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Integrating life cycle and techno-economic assessment for bio-based lactic acid production from industrial residues

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ABSTRACT

Evaluating the economic viability and environmental impact of emerging technologies is crucial for the transition to a bio-based economy. This study proposes a methodology to assess the environmental and economic performance of bio-based lactic acid (LA) production by scaling up from pilot to industrial levels using fiber sludge, a residue from the pulp and paper industry, as a feedstock. Process design, Techno-Economic Analysis (TEA) and Life Cycle Assessment (LCA) were conducted at pilot scale to identify key environmental and economic hotspots. External costs were estimated following the environmental Life Cycle Costing (eLCC) approach using the Environmental Prices (EP) method. At the pilot scale, the LCA indicated a Global Warming Potential (GWP) of 3.87 kg CO_2-eq, which aligns with the values reported in previous studies. Scaling up to different plant capacities revealed the potential economies of scale. At a production rate of 50 kt per year, the Minimum Selling Price (MSP) was estimated at 1.71€/kg, which is comparable to that of other bio-based LA production routes. Assuming proportional environmental impacts from pilot to industrial scale, external costs were integrated into the MSP, resulting in adjusted values of 2.04€/kg (lower value), 2.21€/kg (central value), and 2.46 €/kg (upper value). Sensitivity and uncertainty analyses using Monte Carlo simulations indicated an 87.5 % probability of achieving a positive Net Present Value (NPV). This study highlights the need for standardised methodologies to evaluate the environmental and economic impacts of emerging bio-based technologies, particularly when accounting for external costs.

1. Introduction

The production and use of fossil-based chemicals and plastics impose major environmental costs. According to the most recent report from the OECD (2022), the plastics life cycle emitted about 1.8 Gt CO_2-eq. in 2019, representing more than 3 % of global greenhouse-gas emissions. Emissions from plastics are projected to rise further and could consume up to 15 % of the remaining global carbon budget by 2050 as demand grows (Zheng and Suh, 2019). Conventional plastics derived from petroleum contribute to climate change across their life cycle and generate persistent waste and pollution that pose long-term risks to ecosystems and human health (Jambeck and Walker-Franklin, 2023).

In response, international strategies increasingly prioritise renewable resources and circular economy principles. The European Union's updated Bioeconomy Strategy emphasises the sustainable use of biological resources to replace fossil inputs and foster economic resilience (European Commission, 2018; Lange et al., 2021). Within this framework, the circular bioeconomy highlights the valorisation of industrial

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residues as a pathway to reduce waste and decouple production from virgin resources (Holden et al., 2023; Mesa et al., 2024).

A promising example is fiber sludge, a by-product of the pulp and paper industry. Recent studies demonstrate its potential as a sustainable feedstock for bio-based products, including lactic acid (LA) (Quintana et al., 2024). LA is a versatile platform chemical widely used in food, pharmaceuticals, and cosmetics, and it is the monomer for polylactic acid (PLA), a biodegradable polymer used for the production of bioplastics (Alves de Oliveira et al., 2018; Daful et al., 2023).

The global LA market is expanding rapidly. Analyses from industry estimate the LA market size at about USD 3.45 billion in 2024 with growth to around USD 6.65 billion by 2033, with a compound annual growth rate (CAGR) of 7.7 % (Grand View Research, 2025). In production terms, global LA output was around 1.7 million tonnes in 2023 and is expected to approach 5 million tonnes by 2034 (Chemanalyst, 2024). This expansion is driven by sustainability trends and the substitution of fossil-based materials with bio-based alternatives. A key factor is the rapid increase in bioplastics production, which rose from 1.7 million tonnes in 2023 to a projected 5.1 million tonnes by 2028, underscoring the role of LA as a critical feedstock for bioplastics (European Bioplastics, 2024).

Traditionally, LA is produced from first-generation carbohydrate-rich feedstocks such as corn, sugarcane or starch, which often compete with food supply chains (Ögmundarson et al., 2020a, 2020b). However, increasing pressure to adopt sustainable practices has led to the exploration of alternative non-food biomass or second-generation feedstocks (Malacara-Becerra et al., 2022). Using fiber sludge could mitigate these issues and support more sustainable supply chains. However, scaling bio-based LA raises questions about environmental and economic feasibility compared with fossil-based alternatives due to the maturity of the technologies (Olszewska-Widdrat et al., 2023).

To guide decision-making in early-stage developments, Life Cycle Assessment (LCA) and Techno-Economic Analysis (TEA) are widely used to evaluate innovative bio-based processes (Macias Aragonés and Arroyo Torralvo, 2024). However, most studies apply these methods independently, making it difficult to identify the trade-offs between environmental and economic impacts (Mahmud et al., 2021; Pérez-Almada et al., 2023). Addressing this gap requires integrated frameworks that can combine environmental and economic results into a unified basis for comparison (Ladu and Morone, 2021).

Specifically in LA production from second-generation feedstocks, existing studies consider TEA and LCA separately. For instance, Daful et al. (2023) assesses six process scenarios for LA production from sugarcane bagasse and leaves. Li et al. (2021a, 2021b) uses an open-source tool for the design and evaluation of LA production from lignocellulosic feedstocks, which facilitates the inclusion of uncertainties and different scenarios. Mandegari et al. (2017) gathered LCA and economic results in a multi-criteria analysis for different scenarios to produce LA from sugarcane bagasse and brown leaves, but both analyses remain separate and the sustainability assessment is combined in a graphical representation. Sugarcane bagasse is also evaluated as a feedstock in Munagala et al. (2021) highlighting the importance of integrating biochemical production with existing agricultural processing facilities. Similarly, Brobbey et al. (2024) assessed a sugarcane biorefinery at different production scales and concluded that while larger scales improve economic feasibility, they come at a higher environmental cost, requiring a trade-off between economic and environmental goals.

Despite this, several authors have developed integrated frameworks in the last years by selecting environmental, economic and social indicators and integrating them in a multi-criteria analysis (Thomassen et al., 2019; Van Schoubroeck et al., 2021). This approach is considered in Wunderlich et al. (2021) where a three-step framework is detailed, and in Ferdous et al. (2023), where muti-objective sustainability and optimisation analysis are considered to include stakeholders' criteria. However, the weaknesses of multi-criteria analysis are highlighted by Massarutto (2024), who argues that economic valuation can enhance transparency by making trade-offs between environmental and economic aspects more explicit when underlying assumptions are clearly stated.

In this sense, the monetary valuation of environmental impacts as a way to integrate sustainability assessments has been applied in recent studies to bio-based products. For instance, Vega et al. (2020) demonstrated the feasibility of coupling TEA with LCA for emerging biotechnologies, while Kosamia et al. (2023) stated that developing a sustainable bioeconomy based on lignocellulosic biomass requires addressing multiple challenges simultaneously, including sustainable biomass harvesting, improving pretreatment methods and adopting a holistic sustainability assessment framework that monetises environmental impacts. External costs are considered in several studies such as in Ahmad et al. (2025) and in Musharavati, Ahmad, Javed, Sajid, & Nizami (Musharavati et al., 2024b; Musharavati et al., 2025) where the sustainability of biofertilizers, bio-diesel and other bio-based products from municipal solid waste is assessed including external costs. Albizzati et al. (2021) assessed five food waste valorisation routes combining LCA with conventional and societal Life Cycle Costing (LCC), monetising environmental externalities to capture the full socio-economic costs. Yeboah et al. (2022) assessed the conversion of rice husk into cellulose-based bioplastics using LCA combined with the EcoValue14 monetisation approach. Additionally, Hansson et al. (2024) assessed biodiesel production from bark and black liquor through a combined TEA and LCA, showing negative carbon abatement costs that highlight the economic advantage of substituting fossil diesel with biomass-to-liquid biofuels.

However, these studies consider different monetary valuation methods and do not include external costs in financial analysis, which provides a unified decision metric to facilitate comparison between alternatives, especially between bio-based and fossil-based products. In this regard, Ioannidou et al. (2022) is the only study found that integrated external costs directly into financial analysis through the environmental Life Cycle Costing (eLCC) approach using Environmental Prices (de Vries et al., 2024). The authors included external costs in the cash flow analysis and calculated the Minimum Selling Price (MSP) of different products considering externalities.

Building on this approach, the present study aims to develop a common framework to integrate environmental and economic assessments that can be applied to different bio-based production processes to provide a single indicator (MSP) to facilitate the comparison between alternatives. It follows a stepwise structure (process modelling, TEA, LCA, monetary valuation of externalities and integration into a discounted cash flow analysis) that can be replicated whenever pilot scale or early design data are available. To illustrate this, the different steps of the framework are followed in this study to evaluate the sustainability of LA production from fiber sludge.

The specific objectives of this study are to (i) develop a process model for LA production from fiber sludge at pilot scale and perform a consistent TEA and LCA, (ii) monetise environmental impacts obtained from the LCA and integrate them into financial analysis using the eLCC approach, (iii) determine the MSP at industrial scale including external costs as a single sustainability indicator to compare alternatives, and (iv) conduct sensitivity and uncertainty analyses to assess the influence of key technical and economic parameters. This study goes beyond the current state of the art by applying monetary valuation of environmental impacts at low Technology Readiness Level (TRL) to estimate external costs at industrial scale. To our knowledge, it is the first study that develops a process model, TEA and LCA for a first-of-a-kind plant using fiber sludge as feedstock to produce LA and estimates external costs for an industrial scale (nth-of-a-kind) plant based on pilot data. Beyond methodological contribution, it provides practical insights for industrial developers and policymakers on incorporating external costs into economic decision-making to support sustainable scale-up pathways in the bioeconomy.

2. Methods

In this section, the goal and scope of the study are defined. Then the process model is explained, which is used to obtain the inputs for the mass and energy balance in the baseline economic and environmental assessments. The integration of TEA and LCA is explained in section 2.5, considering the monetary valuation of externalities and their inclusion in the financial analysis. Finally, sensitivity and uncertainty analysis are performed to evaluate the economic risks related to the upscaled evaluation of the process.

2.1. Goal and scope definition

The functional unit for both environmental and economic analyses is defined as the production of 1 kg of LA. This unit allows for consistent comparison of impacts and costs across different process configurations and scales. The analysis follows a cradle-to-gate approach, including all stages from raw material extraction to the final product, but excludes distribution, use and end-of-life stages. The system boundaries include enzymatic hydrolysis of fiber sludge to release sugars, fermentation to produce LA and downstream separation and purification.

2.2. Process model description

The process model for the production of LA from glucose obtained from fiber sludge was developed based on the process described in Olszewska-Widdrat et al. (2023) as part of the H2020 BIOMAC project (GA 952941) and previous literature (López-Gómez et al., 2020; Pleissner et al., 2016). The simulation was performed using SuperPro Designer software v12 (Intelligen Inc., 2024). It is assumed that the plant operates 7920 h/year and the process has been upscaled at various capacities to determine the most adequate scenario to perform the economic assessment at industrial scale.

The Process Flow Description provides a schematic overview of the main parts of the process at laboratory scale, including its main inputs and outputs, and combines the different process steps to obtain the final products: fiber sludge to glucose and glucose to LA. The detailed Superpro Designer models are shown in Fig. S1 and Fig. S2 in the Supplementary Information.

The simplified process flow for glucose production is shown in Fig. 1. Fiber sludge is combined with enzymes in a hydrolysis reaction, that occurs in a fermenter equipped with a heating device. The commercial enzyme preparation "Celic CTec3" from Novonesis is used, with an enzyme loading of 6 % *w*/w, corresponding to 0.06 g of enzyme solution per gram of dry fiber sludge. The fiber sludge loading in the reaction is 15 g per 100 mL. In absolute terms, the hydrolysis process includes 185.5 kg of wet fiber sludge (60 % humidity, equivalent to 75 kg of dry material), 4.5 kg of enzyme preparation, and 310 kg of water. pH control is maintained by continuously adding a total of 2.5 L of 4 M NaOH to keep the pH stable between 5 and 5.2. The reaction is carried out at 50 °C for 72 h under continuous stirring using an anchor impeller set at 100 RPM.

After hydrolysis, the mixture undergoes filtration using a filter press to separate the glucose hydrolysate from the unhydrolyzed fiber sludge. The hydrolysis yield is approximately 80 %, meaning that 20 % of the fiber sludge remains unhydrolyzed and is collected as filter press cake with a moisture content of approximately 30 %.

