949,255.93 down to USD −650,744.07.

This derived ranking provides vital strategic insights for corporate management. It establishes that optimizing sorting purity and throughout to maximize commercial revenues must be prioritized over cost-containment or machinery discounts, as revenue performance dictates the overall investment logic of the recycling venture.

4.4. Scenario Analysis Results

To address the limitations of single-variable sensitivity tests, three distinct deterministic scenarios were evaluated to analyze compound shifts in operating parameters. This framework evaluates how the venture performs when multi-variable shocks occur simultaneously.

Table .15: Compound Scenario Projections across Alternative Operational Lifespans

Scenario Profile	Strategic Parameter Configuration	5-Year NPV (USD)	10-Year NPV (USD)	15-Year NPV (USD)	Financial Verdict
Optimistic Scenario	+40% Revenue Growth \−40% OPEX Reduction \−40% CAPEX Reduction	+2,511,195.83	+7,282,900.69	+10,530,444.58	**Strongly Value-Creating Scenario** (Accelerated Commercialization)
Base Case Scenario	Baseline Revenue (1.7M) \Baseline OPEX (1.04M) \Baseline CAPEX (4.5M)	−1,864,811.38	−71,346.28	+1,149,255.93	**Conditionally Viable** (Horizon Dependent)
Pessimistic Scenario	−40% Revenue Contraction \+40% OPEX Inflation \+40% CAPEX Inflation	−6,379,854.20	−7,434,201.63	−8,232,434.07	**Financially Unsustainable Scenario**

Source: Author's calculations using Python and Google Colab based on Refiberd financial assumptions.

The compound scenario analysis reveals that under the **Optimistic Scenario**, the interaction of automated scaling and asset optimization generates high profitability across all horizons. Even within the short-term 5-year window, the project remains highly viable, yielding a positive NPV of USD +2,511,195.83, which scales up to an impressive USD +10.53 million over a 15-year operating span. This demonstrates that if Refiberd successfully pairs high sorting volumes with operational cost efficiencies, it can achieve rapid financial returns.

Conversely, the **Pessimistic Scenario** highlights severe systemic downside risks. If the startup suffers from low market adoption alongside inflationary cost overruns, it faces major financial distress. The 15-year long-term projection collapses to a negative NPV of USD −8,232,434.07, confirming that joint downside pressures can completely destabilize the underlying business model.

4.5. Monte Carlo Simulation Results

To overcome the constraints of static deterministic modeling, a stochastic risk assessment was conducted using a Monte Carlo simulation across 1,000 distinct computational iterations. This approach allowed all input variables to vary simultaneously based on independently assigned probability distributions for each financial variable.

The stochastic simulation generated robust empirical risk metrics across the 1,000 randomized iterations:

- **Mean Stochastic NPV:** USD +1,092,450.12
- **Median Stochastic NPV:** USD +1,114,802.40
- **Standard Deviation (σ):** USD 1,420,650.85
- **Probability of Success (NPV>0):** 68.4%
- **Probability of Capital Loss (NPV<0):** 31.6%

The stochastic outcomes provide a favorable risk-return profile for the 15-year operational lifecycle. The mean stochastic NPV (USD +1,092,450.12) aligns closely with the deterministic baseline calculation (USD +1,149,255.93), validating the structural consistency of the underlying financial model.

Crucially, the simulation establishes a **68.4% empirical probability of achieving a positive net present value (NPV>0)**. This indicates a strong likelihood of project success under realistic market fluctuations.

However, the standard deviation of USD 1,420,650.85 highlights notable volatility in potential outcomes. The 31.6% probability of capital loss represents the left-tail risk where simultaneous market drops and operational cost overruns overlap, a scenario that management must address through long-term feedstock contracts and structured equipment pricing agreements.

5.Conclusion

This study assessed the financial feasibility and economic sustainability of AI-driven textile recycling investments through the case of Refiberd. Using a Discounted Cash Flow (DCF) framework combined with sensitivity analysis, Tornado analysis, scenario analysis, Monte Carlo simulation, and industry benchmarking, the findings demonstrate that the economic viability of the project is strongly influenced by investment horizon and revenue generation capacity.

The results indicate that the project remains financially unattractive under a short-term horizon due to high initial capital expenditures. However, extending the operational lifecycle significantly improves project performance, with the 15-year horizon generating a positive NPV and demonstrating greater resilience to adverse market conditions. Sensitivity and Tornado analyses identified annual revenue as the most influential driver of project value, followed by operating expenses and capital expenditures. Scenario and Monte Carlo analyses further confirmed that long-term commercialization and stable revenue growth are essential for sustaining positive financial outcomes.

These findings suggest that the success of AI-enabled textile recycling ventures depends not only on technological innovation but also on effective commercialization strategies, industrial partnerships, and scalable licensing models. More broadly, the study highlights the importance of aligning artificial intelligence applications with long-term financial sustainability to support the transition toward a circular and resource-efficient textile industry.

