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Nourishing sustainability innovation: Scientific trajectories in industrial protein research☆

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ABSTRACT

This paper investigates how distinct scientific trajectories inform sustainability-oriented innovation in the protein production sector. Focusing on USPTO patents in subclass A23J (1990–2015), we apply a two-step text analysis that links topic modeling of academic publications to the classification of patent texts. This method identifies four trajectories and evaluates their influence on follow-on innovation, with particular attention to citations from sustainability-related patents. The results reveal substantial heterogeneity: some trajectories, such as those centered on cellular and bioprocessing mechanisms, consistently generate sustainability spillovers, while others, such as protein chemistry, exhibit limited diffusion. These findings contribute to a view of science as a cognitive map that structures industrial research by making more explicit the underlying causal mechanisms that govern each trajectory, thereby shaping which domains are more likely to yield impactful and sustainability-aligned innovations.

1. Introduction

In its 2023 Climate Report for COP28 in Dubai, the Food and Agriculture Organization highlighted a fundamental dilemma in global protein production: the need to feed a growing population while reducing environmental impact. On the one hand, over 735 million people globally suffer from insufficient protein intake, particularly in the Global South. On the other hand, traditional protein production through livestock is one of the most resource-intensive processes in the food system, contributing disproportionately to greenhouse gas emissions, water depletion, and land use (NFNews, 2023). This tension between nutritional sufficiency and ecological degradation underpins a broader challenge faced by the food and agriculture sector, namely, how to foster sustainability transitions in a historically path-dependent and efficiency-constrained industry. Protein production indeed faces an inherent economic efficiency challenge, which limits the ability to exploit economies of scale and achieve greater productivity (Azarkamand et al., 2024).

Recent projections underscore the combined economic, technological, and societal potential of innovation in this field: According to the Boston Consulting Group, the alternative protein market, valued at roughly $5 billion in 2020, is expected to reach $290 billion by 2035. Yet unlocking this growth potential depends on advancing new scientific knowledge and overcoming traditional methods of production, in which firms play a central role through industrial research. The problem is complex since innovation in proteins is shaped by scientific trajectories that span areas such as enzymology, cellular biology, and structural chemistry, each carrying distinct implications for scalability, sustainability, and technological spillovers. This scenario offers a complex landscape at the intersection of research-based technological innovation and mission-oriented sustainability transitions.

Framed within the perspective of sustainability innovation, defined by van der Have and Rubalcaba (2016) as efforts that generate novel social or technological solutions to address grand societal challenges, these protein trajectories are better understood not simply as technological improvements, but as transformations guided by multi-level systemic change and institutional learning. They align with Sustainable Development Goals (SDGs) by tackling both nutritional equity and environmental resilience (Confraria et al., 2024). Sustainable innovation, particularly in domains such as alternative proteins, is driven by

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the evolution of underlying scientific trajectories rather than by firm-level strategies alone. These trajectories reflect cumulative, path-dependent developments shaped by codified scientific knowledge, institutional routines, and epistemic communities (Ciarli and Ràfols, 2019; Cattani and Malerba, 2021). Transitioning toward sustainability within these trajectories is especially complex, as it demands shifts not only in dominant design paradigms but also in the coordination of distributed actors across an innovation ecosystem (Malerba, 2002; Stilgoe et al., 2013). Moreover, such transitions are hindered by learning traps, lock-ins, and the temporal and spatial myopia that characterize organizational learning (Levinthal and March, 1993). Scientific search, particularly when oriented around long-term societal goals, is thus central to enabling transformative pathways (Nill and Kemp, 2009). This perspective calls for renewed attention to how upstream science evolves across time, how it interacts with adjacent technological domains, and how it translates into scalable outputs aligned with policy and market signals (Pel et al., 2020; Pandza and Ellwood, 2013).