As shown in Fig. 2, the LA production process is defined in two different stages: (1) fermentation and (2) clarification & purification. In the fermentation stage, microorganisms such as Bacillus coagulants convert glucose into LA under anaerobic conditions. This process occurs in a fermenter at a controlled temperature of 37 °C, with pH regulated at 6.5 using NaOH. The result of this fermentation process is a broth containing sodium lactate, which is formed through the neutralization of LA due to pH control. Specifically, a kinetic model based on Monod-type equations (Eq.1-Eq.4) was developed using MATLAB to describe the dynamics of the fermentation process, including glucose consumption, biomass growth, and lactic acid production (Tang et al., 1992). The process was modelled as a batch bioreactor under the assumption of perfect mixing, and a sequential modelling approach was adopted to characterize each phase of the fermentation independently. The system of differential equations governing the process was parameterized using experimental data obtained from BIOMAC project, and the resulting model was calibrated through a least squares optimization procedure.

$$\frac{d_x}{d_t} = \mu x \tag{1}$$

$$\frac{d_s}{d_t} = k_1 \mu \mathrm{x} \tag{2}$$

$$\frac{d_p}{d_t} = k_2 \mu x \tag{3}$$

$$\mu = \mu_{max} \frac{s}{k_s + s} \tag{4}$$

Where x is the biomass (g/l), s is the substrate (in this case it is glucose (g/l)), p is the product (in this case it is lactic acid (g/l)). μ is the growth rate (h-1), μ_{max} is the maximum growth rate (h-1), k_s is the substrate affinity constant (g/l), k_1 and k_2 are the kinetic constants. This fitting process focused on minimizing the discrepancy between model predictions and observed experimental data by systematically adjusting the kinetic parameters (μ_{max}, k_s, k_1 and k_2), subject to physically meaningful constraints (μ_{max}, k_s and k_2 must be >0 and $k_1 < 0$). The remaining restrictions were adopted from the experimental data in Glaser and Venus (2017). The obtained parameters (Table 1) offer a precise quantitative representation of the system's behaviour and, importantly, enable the prediction of process performance under varying conditions.

The downstream process aims to purify and concentrate LA through several purification steps. The first step is microfiltration, which removes biomass from the fermentation broth. Further purification is achieved through ultrafiltration, where smaller particles that were not retained during microfiltration are removed. Industrial equipment was considered throughout the modelling, using dimensions adapted to pilot

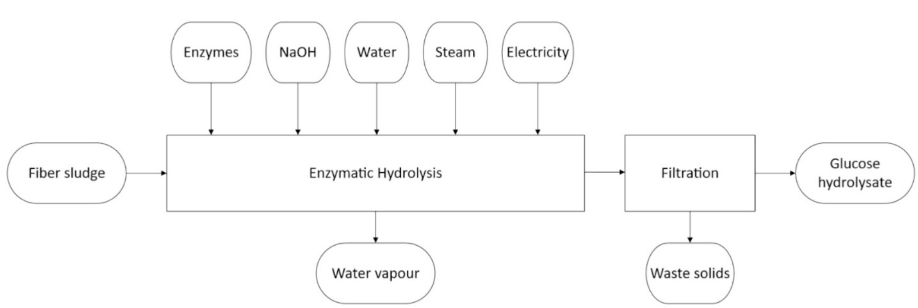

Fig. 1. Glucose production from Fiber Sludge through enzymatic hydrolysis.

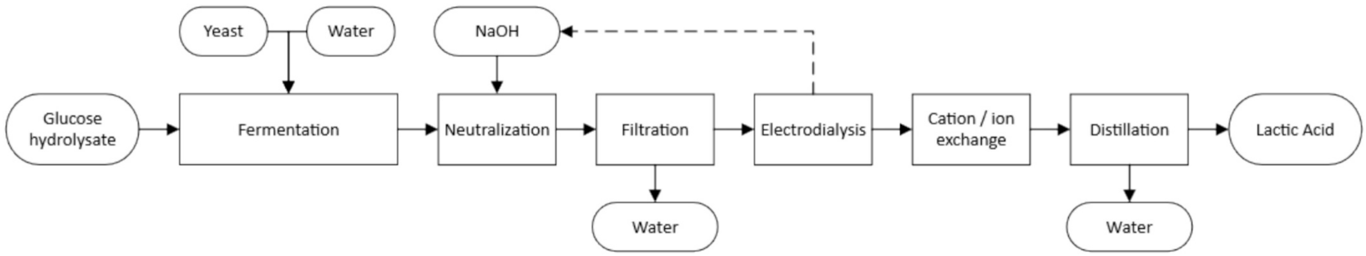

Fig. 2. Lactic acid production flowchart via fermentation of glucose and downstream process.

Table 1
Monod kinetic parameters.

μ_{max} (h^{-1})	k_s (g/l)	k_1	k_2
0.2	35.0	−3.8	2.5

scale. For instance, cartridge filters with a maximum area of 200 m^2 were selected for the micro- and ultrafiltration steps. Electrodialysis is then employed to further purify LA. This stage consists of two steps: monopolar and bipolar electrodialysis. In monopolar electrodialysis, the sodium lactate-rich fermentation broth (approximately 50 g/L) is processed to produce two output streams: the concentrate and the dilute. The monopolar step is completed when the conductivity of the filtrate falls below 1 mS/cm^2. The next step, bipolar electrodialysis, converts lactate to LA. The concentrate stream from the monopolar stage is fed into this step, producing three streams: acid (around 120 g/L of sodium lactate), salt and base. The base stream is recycled and reintegrated into the fermentation process according to Olszewska-Widdrat et al. (2019). The bipolar step is stopped when the conductivity of the filtrate is below 2 mS/cm2.

Following electrodialysis, ion exchange is carried out to enhance LA purity. This process involves two columns: one containing an anion exchange resin (Relite_EXC08) and another containing a cation exchange resin (Purolite_A103S). The final purification step is distillation, which reduces the water content in the solution and increases the LA concentration. This is achieved using a distillation column to ensure that the final LA product meets the required purity specifications.

Overall, the glucose fermentation to LA moves on in a high product yield and favourable productivity indicators. As shown in Table 2, the LA yield on glucose ($Y_{P/S}$) is 0.8835 g/g, indicating that 88.35 % of the consumed substrate was converted into the desired product, with minimal formation of byproducts. Regarding the yield of product on biomass ($Y_{P/X}$) reached 7.53 g/g, it suggested that LA synthesis was highly efficient relative to biomass formation and that the metabolic flux was predominantly directed towards product formation rather than cell growth.

Going through productivity, the volumetric production rate (r_p) was 2.02 g/L·h, while the specific production rate (q_p) was 0.153 g/g·h. These values show a moderate production rate at the cellular level and an overall efficient process performance. Considering the product yields and productivity indicators, it indicates that the fermentation process is well-suited for further scale-up and optimization for industrial LA production.

Table 2
Productivity indicators for lactic acid obtained after the fermentation process.

Parameter	Value	Units
$Y_{P/S}$	0.88	g product/g substrate
$Y_{P/X}$	7.53	g product/g biomass
r_p	2.02	g/L·h
q_p	0.15	g product/g biomass·h

2.3. Economic analysis

TEA is a widely used tool to evaluate the technical performance and economic feasibility by calculating costs and revenues of a new technology (Sinnott and Towler, 2019). Process simulation was employed to estimate the mass and energy balances, as well as the equipment costs required for various plant capacities to estimate the initial TEA results. In this case study, the overall costs associated with different processes were analysed to assess the economic viability of plants operating at different capacities. These costs include capital and operational costs (CAPEX and OPEX), encompassing equipment, raw materials, consumables, utilities, and labour costs, among other factors.

Economic evaluation at the pilot scale provides insights into the primary costs incurred in the process but does not fully reflect the financial viability of a potential industrial scale plant. Consequently, the pilot line was modelled using SuperPro Designer, and simulations were conducted for various production rates. The baseline scenario was calculated using the pilot scale inventory, with a production rate of 1.13 t of LA per year in an operating time of 7920 h per year. The approach described in Ioannidou et al. (2022) was adapted to calculate the Optimal Plant Capacity (OPC), which is identified as the point where the Fixed Capital Investment (FCI) and production costs per kg are constant, reaching an economy of scale. To calculate the OPC, the production rate was increased to 60 kilotonnes (kt) per year.

The equipment cost was calculated using the Chemical Engineering Plant Cost Index (CEPCI) (CEPCI, 2024), and the recalculation of the equipment costs at different scales was estimated using the six-tenth rule, a logarithmic relationship for equipment capacities that establishes that if the cost of a given item is known, the cost of a similar item can be calculated (Eq. 5).

$$P = P_0 * \left(\frac{Q}{Q_0}\right)^n \tag{5}$$

Where P_0 is the base item cost, Q and Q_0 are the new and base capacities of the equipment respectively, and n is the value for the exponent set at 0.6. This rule is generally applied in estimations where there is an absence of information regarding the upscaled process (Peters et al., 2003). The Total Capital Investment (TCI) was calculated using the parameters listed in the Supplementary Information that were retrieved from Kim et al. (2023).

One financial indicator calculated in this case study is the Net Present Value (NPV). The NPV calculation makes it possible to combine revenues and costs arising within a defined time horizon (t) into Cash Flows (CF), while applying a discount rate (r) to reflect the changing value of money over time (Eq. 6).

$$NPV = \sum_{t=0}^{T} \frac{CF_t}{(1 + r_t)^t} \tag{6}$$

A positive NPV indicates that the project is profitable, whereas a negative value suggests it should be rejected and reconsidered. To calculate the NPV, a DCF analysis was performed using the parameters listed in Table 3.

The discount rate is a crucial economic parameter that will be further

Table 3
Techno-Economic parameters.

Parameter	Value	Reference
Plant lifetime	30 years	
Discount rate	10 %	
Construction	3 years	
Investment allocation during construction	1st year: 8 % 2nd year: 60 % 3rd year: 32 %	Humbird et al. (2011)
Salvage value	5 %	
Tax rate	25 %	PWC (2024)
Depreciation method	Straight-Line	Rajendran and Han (2023)
Depreciation period	10 years	

discussed in the results section. As shown in Table 3, a 10 % discount rate is used in this study based on the work from Humbird et al. (2011). This value can also be estimated by the Capital Asset Pricing Model (CAPM), which estimates the expected return on an investment by linking it to its systematic risk relative to the market, and it is often used to determine the discount rate in valuation models, reflecting the minimum return required to compensate for that risk (Eq. 7).

$$E(R) = Rf + \beta\,(Rm - Rf) \tag{7}$$

Where the risk-free rate Rf is estimated at 2.5 %, based on the current yield of German 10-year government bonds, which are widely used as a benchmark for risk-free returns in Europe (Tradingeconomics, 2025). The market risk premium $(Rm - Rf)$ is taken as 6.25 %, which reflects the additional return expected from investing in the market over the risk-free rate in Germany to go in line with the risk-free rate (KPMG, 2025), and the beta (β) is 1.20 as an estimate of the project's sensitivity to market fluctuations obtained for chemical production (Damodaran, 2025). This results in an Expected Return $E(R)$ or discount rate of 10 %.

In addition to the NPV, another key financial indicator calculated is the Minimum Selling Price (MSP). The MSP represents the lowest price at which the product must be sold to make the project economically viable, that is the price that results in an NPV of zero. This metric is widely used in chemical engineering and process economics to benchmark the economic performance of new technologies. By comparing the MSP of the process with similar technologies or market prices, stakeholders can evaluate the competitiveness and potential market adoption of the proposed technology.

Additional financial indicators, such as the Internal Rate of Return (IRR), are commonly calculated in economic analyses to assess process viability (Musharavati et al., 2024a, 2024b). However, in this study, the NPV is used to calculate the MSP, setting the NPV to zero. Under this condition, the IRR corresponds to the discount rate applied (10 %), as it is the rate at which the NPV becomes zero. It should be noted that setting the NPV to zero is used only to determine the MSP, and this does not imply that the project is not profitable, but rather defines the breakeven condition where discounted revenues equal discounted costs at the chosen discount rate.

2.4. Environmental assessment

The LCA methodology is carried out to identify environmental hotspots in the production of LA from fiber sludge and to support decision-making towards process improvement. The LCA follows the principles and requirements of ISO 14040 and ISO 14044 (ISO, 2006a, 2006b) and included the four standard steps: goal and scope definition, inventory analysis, impact assessment and interpretation. The goal and scope of the LCA, defined in section 2.1, considers 1 kg of LA produced at pilot scale as a functional unit within a cradle-to-gate boundary.