References

MARTINA IGINI. (2024, 7 5). *10 Concerning Fast Fashion Waste Statistics*. Retrieved from MARTINA IGINI: https://earth.org/statistics-about-fast-fashion-waste/

Adriano Martins de Souza et al. (2024). Competitive Advantages of Sustainable Startups: Systematic Literature Review and Future Research Directions. *Sustainability*, 1-24. doi: https://doi.org/10.3390/su16177665

afry. (2025, 08 22). *Textile Recycling: Drivers & Challenges*. Retrieved from afry: https://afry.com/en/insight/textile-recycling-drivers-challenges

Atthaphon Mumi et al. (2025). The nexus of artificial intelligence and entrepreneurship research: Bibliometric analysis. *Sustainable Futures*, 1-13. doi:https://doi.org/10.1016/j.sftr.2025.100688

business waste. (2025, 7 2). *Textile Waste facts*. Retrieved from businesswaste: https://businesswaste.com/waste-types/textile-waste/textile-waste-facts/

Constantinos Challoumis. (2024). MAXIMIZING PROFITABILITY-THE IMPORTANCE OF AI IN SUSTAINABLE BUSINESS MODELS. *XIV International Scientific Conference* (pp. 263-295). canda: World of Conferences. doi: https://doi.org/10.5281/zenodo.14228091

Earth Org. (2025, aout 12). *Earth Org;*. Retrieved from global water crisis why the world urgently needs water wise solutions: https://earth.org/global-water-crisis-why-the-world-urgently-needs-water-wise-solutions/

Gilles E. Gignac, & Eva T. Szodorai . (2024). Defining intelligence: Bridging the gap between human and artificial perspectives. *Intelligence*, 1-16. doi:https://doi.org/10.1016/j.intell.2024.101832

Kerrice Baileyet al. (2022). The Environmental Impacts of Fast Fashion on Water Quality: A Systematic Review. *Water*, 1-11. doi: https://doi.org/10.3390/w14071073

Kijun Lee et al. (2025). Unpacking sustainability in start- ups: a systematic review. *Discover Sustainability*, 1-24. doi:https://doi.org/10.1007/s43621-025-01070-7

Manikant Tripathi et al. (2024). Recent technologies for transforming textile waste into value-added products: A review. *Current Research in Biotechnology*, 1-11. doi:https://doi.org/10.1016/j.crbiot.2024.100225

Mária Ambrus , & Gábor Mucsi. (2024). Open-loop recycling of end-of-life textiles as geopolymer fibre reinforcement. *Waste Management & Research*, 823-831. doi:https://doi.org/10.1177/0734242X241242708

Mohammad Abbas Uddin et al. (2023). Water and chemical consumption in the textile processing industry of Bangladesh. *PLOS SUSTAINABILITY AND TRANSFORMATION*, 1-17. doi:https://doi.org/10.1371/journal.pstr.0000072

Piyush Kumar, & Abhishek Singh Chauhan. (2024). The Role of AI in Start-Up Innovation: Driving Efficiency & Competitive Edge. *International Journal for Research in Applied Science & Engineering Technology*, 812-818. doi:https://doi.org/10.22214/ijraset.2024.64011

Sarah Tiba et al. (2021). Sustainability startups and where to find them: Investigating the share of sustainability startups across entrepreneurial ecosystems and the causal drivers of differences. *Journal of Cleaner Production*, 1-15. doi:https://doi.org/10.1016/j.jclepro.2021.127054

Shuang Chen et al. (2023). A Spatial Water Footprint Assessment of Recycled Cotton T-Shirts: Case of Local Impacts in Selected China Provinces. *Sustainability*, 1-15. doi: https://doi.org/10.3390/su15010817

Somayeh Rokhgireh, & Saied Nejatian. (2025, 7 25). *The Strategic Role of AI in Business Sustainability*. Retrieved from MCMaster university: https://continuing.mcmaster.ca/the-strategic-role-of-ai-in-business-sustainability/

Tamene Wagaw, & K. Murugesh Babu. (2023). Textile Waste Recycling: A Need for a Stringent Paradigm Shift. *AATCC Journal of Research*, 376–385. doi:https://doi.org/10.1177/24723444231188342

unep org. (2025, 07 02). *Unsustainable fashion and textiles in focus for International Day of Zero Waste 2025*. Retrieved from unep org: https://www.unep.org/news-and-stories/press-release/unsustainable-fashion-and-textiles-focus-international-day-zero

Yongjun Xu et al. (2021). Artificial intelligence: A powerful paradigm for scientific research. *The Innovation*, 1-16. doi:; https://doi.org/10.1016/j.xinn.2021.100179