This paper highlights a specific but underexplored component of sustainability-oriented innovation: how science can structure the technological search space for industrial R&D. Drawing on the idea of science as a map (Fleming and Sorenson, 2004), we ask: Which scientific trajectories in protein research are most likely to shape follow-on innovation, and to what extent are they associated with sustainability-oriented outcomes? From this perspective, science not only provides technical solutions but also transforms how problems are framed and how causal mechanisms are generalized, thereby altering the logic of search and exploration. Science enables codification by leveraging precise vocabularies and epistemic grammar, which clarify what can be replicated, reused, and scaled. This codification facilitates knowledge diffusion across organizational and sectoral boundaries, especially when innovation is still unfolding and uncertainty is high (Arora and Gambardella, 1994). By contrast, engineering-driven innovations, while critical for market implementation, are often more context-specific and embedded, thus contributing less to broad exploratory learning (Gruber et al., 2013). These features are particularly salient in our context, where causal mechanisms are still under investigation, and firms must navigate high uncertainty, fragmented knowledge, and the risk of technological myopia (Levinthal and March, 1993; Arora and Gambardella, 1994). Importantly, we also consider how the influence of science varies over time, recognizing that the role of a given trajectory may shift as it matures, interacts with adjacent domains, and accumulates institutional or market legitimacy (Malerba, 2002; Cattani and Malerba, 2021). Temporal shifts in trajectory influence are especially salient in mission-driven sectors like food, where emerging societal needs and policy priorities continuously reshape innovation demand (Confraria et al., 2024). This temporal lens aligns with recent calls to assess how scientific contributions to the SDGs evolve across different stages of technological development (Confraria et al., 2024).

We operationalize this question by analyzing how science-based vocabularies embedded in academic publications map onto patent portfolios within the alternative protein sector. Our objective is to construct a science-informed representation of technological search space and use it to identify distinct scientific trajectories. We then assess how these trajectories differ in their contribution to follow-on innovation, with particular attention to their propensity to support sustainability-oriented technological development, as proxied by SDG-related citations. We investigate these dynamics by focusing on patents filed between 1990 and 2015 at USPTO subclass A23J, which encompasses proteins for foodstuffs. By doing so, we narrow our analysis to innovations directly targeting food production, rather than broader value chain processes (Gentile et al., 2023). Our framework builds on Dosi's (1982) canonical distinction between technological paradigms and trajectories. The scientific map we construct from academic knowledge reflects the causal and heuristic logic of Dosi's paradigms, while our analysis of patent citations and dynamics traces how these paradigms unfold as technological trajectories in industrial applications.

Empirically, first, through a two-step machine learning approach, we identify scientific areas, defined as themes of industrial research reflecting shared epistemic logics, from food science publications (2000−2020). Second, we construct a domain-specific dictionary, which we employ to classify patent texts based on the presence of specialized terminology. This enables us to identify four key scientific trajectories in patents filed in the subclass AJ23 related to the protein innovation: (A) Animal-Based Protein, (B) Cellular and Bioprocessing, (C) Protein Chemistry, and (D) Structure and Stability. Moreover, we assess how these scientific trajectories shape follow-on innovation by analyzing forward citations over a standardized five-year window (Baruffaldi and Simeth, 2020). We further distinguish citations that stem from SDG-related patents using a sustainability keyword taxonomy developed by *Corporate Knights*. This allows us to estimate whether specific scientific trajectories are more likely to generate sustainability-oriented technological spillovers. To capture the time dimension of trajectory development, we include temporal interactions that assess how the effects of each trajectory evolve over the sample period. This extension is motivated by the recognition that the influence of scientific trajectories can change dynamically, shaped by cumulative and maturing knowledge, and evolving competitive pressures. Our findings reveal that not all scientific trajectories contribute equally to sustainable innovation. Trajectory A, grounded in traditional animal-based research, has no significant effect on overall citations and exhibits a negative association with SDG-related citations. Trajectory B, centered on cellular functionality and bioprocessing, displays a consistently positive and growing association with sustainability-linked innovation that starts earlier on. Trajectory C, which focuses on enzymatic reactions and bioactive compounds, shows lower overall citation rates, reflecting its high specialization and downstream product orientation. However, when combined with Trajectory D, which relates to emulsification and structural stability, a significant positive interaction emerges, particularly for SDG-related citations.

This paper contributes to the existing debates on innovation and sustainability as follows. First, we refine the literature on sustainability innovation by showing that scientific trajectories differ substantially in their contribution to technological impact and, in particular, to SDG-aligned outcomes (Ciarli and Ràfols, 2019). Whereas classical studies often assume that scientific knowledge uniformly enhances impact (Fleming and Sorenson, 2004; Arora and Gambardella, 1994), we introduce a more nuanced perspective: scientific maps help unpack the causal mechanisms of research trajectories, clarifying why some are more impactful than others. Rather than treating science as a monolithic enabler, we show how its influence depends on how codified knowledge is structured and embedded across domains.