The second step is the inventory analysis or life cycle inventory (LCI), which comprises the collection of data and calculations necessary to quantify the system's inputs (energy, materials, and consumables) and output flows (wastes, emissions, and products). In this case study, Foreground data were obtained from the pilot line and the process model developed in SuperPro Designer software and Ecoinvent v3.10 (Wernet et al., 2016) was used as the background data source. The complete LCI is presented in Table S2 and Table S3 in the Supplementary Information, while the aggregated values are summarised in Table 4.

Regarding the assumptions for this step, a cut-off approach was applied to the fiber sludge, as it is a side stream of the pulp and paper industry. Consequently, no environmental impacts were allocated to its production, and only the impacts associated with its drying and transportation were considered. The energy consumption for drying was based on the values reported in Siedlecka and Siedlecki (2021), and a transportation distance of 100 km was assumed. Additionally, a recirculation of NaOH was considered at a rate of 93 % (7 % of the used NaOH was lost for each production cycle).

In the third step, the data quantified in the inventory is converted into potential environmental impacts through a Life Cycle Impact Assessment (LCIA), which involves the translation of the system's flow exchange with the external environment into elementary environmental burdens (emissions and resource extractions) which are converted into a limited number of potential environmental impacts (or impact categories) through characterisation factors, generally following one or more accepted LCIA methods. In this case study, SimaPro 9.6 software (PRé Sustainability, 2024) was used to model the mass and energy balance of the process. The system model "allocation, at the point of substitution" (APOS) is applied, and the ReCiPe 2016 Midpoint (H) impact assessment method is used to calculate the environmental impacts in midpoints (Huijbregts et al., 2017).

In the final step, the potential environmental impacts obtained are assessed and analysed.

2.5. Monetary valuation of externalities

After calculating the environmental impacts, the LCA results can be weighted by converting them into monetary values. The internalisation of environmental impacts into the economic analysis is considered one of the three variants of Life Cycle Costing (LCC) (Rödger et al., 2018).

LCC is the methodology used to evaluate the economic pillar of Life Cycle Sustainability Assessment (LCSA) and contributes to better decision-making, being one essential tool in Life Cycle Management (Kloepffer, 2008). There are three types of LCC according to Hunkeler et al. (2008): conventional LCC, environmental LCC and societal LCC. The main differences among these types are the degree of completeness (boundaries), the monetisation of externalities, the perspective, and the reference unit. In this study, the environmental LCC approach is followed, as externalities are monetised and included in the economic

Table 4
Life Cycle Inventory data for the production of 1 kg of lactic acid from fiber sludge.

Category	Substance	Quantity	Unit
Inputs			
Materials	Fiber sludge	2.19	kg
	Enzymes	0.13	kg
	Yeast	0.26	kg
	Water	68.13	l
	Sodium hydroxide (NaOH)	0.59	kg
Utilities	Steam	486.97	kcal
	Electricity	2.25	kWh
	Cooling water	1621.52	kcal
	Chilled water	165.32	kcal
Transport	Fiber sludge transport	100	km
Outputs			
Main product	Lactic acid	1	kg
Emissions	Wastewater	62.40	l
	Water vapour	0.27	kg

analysis.

Several methods exist for assigning monetary values to environmental impacts in LCA, each based on different cost perspectives and approaches. These methods include abatement costs, budget constraints and damage costs, among others (Amadei et al., 2021; Pizzol et al., 2015). This study adopts the Environmental Prices (EP) methodology (de Vries et al., 2024). These prices are expressed in euros per kg of pollutant and provide a consistent framework for monetizing the environmental impacts. The methodology is fully aligned with ReCiPe 2016 Midpoint (H) impact categories and is undergoing further development for Environmental Footprint categories, facilitating its integration into standardised LCA frameworks (Fazio et al., 2018; Manfredi et al., 2012). Since the methodology is developed specifically for ReCiPe 2016, it was adopted in this study to ensure the coverage of all midpoint impact categories.

The EP values, as applied in this study, are specific to the EU27 context and are based on the average emission conditions for 2019. Although these values provide robust insights for this region, they may require contextual adjustments for applications in other geographic or temporal settings (de Vries et al., 2024). To account for the inherent uncertainties in monetising environmental impacts, EP are presented as a range of values that can be considered in sensitivity and uncertainty analyses to enhance the robustness of decision-making by capturing variability in environmental and socio-economic valuations.

In this study, environmental impacts are assessed at pilot scale without considering any process optimisation, so the monetary values are expected to be exceptionally high to be included as costs in the DCF analysis for the industrial scale assessment. Therefore, an innovative approach has been developed to estimate the prospective environmental impacts at industrial scale using their monetary values.

First, the proportion of FCI, OPEX, and external costs per kg were calculated at pilot scale. This will help to determine the share of external costs compared to the other two financial indicators (FCI and CAPEX) at pilot scale. Next, it is assumed that the proportion of external costs relative to FCI and CAPEX will remain the same when scaling up to the industrial scale. This means that while the absolute values of FCI and CAPEX change, the percentage of external costs remains constant between the two scales. Therefore, FCI and OPEX per kg was determined by dividing the total FCI and OPEX by the annual production at industrial scale. Once the cost per kg was determined, the percentage of each cost component (FCI, OPEX, and external costs) relative to the sum of these components is calculated. The only unknown variable is the external cost at the industrial scale, which was calculated using the same proportion observed at the pilot scale. This is done by considering the sum of FCI, OPEX, and external costs, and applying the same ratio to the industrial scale.

2.6. Sensitivity and uncertainty analysis

To assess the error propagation from the data sources used in the pilot plant model to the final results obtained in the industrial scale scenario and the potential investment risk of the project, sensitivity and uncertainty analyses were conducted on key economic parameters influencing the MSP. Sensitivity analysis identifies the most impactful factors by systematically varying specific parameters while keeping others constant (Vargas-Farias et al., 2026). The parameters considered include the tax rate, glucose quantity and cost, NaOH quantity and cost, discount rate and external costs, as these represent critical economic inputs in the production process providing insight into the parameters to which the MSP is most sensitive (Thomassen et al., 2018).

For the uncertainty analysis, a PERT distribution was employed to estimate the probability to obtain a positive NPV considering the variation of the inputs mentioned in the sensitivity analysis. The PERT distribution captures uncertainty by defining minimum, maximum, and most-likely values, reflecting realistic ranges for key inputs. Monte Carlo simulation was conducted to deal with parameter uncertainty using stochastic sampling within the defined PERT distributions to generate 10,000 of plausible NPV outcomes, creating an NPV distribution. Each iteration represents a unique combination of input values, allowing for the estimation of the probability of achieving a positive NPV (Ioannidou et al., 2022).

A summary of the information stated in this section is shown in Fig. 3 to observe the data sources and the interconnection between the different methodologies to obtain the final results.

3. Results and discussion

This section presents and discusses the main results of the study, encompassing economic and environmental assessments, the monetary valuation of externalities and the sensitivity and uncertainty analyses.

3.1. Economic analysis

The FCI and production costs per kg of LA at different scales are shown in Fig. 4. This figure only represents the costs from 1 to 60 kt per year so the values can be observed in more detail in the graph. The OPC is determine at a production rate of 50 kt per year, which is the point where the economies of scale are reached because the production costs and FCI per kg remain constant. At the OPC, the FCI per kg is 1.90€ and production costs are 1.57€/kg. Equipment cost and other FCI parameters at different plant capacities are listed in the Supplementary Information.

The operational costs at pilot scale were calculated considering the information from the process in the BIOMAC project (GA 952941) in terms of mass and energy balance. The unitary costs for the different raw materials are listed in Table 5. The initial model was upscaled to different production rates in which the consumption of raw materials and energy is assumed to increase linearly. This means that the optimisation of the process in terms of consumption efficiency is not considered in the industrial scenario. Labour costs are calculated in SuperPro Designer considering 69€/hour and the remaining operating costs are estimated by the software. Operating costs are also listed in the Supplementary Information.

The DCF analysis was conducted using the parameters listed in Table 3. At the OPC, the MSP for LA is 1.71€/kg, which corresponds to 1.85 $/kg using the 2024 average exchange rate (European Central Bank, 2025). As shown in Table 6, this value is competitive with other bio-based production routes and notably lower than the fossil-based pathway reported by Fei et al. (2020), which ranges from 5.83 to 2.17 $/kg for a 22 kt plant capacity using natural gas. While this value is higher than the 1.58$/kg reported by Ioannidou et al. (2023) for the same OPC using organic fraction of municipal solid waste and the 1.20 $/kg calculated by Manandhar and Shah (2020) for a larger plant capacity and using a first-generation feedstock (corn grain), it falls within the range of MSP values found in studies using lignocellulosic biomass and agroforestry waste at different plant capacities. For example, Li et al. (2021a, 2021b) report values between 1.38 and 1.91 $/kg for a 219 kt plant using lignocellulosic biomass, while Mandegari et al. (2017), Munagala et al. (2021) and Gezae Daful and Görgens (2017) present broader ranges depending on feedstock combinations and process assumptions. Furthermore, the MSP in this study is higher than the 0.94 $/kg reported by Kwan et al. (2018) at a smaller plant capacity, which can largely be attributed to the use of a lower discount rate (5 %) in their analysis, whereas most other studies, including the present one, apply a rate of approximately 10 % as shown in Table 6.

The choice of the discount rate can have a major impact on the viability of the project as it can be used as an indicator to reflect the risk of the project. In this case study, the 10 % discount rate applied is the one commonly applied in chemical plant design (Humbird et al., 2011). However, some authors indicate that a higher discount rate should be used to analyse product development (Thomassen et al., 2019). This parameter is further examined in the sensitivity and uncertainty analyses in section 3.4.

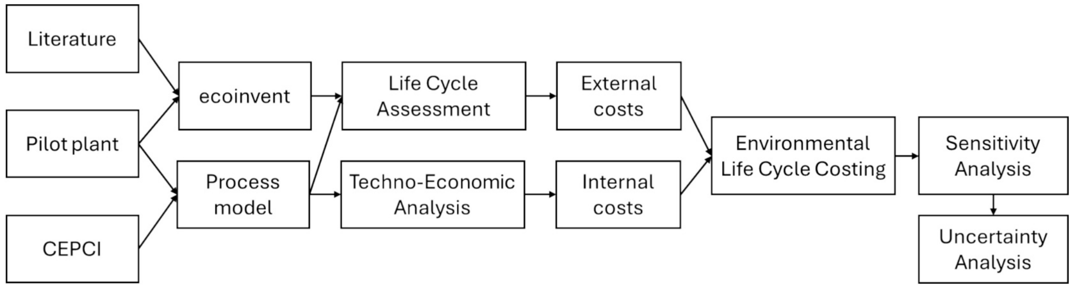

Fig. 3. Data sources and methodologies applied in this study.

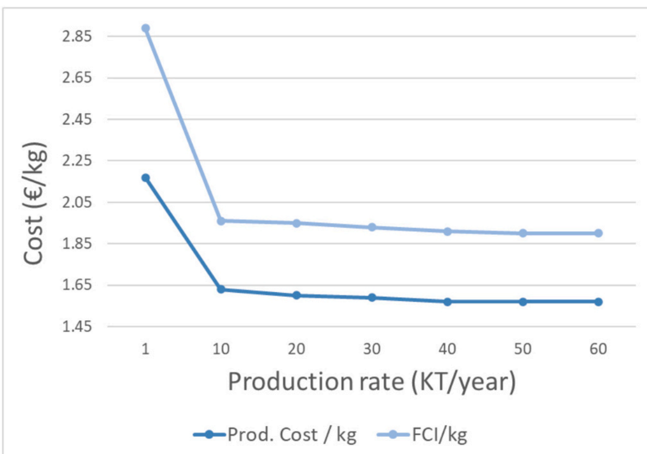

Fig. 4. Fixed Capital Investment (FCI) and Production costs per kilogram of lactic acid at different production rates (1–60 kilotonnes (KT) per year).

Table 5
Raw material costs for lactic acid production from fiber sludge.

Material	Unit cost	Reference
Enzyme	3.8 €/kg	Mailaram et al. (2023)
Fiber sludge	0.1 €/lb	Eikelboom et al. (2018)
NaOH	0.13 €/kg	e-Industria (2024)
Water	1.3 €/m^3	INE (2020)
Yeast	0.0052 €/kg	Chong et al. (2020)

3.2. Environmental assessment

The environmental impact results of the pilot scale production of 1 kg of LA are shown in Table 7, whereas Fig. 5 shows the relative breakdown, showcasing the contribution of each production step (left), and the aggregated contribution of each flow type (right) to the total environmental impact. In this study, the main environmental hotspots of LA production from fiber sludge are a Global Warming Potential (GWP) of 3.87 kg CO2-eq, a Terrestrial ecotoxicity (ET) of 3.95×10^1 kg 1,4-DCB and a Human carcinogenic toxicity (HT) of 8.75 kg 1,4-DCB. Both the glucose production and the fermentation steps are responsible for most of the environmental impact of LA production, across all analysed impact categories except Water Consumption (WC). In fact, glucose production alone is responsible for an average of 57 % of the total environmental impact (Fig. 5, on the right). This is in large part due to the necessary enzyme used to obtain glucose, since the enzyme production is highly intense in terms of energy and steam, leading to high environmental impacts (González-García et al., 2018).

As for the fermentation step, its high impacts are a result of the high energy consumption of the process. It is worth noting that the electrodialysis step presents high impacts in the WC category, due to the high chilled water input. The other purification processes, such as distillation and ion exchange also contribute to the environmental impact profile, but to a lesser extent.

Table 6
Minimum Selling Prices (MSP) of lactic acid production at different plant capacities from different feedstocks.

Reference	Feedstock	Annual plant capacity (tonnes)	MSP (USD)	Discount rate
Present study	Fiber sludge	50,000	1.85	10 %
Fei et al. (2020)	Natural gas	22,000	2.17–5.83	10 %
Munagala et al. (2021)	Sugarcane bagasse	37,960	3.21	10.36 %
Ioannidou et al. (2023)	Organic fraction of municipal solid waste	50,000	1.58	10 %
Manandhar and Shah (2020)	Corn grain	100,000	1.20	10 %
Li et al. (2021a, 2021b)	Lignocellulosic biomass	219,000	1.38–1.91	10 %
Kwan et al. (2018)	Food waste	24,983	0.94	5 %
Gezae Daful and Görgens (2017)	Sugarcane lignocellulose	73,000*	1.30–5.00	9.30 %
Mandegari et al. (2017)	Sugarcane bagasse and brown leaves	71,300–93,400*	1.08–1.80	9.70 %

* Estimated values based on the plant operating hours and production rate per hour.

Table 7
Life Cycle Assessment results for the production of 1 kg of lactic acid from fiber sludge using ReCiPe 2016 Midpoint (H).

Impact Category	Unit	Value
Global warming potential (GWP)	kg CO_2-eq	3.87
Stratospheric ozone depletion (OD)	kg CFC11-eq	1.29×10^{-5}
Ionizing radiation (IR)	kBq Co-60-eq	4.67×10^{-1}
Ozone formation, Human health (OF)	kg NO_x-eq	1.57×10^{-2}
Fine particulate matter formation (FPM)	kg $PM_{2.5}$-eq	4.83×10^{-3}
Terrestrial acidification (TA)	kg SO_2-eq	1.81×10^{-2}
Freshwater eutrophication (FE)	kg P-eq	3.24×10^{-3}
Marine eutrophication (ME)	kg N-eq	4.73×10^{-3}
Terrestrial ecotoxicity (ET)	kg 1,4-DCB	3.95×10^{1}
Freshwater ecotoxicity (EF)	kg 1,4-DCB	2.50×10^{-1}
Marine ecotoxicity (EM)	kg 1,4-DCB	3.16×10^{-1}
Human carcinogenic toxicity (HT)	kg 1,4-DCB	8.75
Land use (LU)	m^2a crop-eq	2.08
Mineral resource scarcity (MRS)	kg Cu-eq	1.32×10^{-2}
Fossil resource scarcity (FRS)	kg oil-eq	8.63×10^{-1}
Water consumption (WC)	m^3	3.56×10^{-1}

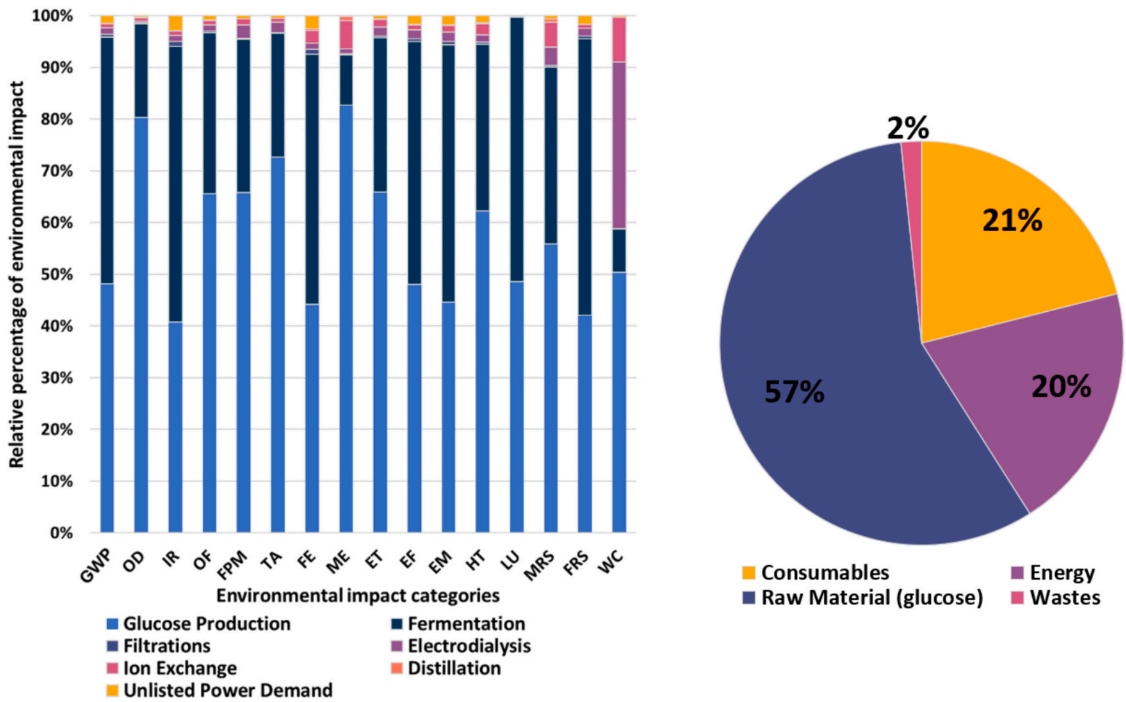

Fig. 5. Cradle-to-gate Life Cycle Assessment results of lactic acid production from fiber sludge, with relative impact per process and impact category (left), and aggregated relative impact per flow type (right). Note: Global warming potential (GWP), Stratospheric ozone depletion (OD), Ionizing radiation (IR), Ozone formation Human health (OF), Fine particulate matter formation (FPM), Terrestrial acidification (TA), Freshwater eutrophication (FE), Marine eutrophication (ME), Terrestrial ecotoxicity (ET), Freshwater ecotoxicity (EF), Marine ecotoxicity (EM), Human carcinogenic toxicity (HT), Land use (LU), Mineral resource scarcity (MRS), Fossil resource scarcity (FRS), Water consumption (WC).

Table 8
Global Warming Potential (GWP) results, assumptions and process parameters of lactic acid (LA) production in previously published literature, compared to the present work.

Reference	GWP (kg CO_2-eq/kg LA)	LA production capacity	Feedstock	System boundaries, method, assumptions	Highlights
Present work	3.87	1.13 t/year	Fiber sludge (from pulp and paper industry)	- Cradle-to-gate - ReCiPe Midpoint (H) method -Recycled content/cut-off approach used for fiber sludge feedstock	Pilot-scale LCA using a waste-derived feedstock
Fei et al. (2020)	8.92	22,000 t/year	Natural gas	- Cradle-to-gate - DATASMART - Preliminary LCA focused on energy-related emissions	Establishes a fossil-based benchmark
Munagala et al. (2021)	4.62	37,960 t/year	Sugarcane bagasse	- Cradle-to-gate - ReCiPe Midpoint (H) method - Annexed to sugar mill scenario	Pretreatment identified as main hotspot and co-location with sugar mills improves sustainability
Ioannidou et al. (2023)	2.95 (Grid energy) 1.49 (Renewable energy)	50,000 t/year	Organic fraction of municipal solid waste	- Cradle-to-gate - CML 2001 - Scenarios with grid and renewable electricity	Multi-product biorefinery demonstrating GWP reduction and energy integration benefits
Gezae Daful and Görgens (2017)	0.025–0.16	576–1639 kg/h	Sugarcane lignocellulose	- Cradle-to-gate - ReCiPe Midpoint (H) method - Economic allocation and system expansion	Six process scenarios
Li et al. (2021a, 2021b)	2.79	219,000 t/year	Lignocellulosic biomass	- Gate-to-gate - BioSTEAM open-source model - Excludes upstream feedstock and waste stages	Framework with uncertainty and sensitivity analyses
Mandegari et al. (2017)	3.8	4647–19,223 kg/h	Sugarcane bagasse and brown leaves	- Cradle-to-gate - CML-IA baseline - Economic allocation of sugar mill products	Multi-product biorefinery co-producing LA, ethanol and electricity
Ögmundarson et al. (2020a, 2020b)	4.2	110,000 t/year	Corn, corn stover, macroalgae	- Cradle-to-grave - ReCiPe Midpoint (H) - System expansion for energy and material credits	Cross-feedstock comparison of different TRLs

Table 8 presents a comparison between the present work and other studies that have estimated the environmental impacts associated with LA production. The environmental impacts reported here are consistent with those reported in previous studies. However, Table 8 highlights that cross-study comparisons should be made cautiously, because there are large discrepancies in the study assumptions, system boundaries, allocation procedures, and impact assessment methods used. Even when comparing impact categories with the same unit (i.e. kg CO2-eq), caution is necessary because these methodological differences can significantly influence the results (Ibáñez et al., 2024).

Generally, studies considering LA from corn or other feedstock crops, pinpoint both biomass production and refinery processes as environmental hotspots, with potential land-use change, use of fertilizers and energy consumption of refinery processes usually being accountable for such hotspots (Ögmundarson et al., 2020a, 2020b). In our study, since we assumed a recycled content/cut off approach for the fiber sludge feedstock, this flow embodies the impacts of transportation and drying.

As shown in Table 8 the production volume in this LCA model is lower than that in other studies. However, scaling up production results in a directly proportional increase in resource use, meaning that only equipment costs benefit from economies of scale, whereas mass and energy balances remain unchanged. This perspective aligns with the discussion by Pizzol et al. (2020), who highlight that, under a fixed product system model and the current LCA framework, the environmental impacts associated with producing one thousand units of a product are calculated as one thousand times the impacts of producing a single unit following a linear relationship. However, they also argued that real-world processes deviate from this straightforward multiplication owing to industrial synergies, efficiency improvements and optimised system design, which make the environmental impact less predictable as scale increases.

To compensate for the lack of data needed to calculate prospective environmental impacts at an industrial scale and to provide a rapid estimation of externalities in upscaled scenarios, the following section employs the monetary valuation of LCA, which allows for the estimation of external costs by extrapolating from the data available at the pilot scale. As such, the results presented here should be interpreted as conservative approximations in the absence of detailed industrial scale environmental data.

3.3. Monetary valuation of externalities

The environmental impacts in Table 7 were translated into monetary terms using the EP values based on the eLCC approach. As shown in Table 9, total external costs at pilot scale reach 36.52 €/kg (central EP values). These values are exceptionally high due to the lack of process optimisation and the small production volume. The values obtained are expressed per kg of LA, which causes the MSP at the industrial scale to be out of the range of literature values.

To address this issue, external costs at industrial scale are estimated by considering the contribution of FCI, OPEX and external costs per kg following the description in section 2.5. First, total FCI and OPEX were considered for each production level. In the case of the pilot scale with an annual production of 1131 kg, the FCI is 72,480 €, and the OPEX is 206,950 €. At the industrial scale, with a production of 50 kt, the FCI is 94,898,780 €, and the OPEX is 78,391,920 €. These values are calculated per kg of LA produced, and external costs obtained in Table 9 are included to determine the proportion of the three indicators, and estimate external costs per kg at industrial scale.

As shown in Table 10, external costs represent 9 %, 13 % and 18 % of

Table 10

Fixed Capital Investment (FCI), operational expenditures (OPEX) and external costs at pilot and industrial scale considering the lower, central and upper Environmental Prices values.