Second, we advance text-based methods in innovation research (Kaplan and Vakili, 2015) by developing a hybrid approach that combines unsupervised topic modeling of academic publications with supervised classification of patent texts. This enables us to identify epistemic clusters that transcend conventional patent classifications and reveal hidden differentiation in firms' innovation portfolios. In so doing, we propose a conceptual lens that views science not merely as a source of citations or licensing activity (Thursby et al., 2001; Rogers et al., 2001; Bercovitz and Feldman, 2008), but as an epistemic infrastructure that shapes how firms search, recombine, and scale knowledge within industrial R&D, thereby clarifying the connection between science and technological paradigms and trajectories (Dosi, 1982). This perspective aligns with recent calls to understand science's role not only as input, but as a structuring force in long-run innovation and sustainability transitions.

2. Literature review

2.1. Sustainability innovation and their trajectories

Sustainability innovation sits at the nexus of technological, economic, and societal transformation. Following van der Have and Rubalcaba (2016), we define sustainability innovation as the development of new products, processes, or systems that actively address global environmental, social, and economic challenges, particularly those articulated in the SDGs. These innovations demand not only new technologies but also new ways of organizing and directing knowledge production. As sustainability priorities become more urgent, firms must increasingly navigate complex ecosystems, coordinate across diverse stakeholders, and commit to long-term R&D investments under conditions of high uncertainty (Owen et al., 2021; Stilgoe et al., 2013; Nill and Kemp, 2009). These dynamics increasingly require integrating scientific and technological knowledge with evolving institutional expectations and sociopolitical goals (Pel et al., 2020). Dosi (1982) reconciles the tension between demand-pull and technology-push forces by introducing the concept of a technological paradigm, understood as both a model and a pattern of enquiry that guides inventive activity. In his view, a technological paradigm is primarily a technology-push construct, driven by the internal logic and heuristics of science. Dosi explicitly describes paradigms as channels connecting "big science to production" (p. 153), emphasizing their exclusion effect: by choosing one direction on the map of possible solutions, a paradigm necessarily rules out others, thereby determining which mechanisms and search routines will dominate. Importantly, this directional choice is not arbitrary but rests on causal assumptions derived from scientific theories, which define how certain variables or mechanisms are expected to generate particular outcomes. In this sense, a paradigm embeds both a cognitive model of causality and a methodological template for exploring it. Scientific or innovation trajectories, the cumulative paths along which knowledge and technologies evolve, have emerged as a critical unit of analysis in this context (Ciarli and Ràfols, 2019). These scientific trajectories are inherently heterogeneous, shaped by both epistemic foundations and organizational dynamics such as path dependence, switching costs, and bounded search behaviors (Dosi, 1982). Crucially, scientific trajectories are not neutral; they reflect the cognitive, institutional, and technical logics embedded in specific communities, and often become the substrate upon which future technological developments and spillovers unfold (Arora and Gambardella, 1994; Malerba, 2002). Over time, the capacity of a trajectory to influence sustainable transformation depends on its alignment with policy goals, its ability to scale, and its resonance with broader societal narratives (Cattani and Malerba, 2021; Confraria et al., 2024).

To conceptualize the relationship between paradigm and trajectories, between science and industrial innovation, we add the notion of science as a map (Fleming and Sorenson, 2004). This view frames science not merely as a stock of codified inputs or formal citations, but as a dynamic cognitive framework that organizes problem-solving and exploration. Scientific theories do more than solve existing problems, they generalize them, abstract causal mechanisms, and render the search landscape navigable. They define what is known, what is adjacent to the known, and what (or what is not) replicable. In this sense, scientific knowledge enhances innovation not only by providing solutions, but by transforming how firms identify, frame, and operationalize innovation opportunities. This cognitive infrastructure shapes not only direction but also the timing of innovation impacts, as trajectories may exert influence at different stages depending on their epistemic coherence and fit with technological regimes (Sorenson and Fleming, 2004). In our framework, the notions of paradigm and scientific map are closely interrelated. Within a scientific map, trajectories represent the patterns of problem-solving activity through which paradigms unfold in practice. They capture how scientific heuristics are translated into industrial applications, sometimes reinforced by positive feedback loops that consolidate progress, and at other times weakened by negative feedbacks that lead to the abandonment of specific research directions, as demand-pull factors begin to play a more prominent role.