	Pilot scale		Industrial scale	
Prod kg/year	1131		50,000,000	
FCI	72,480 €		94,898,780 €	
OPEX	206,950 €		78,391,920 €	
Lower values				
FCI/kg	64.08 €	24 %	1.90 €	50 %
OPEX/kg	182.98 €	67 %	1.57 €	41 %
Externality/kg	24.41 €	9 %	0.34 €	9 %
TOTAL	271.47 €		3.81 €	
Central				
FCI/kg	64.08 €	23 %	1.90 €	48 %
OPEX/kg	182.98 €	65 %	1.57 €	39 %
Externality/kg	36.52 €	13 %	0.51 €	13 %
TOTAL	283.58 €		3.98 €	
Upper				
FCI/kg	64.08 €	21 %	1.90 €	45 %
OPEX/kg	182.98 €	61 %	1.57 €	37 %
Externality/kg	55.01 €	18 %	0.77 €	18 %
TOTAL	302.07 €		4.24 €	

Table 9

Monetary valuation of environmental impacts per kilogram(kg) of lactic acid using Environmental Prices.

Impact Category	Unit	Value	Lower	Central	Upper	External cost lower	External cost central	External cost upper
Global warming potential (GWP)	kg Co2-eq	3.87	0.05 €	0.13 €	0.16 €	0.19 €	0.50 €	0.62 €
Stratospheric ozone depletion (OD)	kg CFC11-eq	1.29×10^{-5}	15.20 €	29.10 €	69.60 €	0.00 €	0.00 €	0.00 €
Ionizing radiation (IR)	kBq Co-60-eq	4.67×10^{-1}	0.00 €	0.00 €	0.01 €	0.00 €	0.00 €	0.00 €
Ozone formation, Human health (OF)	kg NOx-eq	1.57×10^{-2}	1.38 €	2.17 €	2.98 €	0.02 €	0.03 €	0.05 €
Fine particulate matter formation (FPM)	kg PM2,5-eq	4.83×10^{-3}	61.70 €	99.20 €	138.10 €	0.30 €	0.48 €	0.67 €
Terrestrial acidification (TA)	kg SO2-eq	1.81×10^{-2}	2.66 €	5.27 €	9.30 €	0.05 €	0.10 €	0.17 €
Freshwater eutrophication (FE)	kg P-eq	3.24×10^{-3}	2.56 €	3.74 €	10.13 €	0.01 €	0.01 €	0.03 €
Marine eutrophication (ME)	kg N-eq	4.73×10^{-3}	7.64 €	14.25 €	27.60 €	0.04 €	0.07 €	0.13 €
Terrestrial ecotoxicity (ET)	kg 1,4-DCB-eq	3.95×10^{1}	0.00 €	0.00 €	0.00 €	0.02 €	0.03 €	0.03 €
Freshwater ecotoxicity (EF)	kg 1,4-DCB-eq	2.50×10^{-1}	0.01 €	0.02 €	0.03 €	0.00 €	0.01 €	0.01 €
Marine ecotoxicity (EM)	kg 1,4-DCB-eq	3.16×10^{-1}	0.00 €	0.00 €	0.00 €	0.00 €	0.00 €	0.00 €
Human carcinogenic toxicity (HT)	kg 1,4-DCB-eq	8.75	2.70 €	3.99 €	6.01 €	23.63 €	34.92 €	52.60 €
Land use (LU)	m2a crop-eq	2.08	0.07 €	0.10 €	0.13 €	0.15 €	0.21 €	0.27 €
Mineral resource scarcity (MRS)	kg CU-eq	1.32×10^{-2}	0.00 €	0.01 €	0.08 €	0.00 €	0.00 €	0.00 €
Fossil resource scarcity (FRS)	kg oil-eq	8.63×10^{-1}	0.00 €	0.03 €	0.16 €	0.00 €	0.02 €	0.14 €
Water consumption (WC)	m3	3.56×10^{-1}	0.00 €	0.41 €	0.81 €	0.00 €	0.14 €	0.29 €
Total External Cost						**24.41 €**	**36.52 €**	**55.01 €**

the total cost contribution considering the lower, central and upper EP values respectively and therefore, the external costs obtained for the three ranges of EP values are 0.34 €/kg for the lowest values, 0.51 €/kg for the central values and 0.77 €/kg for the highest values at industrial scale. After including these values as additional costs in the DCF analysis for the OPC, the MSP values are 2.04, 2.21 and 2.46 €/kg of LA for the lower, central and upper EP values respectively.

These results demonstrate that even when environmental externalities are internalised, the process remains within the range of literature values where external costs are not considered (Table 6). The monetisation of externalities corrects market distortions arising from unpriced environmental and health impacts (Pigou, 2017) and offers a transparent way to inform decision-makers about the true cost of LA production (Bianchi et al., 2024; Kosamia et al., 2023).

Monetising externalities also clarifies trade-offs between economic feasibility and environmental performance at different production scales. Small decentralised bio-based systems often achieve better environmental outcomes because of lower transport emissions and local biomass sourcing, but they usually have higher production costs due to limited economies of scale (Vasilakou et al., 2023a, 2023b). In contrast, large industrial plants benefit from cost efficiency but may incur greater environmental burdens linked to logistics, land use, or energy intensity (Salvador et al., 2022). Including monetised externalities allows these trade-offs to be evaluated consistently, supporting more targeted policy decisions regarding scale, location and system design (Grilli et al., 2024).

From a policy perspective, integrating external costs into financial indicators such as the MSP can guide the design of carbon pricing mechanisms, tax incentives or subsidies that level the competitive conditions between fossil-based and bio-based products (Kosamia et al., 2023; Zhan et al., 2023).

As mentioned in section 3.2, comparison between the environmental impacts of different studies must be performed considering the same scope and impact assessment method. Therefore, this study is limited by the lack of a common methodology to evaluate environmental impacts in other studies, and MSP including external costs cannot be compared with other results from the literature where externalities are considered. However, the sensitivity of the MSP to the variation in externalities and other parameters is assessed in the following section.

3.4. Sensitivity and uncertainty analysis

Several parameters have been studied for LA production to identify their contribution to the economic viability of the process. A sensitivity analysis was conducted to observe the inputs that most affects the MSP.

Fig. 6 illustrates the variation in the MSP based on different input parameters. The sensitivity analysis incorporates the external costs calculated in the previous section, with the base MSP set at 2.21 €/kg using central EP values. The results highlight that externalities have the strongest influence on MSP, as seen in the graph. When no externalities are considered, the MSP reaches its minimum value of 1.71 €/kg, whereas at its highest impact, it increases to 2.46 €/kg, which reinforces the findings from the previous section, where external costs substantially influence the economic feasibility of the process. Discount rate is the second most influential factor. As discussed in section 3.1, the choice of the discount rate plays a critical role in project feasibility. A low social discount rate of 4 %, considered from a societal perspective (European Commission, 2014), leads to a 4.34 % reduction in MSP, while from an investor's perspective, a higher discount rate of 22 % aligned with literature values for product development (Suresh et al., 2018; Thomassen et al., 2019) results in a 14 % increase in MSP compared to the 10 % discount rate used in the baseline scenario. Tax rate variations go from the lowest (9 %) to the highest (30 %) in the European countries (Trading Economics, 2025), which have a moderate effect, ranging between 2.18 €/kg and 2.22 €/kg.

Glucose and NaOH costs were varied by ±20 % to assess their impact on MSP relative to the base value. This analysis highlights the potential volatility of market prices and its effects on the project's economic feasibility. Both parameters influence MSP by approximately 3 %, indicating a moderate but noteworthy sensitivity to raw material costs. Regarding raw material quantities, glucose was also varied by ±20 %, while NaOH consumption was assumed to decrease because of its potential for recycling across multiple batches. However, given the uncertainty surrounding the actual recycling efficiency at an industrial scale, two scenarios were considered: a 50 % reduction in NaOH usage, leading to an MSP of 1.99 €/kg, and a 90 % reduction, further decreasing MSP to 1.82 €/kg.

The uncertainty associated with the configuration at different production scales is accounted for by applying a ± 20 % variation to equipment costs. As described in Section 2.3, equipment cost is estimated at different plant capacities considering the six-tenth rule, being the main variable to calculate the remaining economic parameters. This

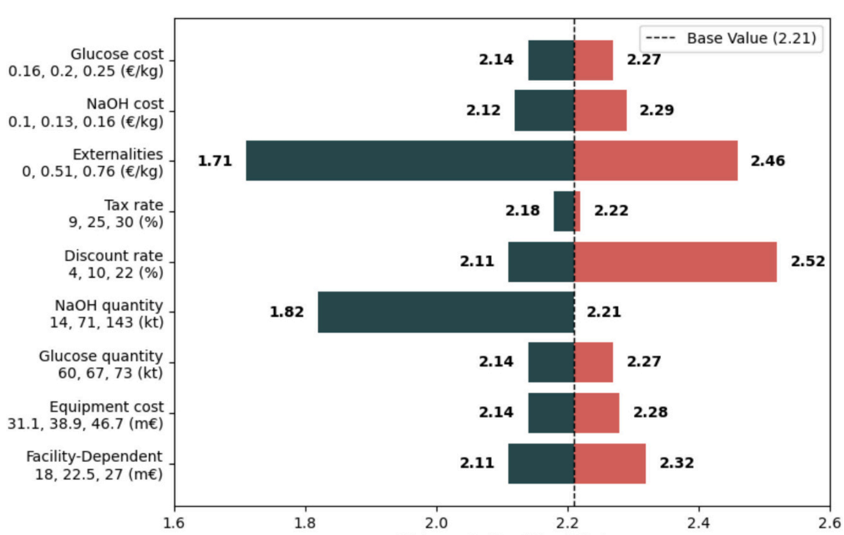

Fig. 6. Sensitivity analysis. Tornado diagram representing the parameters that contribute the most to Minimum Selling Price of lactic acid production from fiber sludge.

variation leads to a MSP range of 2.14 to 2.28, which is similar to the variation of raw materials quantities and costs. Facility-dependent costs are also variated a ± 20 % as they represent a critical factor in modelling manufacturing constraints. In SuperPro Designer, these costs are calculated based on maintenance and depreciation settings embedded in the FCI parameter. Variations in facility-dependent costs have a greater impact on the MSP than equipment costs, ranging from 2.11 to 2.32.

The same input parameters (glucose and NaOH quantities and costs, externalities, tax rate, discount rate, equipment costs and facility-dependent costs) with the same ranges indicated in the previous paragraph are considered in an uncertainty analysis to evaluate the probability of obtaining a positive NPV. A Monte Carlo simulation was performed using Microsoft Excel and Python to generate 10,000 iterations. Each iteration represents a scenario based on a combination of the modified parameters following a PERT distribution with the ranges indicated in the sensitivity analysis for each parameter. As shown in Fig. 7, the probability of obtaining a positive NPV is 85.24 %.

This result suggests that the project is highly likely to be profitable and worth investing in, given the variables analysed. However, further analyses are necessary to assess the uncertainty associated with future costs and revenues, as well as the potential to introduce investment flexibility not only in year 0 but throughout the project's life cycle. This flexibility should account for market conditions, process optimization and externalities. These aspects will be discussed in the following section.

3.5. Investment flexibility and learning potential

To address dynamic market and technological uncertainty, incorporating learning curves and Real Option Analysis (ROA) can enhance the evaluation of low-TRL technologies. Learning curves estimate how production costs decline with accumulated experience (Thomassen et al., 2020; Vasilakou et al., 2023a, 2023b), while ROA quantifies the value of expanding, contracting or delaying investments in response to these trends (Compernolle et al., 2017; Welkenhuysen et al., 2017).

For LA production, learning effects can be inferred from the bioplastics sector, where PLA production capacity has doubled approximately every four years since 2007 (Börner and Zinn, 2024). Applying similar learning effects allows future cost reductions to be projected and investment timing to be optimised. ROA enables investors to postpone projects until production costs fall below a target level or to scale up operations once market conditions are favourable. The combination of learning curves and ROA can enhance the assessment of emerging technologies, as the former provides dynamic inputs of projected cost reductions over time, whereas the latter uses these inputs to inform strategic decisions at critical points in the project lifecycle. The integration of ROA and learning curves has rarely been explored, with some studies focusing on renewable energy (Gazheli and van den Bergh, 2018) and fuel cells (Johannes Poulsen and Aarup, 2016). This integration can be applied to the case study presented herein. For instance, learning curves can model the decline in CAPEX and raw material costs (e.g., glucose and NaOH), whereas ROA can evaluate the timing and scale of investment based on projected cost trajectories and market uncertainties.

Discounting also plays a critical role in assessing risk under uncertainty. In ROA, different discount rates can be applied to various cash flows to reflect their relative risks, with revenues discounted more heavily than stable costs (De Reyck et al., 2008; Mathews et al., 2007). This approach allows more accurate valuations that reflect both time value and strategic flexibility (Samis et al., 2005).

3.6. Limitations and future perspectives

This study provides a comprehensive assessment of LA production using fiber sludge, from pilot to industrial scale, integrating environmental and economic impacts through the monetary valuation of externalities. However, several limitations must be acknowledged which could inform future research directions.

One key limitation relates to the scalability of pilot scale results. Although the six-tenth rule was applied to estimate equipment costs, this approximation does not fully capture the operational complexities, optimisation options or non-linearities encountered at full industrial scale (Pizzol et al., 2020). This study aims to provide a rapid extrapolation of external costs between pilot and industrial scale considering a proportional scaling of environmental impacts. However, raw materials and energy consumption may differ significantly in large scale settings, potentially affecting both costs and environmental impacts. Future studies should address this limitation by performing complex models that incorporate scaling exponents into digital twins of plants, enabling sensitivity analysis for capacity changes and prospective environmental assessments including external costs (Schweidtmann et al., 2021; Sustainability Directory, 2025). In addition, while the fermentation model integrates Monod-type kinetic equations derived from experimental data and validated at pilot scale, future work should include recalibration of the kinetic parameters and incorporation of thermodynamic refinements to improve prediction accuracy under industrial conditions and alternative process configurations.

Another aspect that must be considered is the feedstock composition.

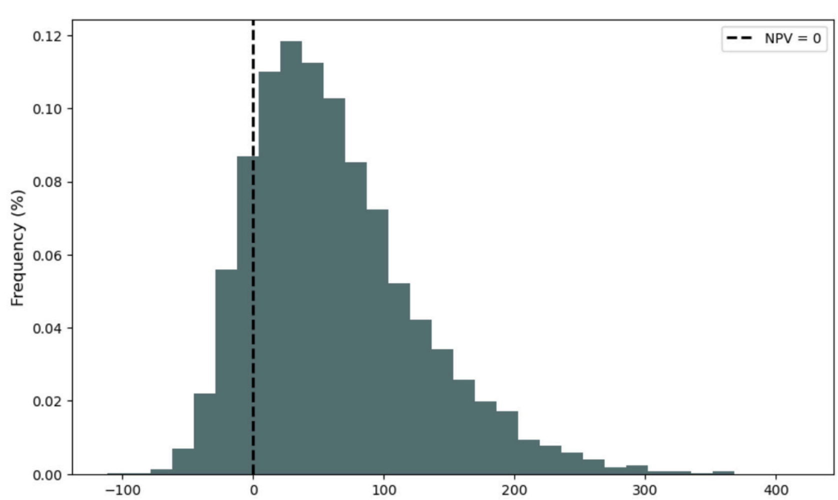

Fig. 7. Uncertainty analysis to evaluate the probability to obtain a positive Net Present Value in a Monte Carlo simulation (10,000 iterations).

In this study, it is assumed that fiber sludge composition is constant, but in practice, their characteristics can vary depending on pulp type and processing conditions which can influence hydrolysis efficiency, enzyme demand and fermentation performance, with effects on LA yields and productivity (Li et al., 2021a, 2021b). Feedstock availability must also be considered to cover production demands at industrial scale and ensure a responsible management of the biomass (Ghani et al., 2025). This study considers global fiber sludge availability to cover LA production, which is around 14,000 kt per year (Quintana et al., 2024). Future studies should incorporate feedstock variability and availability scenarios to better reflect real-world conditions, for instance, by considering geospatial models as in Vasilakou et al. (2023a, 2023b).

Regarding economic modelling, uncertainties associated with raw materials, equipment costs and market prices for bio-based LA production at early design stage are significant. While sensitivity and uncertainty analyses are included in this study, future work should explore stochastic or probabilistic methods to quantify uncertainties more robustly. Moreover, scenario modelling integrating carbon pricing, policy incentives or biorefinery integration could help assess the robustness of the business case under evolving market and regulatory conditions (Wenger et al., 2024).

Finally, while this study focused on environmental and economic aspects, future research should also consider social dimensions through social LCA (S-LCA) and circularity indicators to provide a more holistic evaluation (Alejandrino et al., 2021; Ferreira et al., 2022).

4. Conclusions

The increasing demand for sustainable alternatives to fossil-based materials calls for quantitative frameworks that integrate environmental and economic assessments. This study addresses that need by developing and applying an integrated framework to assess the production of bio-based lactic acid (LA) from fiber sludge, a low-cost residue from the pulp and paper industry. The approach combines process modelling, Techno-Economic Analysis (TEA), Life Cycle Assessment (LCA) and environmental Life Cycle Costing (eLCC), providing a unified indicator that incorporates external costs into the economic evaluation, the Minimum Selling Price (MSP).

Results from pilot scale modelling scaled to industrial capacity indicate an Optimum Plant Capacity of 50 kilotonnes per year and a MSP of 1.71 €/kg, which increases to 2.04–2.46 €/kg when environmental externalities are monetised and internalised in the financial analysis. Environmental assessment revealed a Global Warming Potential (GWP) of 3.87 kg CO_2-eq per kg LA, associated with enzyme production and fermentation. Sensitivity and uncertainty analyses confirmed that externalities and discount rate assumptions are the most influential factors for economic viability, with an 85 % probability of achieving a positive Net Present Value, indicating a high likelihood of project profitability under realistic variations in technical and economic conditions.

Beyond the numerical outcomes, this study demonstrates the importance and practicality of monetising environmental impacts into financial analysis for emerging bio-based technologies. By linking environmental and economic dimensions through the MSP including externalities, the framework allows direct and transparent comparison between alternatives, supporting evidence-based policy and investment decisions. The method is general and adaptable to other bio-based systems where pilot scale data are available, providing a structured approach to quantify trade-offs and identify the cost implications of sustainability improvements.

The study also highlights current limitations related to linear upscaling assumptions, variability in feedstock composition and differences in impact assessment methodologies. Future research should focus on refining scalability models using digital twins, incorporating feedstock availability and regional scenarios, and adopting advanced financial tools to capture investment flexibility under uncertainty. These developments would enhance the predictive accuracy and decision-support potential of integrated sustainability assessments, ultimately facilitating the sustainable scale-up of circular bioeconomy processes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2025.108291.

Data availability

Data will be made available on request.

References

Ahmad, A., Javed, M.H., Musharavati, F., Khan, M.I., Al-Muhtaseb, A.H., Naqvi, M., Abu, R., Anjum, M.W., Rehan, M., Asam, Z.U.Z., Hussain, R., Nizami, A.S., 2025. Achieving circular economy through sustainable biofertilizer production from mixed municipal waste: a life cycle analysis approach. Biomass Convers. Biorefinery 1–19. https://doi.org/10.1007/S13399-025-06709-Z/TABLES/8.

Albizzati, P.F., Tonini, D., Astrup, T.F., 2021. High-value products from food waste: an environmental and socio-economic assessment. Sci. Total Environ. 755, 142466. https://doi.org/10.1016/j.scitotenv.2020.142466.

Alejandrino, C., Mercante, I., Bovea, M.D., 2021. Life cycle sustainability assessment: lessons learned from case studies. Environ. Impact Assess. Rev. 87, 106517. https://doi.org/10.1016/J.EIAR.2020.106517.

Alves de Oliveira, R., Komesu, A., Vaz Rossell, C.E., Maciel Filho, R., 2018. Challenges and opportunities in lactic acid bioprocess design—from economic to production aspects. Biochem. Eng. J. 133, 219–239. https://doi.org/10.1016/J.BEJ.2018.03.003.

Amadei, A.M., De Laurentiis, V., Sala, S., 2021. A review of monetary valuation in life cycle assessment: state of the art and future needs. J. Clean. Prod. 329, 129668. https://doi.org/10.1016/J.JCLEPRO.2021.129668.

Bianchi, M., Cascavilla, A., Diaz, J.C., Ladu, L., Blazquez, B.P., Pierre, M., Staffieri, E., Yilan, G., 2024. Circular bioeconomy: A review of empirical practices across implementation scales. J. Clean. Prod. 477, 143816. https://doi.org/10.1016/j.jclepro.2024.143816.

Börner, T., Zinn, M., 2024. Key challenges in the advancement and industrialization of biobased and biodegradable plastics: a value chain overarching perspective. Front. Bioeng. Biotechnol. 12, 1406278. https://doi.org/10.3389/FBIOE.2024.1406278/BIBTEX.

Brobbey, M.S., Louw, J.P., Louw, J., Görgens, J.F., 2024. Effect of production scale on the techno-economic viability and environmental life cycle analysis of lactic acid production in a sugarcane biorefinery. Food Bioprod. Process. 148, 269–284. https://doi.org/10.1016/J.FBP.2024.09.020.

CEPCI, 2024. The Chemical Engineering Plant Cost Index ® - Chemical Engineering. https://www.chemengonline.com/pci-home.

Chemanalyst, 2024. Lactic acid market analysis. https://www.chemanalyst.com/industry-report/lactic-acid-market-3078.

Chong, T.Y., Cheah, S.A., Ong, C.T., Wong, L.Y., Goh, C.R., Tan, I.S., Foo, H.C.Y., Lam, M.K., Lim, S., 2020. Techno-economic evaluation of third-generation bioethanol production utilizing the macroalgae waste: A case study in Malaysia. Energy 210, 118491. https://doi.org/10.1016/J.ENERGY.2020.118491.

Compernolle, T., Welkenhuysen, K., Huisman, K., Piessens, K., Kort, P., 2017. Off-shore enhanced oil recovery in the North Sea: the impact of price uncertainty on the investment decisions. Energy Policy 101, 123–137. https://doi.org/10.1016/J.ENPOL.2016.11.034.

Daful, A.G., Loridon, M., Chandraratne, M.R., 2023. Lactic acid production from lignocellulosic biomass. In: From Biomass to Biobased Products. https://doi.org/10.5772/INTECHOPEN.112739.

Damodaran, A., 2025. Betas by Sector. https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/Betas.html.

De Reyck, B., Degraeve, Z., Vandenborre, R., 2008. Project options valuation with net present value and decision tree analysis. Eur. J. Oper. Res. 184 (1), 341–355. https://doi.org/10.1016/J.EJOR.2006.07.047.

de Vries, J., de Bruyn, S., Juijn, D., Bijleveld, M., van der Giesen, C., Korteland, M., van Santen, W., Pápai, S., 2024. Environmental prices handbook 2024: EU27 version. CE Delft. https://cedelft.eu/publications/environmental-prices-handbook-2023/.

Eikelboom, M., do Carmo Precci Lopes, A., Silva, C.M., de Ávila Rodrigues, F., Zanuncio, A.J.V., Zanuncio, J.C., 2018. A multi-criteria decision analysis of management alternatives for anaerobically digested Kraft pulp mill sludge. PLoS One 13 (1), e0188732. https://doi.org/10.1371/JOURNAL.PONE.0188732.

e-Industria, 2024. Precios de Hidroxido de sodio (Sosa caustica). https://www.eindustria.com/productos/hidroxido-de-sodio-sosa-caustica-168010455066/precios.htm.

European Bioplastics, 2024. Bioplastics market development update 2024. https://www.european-bioplastics.org/bioplastics-market-development-update-2024.

European Central Bank, 2025. US dollar (USD). https://www.ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/html/eurofxref-graph-usd.en.html.

European Commission, 2014. Guide to Cost-benefit Analysis of Investment Projects: Economic appraisal tool for Cohesion Policy 2014-2020. Publications Office of the European Union (Issue December). https://doi.org/10.2776/97516.

European Commission, 2018. A sustainable bioeconomy for Europe: strengthening the connection between economy, society and the environment, 107. https://doi.org/10.2777/478385.

Fazio, S., Biganzoli, F., De Laurentis, V., Zampori, L., Sala, S., Diaconu, E., 2018. Supporting information to the characterisation factors of recommended EF Life Cycle Impact Assessment methods. https://doi.org/10.2760/002447.

Fei, Q., Liang, B., Tao, L., Tan, E.C.D., Gonzalez, R., Henard, C.A., Guarnieri, M.T., 2020. Biological valorization of natural gas for the production of lactic acid: techno-economic analysis and life cycle assessment. Biochem. Eng. J. 158, 107500. https://doi.org/10.1016/J.BEJ.2020.107500.

Ferdous, J., Bensebaa, F., Pelletier, N., 2023. Integration of LCA, TEA, process simulation and optimization: A systematic review of current practices and scope to propose a framework for pulse processing pathways. J. Clean. Prod. 402, 136804. https://doi.org/10.1016/J.JCLEPRO.2023.136804.

Ferreira, V., Fabregat-Aibar, L., Pié, L., Terceño, A., 2022. Research trends and hotspots in bioeconomy impact analysis: a study of economic, social and environmental impacts. Environ. Impact Assess. Rev. 96, 106842. https://doi.org/10.1016/J.EIAR.2022.106842.

Gazheli, A., van den Bergh, J., 2018. Real options analysis of investment in solar vs. wind energy: diversification strategies under uncertain prices and costs. Renew. Sust. Energ. Rev. 82, 2693–2704. https://doi.org/10.1016/j.rser.2017.09.096.

Gezae Daful, A., Görgens, J.F., 2017. Techno-economic analysis and environmental impact assessment of lignocellulosic lactic acid production. Chem. Eng. Sci. 162, 53–65. https://doi.org/10.1016/J.CES.2016.12.054.

Ghani, H.U., Ilvesniemi, H., Leinonen, I., Ruuttunen, K., Khan, M.M.H., Oinas, P., Anttila, P., 2025. Evaluating sawdust-based bioethanol and pyrolysis products in the European Union: feedstock availability, life cycle assessment, and techno-economic analysis. Environ. Impact Assess. Rev. 115, 108035. https://doi.org/10.1016/J.EIAR.2025.108035.

Glaser, R., Venus, J., 2017. Model-based characterisation of growth performance and l-lactic acid production with high optical purity by thermophilic Bacillus coagulans in a lignin-supplemented mixed substrate medium. New Biotechnol. 37, 180–193. https://doi.org/10.1016/J.NBT.2016.12.006.

González-García, S., Argiz, L., Míguez, P., Gullón, B., 2018. Exploring the production of bio-succinic acid from apple pomace using an environmental approach. Chem. Eng. J. 350, 982–991. https://doi.org/10.1016/J.CEJ.2018.06.052.

Grand View Research, 2025. Lactic Acid Market Size (2025–2033). https://www.grandviewresearch.com/industry-analysis/lactic-acid-and-poly-lactic-acid-market.

Grilli, G., Cantillo, T., Turner, K., Erazo, J., Murcia López, M.A., Valle Parra, J.S., Cardona, F.G., Ferrini, S., 2024. A decision support procedure for the bioeconomy transition: A Colombian case study. J. Environ. Manag. 352, 120042. https://doi.org/10.1016/J.JENVMAN.2024.120042.

Hansson, J., Klugman, S., Lönnqvist, T., Elginoz, N., Granacher, J., Hasselberg, P., Hedman, F., Efraimsson, N., Johnsson, S., Poulikidou, S., Safarian, S., Tjus, K., 2024. Biodiesel from bark and black liquor—A techno-economic, social, and environmental assessment. Energies 17 (1), 99. https://doi.org/10.3390/EN17010099/S1.

Holden, N.M., Neill, A.M., Stout, J.C., O'Brien, D., Morris, M.A., 2023. Biocircularity: a framework to define sustainable, circular bioeconomy. Circ. Econ. Sustain. 3 (1), 77–91. https://doi.org/10.1007/S43615-022-00180-Y/TABLES/2.

Huijbregts, M.A.J., Steinmann, Z.J.N., Elshout, P.M.F., Stam, G., Verones, F., Vieira, M., Zijp, M., Hollander, A., van Zelm, R., 2017. ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. Int. J. Life Cycle Assess. 22 (2), 138–147. https://doi.org/10.1007/S11367-016-1246-Y/TABLES/2.

Humbird, D., Davis, R., Tao, L., Kinchin, C., Hsu, D., Aden, A., Schoen, P., Lukas, J., Olthof, B., Worley, M., Sexton, D., Dudgeon, D., 2011. Process design and economics for conversion of lignocellulosic biomass to ethanol. In: NREL Technical Report NREL/TP-5100-51400, 303, pp. 275–3000. May 2011. http://www.nrel.gov/docs/fy11osti/51400.pdf%5Cnpapers2://publication/uuid/49A5007E-9A58-4E2B-AB4E-4A4428F6EA66.

Hunkeler, D., Lichtenvort, K., Rebitzer, G., 2008. Environmental life cycle costing. In: Environmental Life Cycle Costing. CRC Press. https://doi.org/10.1201/9781420054736.

Ibáñez, J., Pérez-de-Mora, A., Santiago-Herrera, M., Belloncle, B., de Wilde, H., Martel-Martín, S., Blanco-Alcántara, D., Barros, R., 2024. Environmental and socio-economic evaluation of a groundwater bioremediation technology using social cost-benefit analysis: application to an in-situ metal(loid) precipitation case study. Sci. Total Environ. 954, 176720. https://doi.org/10.1016/j.scitotenv.2024.176720.

INE, I. N. de E, 2020. Survey on Water Supply and Sewerage. https://www.ine.es/en/prensa/essa_2020_en.pdf.

Intelligen Inc, 2024. SuperPro Designer. https://www.intelligen.com/products/superpro-overview/.

Ioannidou, S.M., Ladakis, D., Moutousidi, E., Dheskali, E., Kookos, I.K., Câmara-Salim, I., Moreira, M.T., Koutinas, A., 2022. Techno-economic risk assessment, life cycle analysis and life cycle costing for poly(butylene succinate) and poly(lactic acid) production using renewable resources. Sci. Total Environ. 806. https://doi.org/10.1016/j.scitotenv.2021.150594.

Ioannidou, S.M., López-Gómez, J.P., Venus, J., Valera, M.A., Eßmann, V., Alegria-Dallo, I., Kookos, I.K., Koutinas, A., Ladakis, D., 2023. Techno-economic evaluation and life cycle assessment for sustainable alternative biorefinery concepts using the organic fraction of municipal solid waste. Green Chem. 25 (11), 4482–4500. https://doi.org/10.1039/D3GC00244F.

ISO, 2006a. ISO 14040:2006 - Environmental management — Life cycle assessment — Principles and framework. https://www.iso.org/standard/37456.html.

ISO, 2006b. ISO 14044:2006 - Environmental management — Life cycle assessment — Requirements and guidelines. https://www.iso.org/standard/38498.html.

Jambeck, J.R., Walker-Franklin, I., 2023. The impacts of plastics' life cycle. One Earth 6 (6), 600–606. https://doi.org/10.1016/J.ONEEAR.2023.05.015.

Johannes Poulsen, C., Aarup, J., 2016. Valuing Learning Effects as a Real Option. Application to PEM Fuel Cells in the Indian Telco Market.

Kim, H., Sang, B.I., Tsapekos, P., Angelidaki, I., Alvarado-Morales, M., 2023. Techno-economic analysis of succinic acid production from sugar-rich wastewater. Energies 16 (7), 3227. https://doi.org/10.3390/EN16073227/S1.

Kloepffer, W., 2008. State-of-the-art in life cycle Sustainability assessment (LCSA) life cycle Sustainability assessment of products. Int. J. LCA 13 (2), 89–95.

Kosamia, N., Sanchez, A., Rakshit, S., 2023. Scenario-based life cycle assessment and environmental monetary valuation of biosuccinic acid production from lignocellulosic biomass. Ind. Crop. Prod. 202, 117101. https://doi.org/10.1016/J.INDCROP.2023.117101.

KPMG, 2025. Latest risk-free rate and market risk premium. https://atlas.kpmg.com/de/en/deal-advisory-services/cost-of-capital-and-multiples/market-risk-premium-and-risk-free-rate.

Kwan, T.H., Hu, Y., Lin, C.S.K., 2018. Techno-economic analysis of a food waste valorisation process for lactic acid, lactide and poly(lactic acid) production. J. Clean. Prod. 181, 72–87. https://doi.org/10.1016/j.jclepro.2018.01.179.

Ladu, L., Morone, P.P., 2021. Holistic approach in the evaluation of the sustainability of bio-based products: an integrated assessment tool. Sustainable Prod. Consumption 28. https://doi.org/10.1016/J.SPC.2021.07.006, 911-924e6.

Lange, L., Connor, K.O., Arason, S., Bundgård-Jørgensen, U., Canalis, A., Carrez, D., Gallagher, J., Gøtke, N., Huyghe, C., Jarry, B., Llorente, P., Marinova, M., Martins, L. O., Mengal, P., Paiano, P., Panoutsou, C., Rodrigues, L., Stengel, D.B., van der Meer, Y., Vieira, H., 2021. Developing a sustainable and circular bio-based economy in EU: by partnering across sectors, upscaling and using new knowledge faster, and for the benefit of climate, Environment & Biodiversity, and people & business. Front. Bioeng. Biotechnol. 8, 619066. https://doi.org/10.3389/FBIOE.2020.619066/BIBTEX.

Li, Y., Bhagwat, S.S., Cortés-Penã, Y.R., Ki, D., Rao, C.V., Jin, Y.S., Guest, J.S., 2021a. Sustainable lactic acid production from lignocellulosic biomass. ACS Sustain. Chem. Eng. 9 (3), 1341–1351. https://doi.org/10.1021/acssuschemeng.0c08055.

Li, J., Shi, S., Wang, Y., Jiang, Z., 2021b. Integrated production of optically pure l-lactic acid from paper mill sludge by simultaneous saccharification and co-fermentation (SSCF). Waste Manag. 129, 35–46. https://doi.org/10.1016/J.WASMAN.2021.05.008.

López-Gómez, J.P., Alexandri, M., Schneider, R., Latorre-Sánchez, M., Coll Lozano, C., Venus, J., 2020. Organic fraction of municipal solid waste for the production of L-lactic acid with high optical purity. J. Clean. Prod. 247, 119165. https://doi.org/10.1016/J.JCLEPRO.2019.119165.

Macias Aragonés, M., Arroyo Torralvo, F., 2024. How to select the best approach for circular economy assessment? 3D positioning framework, decision support tool and critical analysis for bio-based systems. Environ. Impact Assess. Rev. 106, 107493. https://doi.org/10.1016/J.EIAR.2024.107493.

Mahmud, R., Moni, S.M., High, K., Carbajales-Dale, M., 2021. Integration of techno-economic analysis and life cycle assessment for sustainable process design – A review. J. Clean. Prod. 317, 128247. https://doi.org/10.1016/J.JCLEPRO.2021.128247.

Mailaram, S., Narisetty, V., Maity, S.K., Gadkari, S., Thakur, V.K., Russell, S., Kumar, V., 2023. Lactic acid and biomethane production from bread waste: a techno-economic and profitability analysis using pinch technology. Sustain. Energy Fuels 7 (13), 3034–3046. https://doi.org/10.1039/D3SE00119A.

Malacara-Becerra, A., Melchor-Martínez, E.M., Sosa-Hernández, J.E., Riquelme-Jiménez, L.M., Mansouri, S.S., Iqbal, H.M.N., Parra-Saldívar, R., 2022. Bioconversion of corn crop residues: lactic acid production through simultaneous Saccharification and fermentation. Sustainability 14 (19), 11799. https://doi.org/10.3390/SU141911799.

Manandhar, A., Shah, A., 2020. Techno-economic analysis of bio-based lactic acid production utilizing corn grain as feedstock. Processes 8 (2). https://doi.org/10.3390/pr8020199.

Mandegari, M.A., Farzad, S., van Rensburg, E., Görgens, J.F., 2017. Multi-criteria analysis of a biorefinery for co-production of lactic acid and ethanol from sugarcane lignocellulose. Biofuels Bioprod. Biorefin. 11 (6), 971–990. https://doi.org/10.1002/BBB.1801.

Manfredi, S., Allacker, K., Chomkhamsri, K., Pelletier, N., Maia De Souza, D., 2012. Product Environmental Footprint (PEF) Guide. European Commission, Joint Research Centre.
Massarutto, A., 2024. Monetary evaluation in LCA of WM: everything engineers always wanted to know about it (but were afraid to ask). Waste Manag. 178, 12–25. https://doi.org/10.1016/j.wasman.2024.02.018.
Mathews, S., Datar, V., Johnson, B., 2007. A practical method for valuing real options: the Boeing approach. J. Appl. Corp. Financ. 19 (2), 95–104. https://doi.org/10.1111/J.1745-6622.2007.00140.X.
Mesa, J.A., Sierra-Fontalvo, L., Ortegon, K., Gonzalez-Quiroga, A., 2024. Advancing circular bioeconomy: A critical review and assessment of indicators. Sustainable Prod. Consumption 46, 324–342. https://doi.org/10.1016/J.SPC.2024.03.006.
Munagala, M., Shastri, Y., Nalawade, K., Konde, K., Patil, S., 2021. Life cycle and economic assessment of sugarcane bagasse valorization to lactic acid. Waste Manag. 126, 52–64. https://doi.org/10.1016/J.WASMAN.2021.02.052.
Musharavati, F., Ahmad, A., Javed, M.H., Sajid, K., Naqvi, M., 2024a. Sustainability assessment of biofuel and value-added product from organic fraction of municipal solid waste. Environ. Res. 246, 118121. https://doi.org/10.1016/J.ENVRES.2024.118121.
Musharavati, F., Ahmad, A., Javed, M.H., Sajid, K., Nizami, A.S., 2024b. Advancing biorefinery technologies through transesterification and hydrothermal liquefaction for biodiesel and bioproducts production. J. Taiwan Inst. Chem. Eng. 105661. https://doi.org/10.1016/J.JTICE.2024.105661.
Musharavati, F., Ahmad, A., Javed, M.H., Sajid, K., Nizami, A.-S., 2025. Advancing biohydrogen production from organic fraction of municipal solid waste through thermal liquefaction. Int. J. Hydrog. Energy 137, 870–881. https://doi.org/10.1016/j.ijhydene.2024.05.144.
OECD, 2022. Global plastics outlook: economic drivers. In: Environmental Impacts and Policy Options.. https://doi.org/10.1787/de747aef-en.
Ögmundarson, Ó., Sukumara, S., Herrgård, M.J., Fantke, P., 2020a. Combining environmental and economic performance for bioprocess optimization. Trends Biotechnol. 38 (11), 1203–1214. https://doi.org/10.1016/J.TIBTECH.2020.04.011.
Ögmundarson, Ó., Sukumara, S., Laurent, A., Fantke, P., 2020b. Environmental hotspots of lactic acid production systems. GCB Bioenergy 12 (1), 19–38. https://doi.org/10.1111/gcbb.12652.
Olszewska-Widdrat, A., Alexandri, M., López-Gómez, J.P., Schneider, R., Mandl, M., Venus, J., 2019. Production and purification of l-lactic acid in lab and pilot scales using sweet Sorghum juice. Fermentation 5 (2), 36. https://doi.org/10.3390/FERMENTATION5020036.
Olszewska-Widdrat, A., Xiros, C., Wallenius, A., Schneider, R., da Costa, Rios, Pereira, L. P., Venus, J., 2023. Bioprocess optimization for lactic and succinic acid production from a pulp and paper industry side stream. Front. Bioeng. Biotechnol. 11, 1176043. https://doi.org/10.3389/FBIOE.2023.1176043/BIBTEX.
Pérez-Almada, D., Galán-Martín, Á., Contreras, M., Castro, E., 2023. Integrated techno-economic and environmental assessment of biorefineries: review and future research directions. Sustainable Energy Fuels 7 (17), 4031–4050. https://doi.org/10.1039/D3SE00405H.
Peters, A.M., Timmerhaus, K., West, R.E., 2003. Plant design and economics for chemical engineers, p. 1. https://www.just.edu.jo/FacultiesandDepartments/FacultyofEngineering/Departments/ChemicalEngineering/SiteAssets/Pages/Courses/ABET-Syllabi-ChE575.pdf.
Pigou, A.C., 2017. The economics of welfare. In: The Economics of Welfare. Taylor and Francis. https://doi.org/10.4324/9781351304368/ECONOMICS-WELFARE-ARTHUR-PIGOU.
Pizzol, M., Weidema, B., Brandão, M., Osset, P., 2015. Monetary valuation in life cycle assessment: a review. J. Clean. Prod. 86, 170–179. https://doi.org/10.1016/J.JCLEPRO.2014.08.007.
Pizzol, M., Sacchi, R., Köhler, S., Anderson Erjavec, A., 2020. Non-linearity in the life cycle assessment of scalable and emerging technologies. Frontiers in Sustainability 1, 611593. https://doi.org/10.3389/FRSUS.2020.611593/BIBTEX.
Pleissner, D., Neu, A.K., Mehlmann, K., Schneider, R., Puerta-Quintero, G.I., Venus, J., 2016. Fermentative lactic acid production from coffee pulp hydrolysate using Bacillus coagulans at laboratory and pilot scales. Bioresour. Technol. 218, 167–173. https://doi.org/10.1016/J.BIORTECH.2016.06.078.
PRé Sustainability, B.V., 2024. SimaPro | LCA software for informed changemakers. https://simapro.com/.https://simapro.com/.
PWC, 2024. Corporate - Taxes on Corporate Income. https://taxsummaries.pwc.com/spain/corporate/taxes-on-corporate-income.
Quintana, E., Valls, C., Roncero, M.B., 2024. Valorization of waste paper sludge as a sustainable source for packaging applications. Polym. Bull. 81 (10), 9321–9345. https://doi.org/10.1007/S00289-024-05138-8/FIGURES/8.
Rajendran, N., Han, J., 2023. Techno-economic analysis and life cycle assessment of poly (butylene succinate) production using food waste. Waste Manag. 156, 168–176. https://doi.org/10.1016/J.WASMAN.2022.11.037.
Rödger, J.M., Kjær, L.L., Pagoropoulos, A., 2018. Life cycle costing: an introduction. In: Life Cycle Assessment: Theory and Practice, 373–399. https://doi.org/10.1007/978-3-319-56475-3_15.
Salvador, G.V., Salim, V.M.M., Toniolo, F.S., 2022. Sustainability assessment of a decentralized green diesel production in small-scale biorefineries. Biofuels Bioprod. Biorefin. 16 (6), 1527–1550. https://doi.org/10.1002/BBB.2419.
Samis, M., Davis, G.A., Laughton, D., Poulin, R., 2005. Valuing uncertain asset cash flows when there are no options: A real options approach. Res. Policy 30 (4), 285–298. https://doi.org/10.1016/J.RESOURPOL.2006.03.003.
Schweidtmann, A.M., Esche, E., Fischer, A., Kloft, M., Repke, J.U., Sager, S., Mitsos, A., 2021. Machine learning in chemical engineering: A perspective. Chem. Ing. Tech. 93 (12), 2029–2039. https://doi.org/10.1002/CITE.202100083.
Siedlecka, E., Siedlecki, J., 2021. Influence of valorization of sewage sludge on energy consumption in the drying process. Energies 14 (15), 4511. https://doi.org/10.3390/en14154511.
Sinnott, R., Towler, G., 2019. Chemical engineering design. In: Chemical Engineering Design: SI Edition. Elsevier. https://doi.org/10.1016/B978-0-08-102599-4.09980-X.
Suresh, P., Malina, R., Staples, M.D., Lizin, S., Olcay, H., Blazy, D., Pearlson, M.N., Barrett, S.R.H., 2018. Life cycle greenhouse gas emissions and costs of production of diesel and jet fuel from municipal solid waste. Environ. Sci. Technol. 52 (21), 12055–12065. https://doi.org/10.1021/ACS.EST.7B04277/ASSET/IMAGES/LARGE/ES-2017-04277N_0003.JPEG.
Sustainability Directory, 2025, March 26. How Can Digital Twins Be Used For Sustainability Assessments? https://sustainability-directory.com/question/how-can-digital-twins-be-used-for-sustainability-assessments.
Tang, R., Jalel, N.A., Mirzai, A.R., Leigh, J.R., 1992. Identification and modelling of fermentation process using MATLAB: A case study. IFAC Proc. 25 (2), 331–334. https://doi.org/10.1016/S1474-6670(17)50384-5.
Thomassen, G., Van Dael, M., Van Passel, S., 2018. The potential of microalgae biorefineries in Belgium and India: an environmental techno-economic assessment. Bioresour. Technol. 267, 271–280. https://doi.org/10.1016/J.BIORTECH.2018.07.037.
Thomassen, G., Van Dael, M., Van Passel, S., You, F., 2019. How to assess the potential of emerging green technologies? Towards a prospective environmental and techno-economic assessment framework. In: Green Chemistry, 21. Royal Society of Chemistry, pp. 4868–4886. https://doi.org/10.1039/c9gc02223f. Issue 18.
Thomassen, G., Van Passel, S., Dewulf, J., 2020. A review on learning effects in prospective technology assessment. Renew. Sust. Energ. Rev. 130, 109937. https://doi.org/10.1016/J.RSER.2020.109937.
Trading Economics, 2025. Tax Rates List - European Countries. https://es.tradingeconomics.com/country-list/corporate-tax-rate?continent=europe.
Tradingeconomics, 2025. Germany 10-Year Bond Yield. https://tradingeconomics.com/germany/government-bond-yield.
Van Schoubroeck, S., Thomassen, G., Van Passel, S., Malina, R., Springael, J., Lizin, S., Venditti, R.A., Yao, Y., Van Dael, M., 2021. An integrated techno-sustainability assessment (TSA) framework for emerging technologies. Green Chem. 23 (4), 1700–1715. https://doi.org/10.1039/d1gc00036e.
Vargas-Farias, A., Santos, J., Stipanovic, I., Hartmann, A., 2026. Anticipating uncertainty in infrastructure LCC, LCA, and S-LCA: A systematic, context-aware early identification framework. Environ. Impact Assess. Rev. 117, 108175. https://doi.org/10.1016/J.EIAR.2025.108175.
Vasilakou, K., Nimmegeers, P., Billen, P., Van Passel, S., 2023a. Geospatial environmental techno-economic assessment of pretreatment technologies for bioethanol production. Renew. Sust. Energ. Rev. 187, 113743. https://doi.org/10.1016/J.RSER.2023.113743.
Vasilakou, K., Nimmegeers, P., Thomassen, G., Billen, P., Van Passel, S., 2023b. Assessing the future of second-generation bioethanol by 2030 – A techno-economic assessment integrating technology learning curves. Appl. Energy 344, 121263. https://doi.org/10.1016/j.apenergy.2023.121263.
Vega, G.C., Voogt, J., Sohn, J., Birkved, M., Olsen, S.I., 2020. Assessing new biotechnologies by combining TEA and TM-LCA for an efficient use of biomass resources. Sustainability 12 (9), 3676. https://doi.org/10.3390/SU12093676.
Welkenhuysen, K., Rupert, J., Compernolle, T., Ramirez, A., Swennen, R., Piessens, K., 2017. Considering economic and geological uncertainty in the simulation of realistic investment decisions for CO2-EOR projects in the North Sea. Appl. Energy 185, 745–761. https://doi.org/10.1016/j.apenergy.2016.10.105.
Wenger, J., Jäger, G., Näyhä, A., Plakolb, S., Krassnitzer, P.E., Stern, T., 2024. Exploring potential diffusion pathways of biorefinery innovations—an agent-based simulation approach for facilitating shared value creation. Bus. Strateg. Environ. 33 (5), 4652–4693. https://doi.org/10.1002/BSE.3671.
Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., Weidema, B., 2016. The ecoinvent database version 3 (part I): overview and methodology. Int. J. Life Cycle Assess. 21 (9), 1218–1230. https://doi.org/10.1007/s11367-016-1087-8.
Wunderlich, J., Armstrong, K., Buchner, G.A., Styring, P., Schomäcker, R., 2021. Integration of techno-economic and life cycle assessment: defining and applying integration types for chemical technology development. J. Clean. Prod. 287. https://doi.org/10.1016/j.jclepro.2020.125021.
Yeboah, W.O., Kwofie, E.M., Wang, D., 2022. Circular bioeconomy potential of rice husk as a bioplastic resource: techno-environmental assessment. Bioresour. Technol. Rep. 20, 101248. https://doi.org/10.1016/j.biteb.2022.101248. October.
Zhan, Z., Stokoe, P., Gonguet, F., Wendling, C., Haščič, I., Mante, F., Rodríguez, M.C., 2023. Chapter 5 carbon pricing around the World. In: Data for a Greener World: A Guide for Practitioners and Policymakers. International Monetary Fund. https://www.elibrary.imf.org/display/book/9798400217296/CH005.xml.
Zheng, J., Suh, S., 2019. Strategies to reduce the global carbon footprint of plastics. Nat. Clim. Chang. 9 (5), 374–378. https://doi.org/10.1038/s41558-019-0459-z.