Science also alters the dynamics of diffusion through different level of codification. Scientific language relies on highly specialized vocabularies and grammar that condense complex ideas into epistemically tractable forms. This codification facilitates reuse, scaling, and cross-domain coordination (Arora and Gambardella, 1994; Kaplan and Vakili, 2015). Yet, as R&D advances from mechanism to application, i.e. in industrial patents, not all scientific domains scale equally, especially in terms of codification. Some mechanisms generalize across domains; others remain locked into narrow use-cases or technological specialized niches (Levinthal and March, 1993; Katila and Ahuja, 2002). As a result, scientific trajectories differ not only in their direction, but also in their capacity to support sustainability outcomes and facilitate recombination with complementary knowledge domains (Cassiman and Veugelers, 2002; Cattani and Malerba, 2021). This capacity is closely linked to firms' absorptive capacity; namely, their ability to identify, assimilate, and apply external scientific knowledge, which varies across domains depending on the generality, codification, and complexity of the underlying science (Cohen and Levinthal, 1990; Zahra and George, 2002). In this vein, recent research suggests that sustainability-oriented innovation is shaped by the interplay between abstract scientific maps and applied socio-technical frames, which together influence both the absorptive capacity of firms and the downstream relevance of scientific knowledge (Pandza and Ellwood, 2013; Cutolo and Ferriani, 2024).

The epistemic architecture of scientific trajectories is further shaped by how problems are framed and communicated. Increasingly, innovation pathways are codified in text-based artifacts, such as patents, publications, and technical disclosures, that encode scientific meaning through language (Meindl et al., 1994; Gavetti and Ocasio, 2015; Cattani et al., 2018; Falchetti et al., 2022; Cutolo and Ferriani, 2024). Language, in this view, is not simply descriptive but constitutive: it shapes how innovation is categorized, perceived, and evaluated by different audiences. For instance, prior work has shown that patents could be mapped across different trajectories and taxonomies (Kaplan and Vakili, 2015; Carnabuci et al., 2015). Thus, the visibility and framing of scientific knowledge influence not only its resonance, but also its capacity to mobilize resources, engage stakeholders, and foster legitimacy in sustainability transitions (Stilgoe et al., 2013; Otero et al., 2022).

These features are particularly salient in sectors like protein production, where core innovation challenges, such as enzymatic control, metabolic processing, or structural protein stabilization, are deeply grounded in scientific knowledge. Our focus is on the production of proteins for food. By concentrating specifically on the production stage, rather than the full value chain or broader international ecosystems, we investigate how the scientific foundations of industrial R&D shape innovation outputs that are most directly linked to core production processes. While prior studies have explored themes such as circularity, governance, regulatory dynamics, or the international diffusion of green technologies (Gentile et al., 2023; Miguelez and Moreno, 2018; Dechezleprêtre et al., 2015), our approach is thus intentionally narrower.

3. Proteins for food

3.1. *Economic and sustainability challenges of protein production*

Protein production offers a distinctive opportunity to investigate the potential synergies of business and social objectives from an R&D perspective. Proteins are vital for human health, as they constitute the essential components of muscles, enzymes, and numerous other crucial elements of our bodies. However, protein production entails significant economic and sustainability trade-offs.

3.1.1. *Economic perspective*

From an economic viewpoint, protein production involves substantial cost considerations. It has been estimated that seafood proteins' costs are about 179 euros per kg, meat 131 euros per kg, and plant-based 116 euros per kg (Azarkamand et al., 2024). Traditional livestock farming, a primary source of protein, requires considerable financial investment. The costs associated with feed, land, and maintenance accumulate rapidly, making it one of the most resource-intensive agricultural activities. A major economic challenge of protein production is also water usage. Livestock farming necessitates vast amounts of water, not only for the animals but also for growing their feed (Mekonnen and Hoekstra, 2010). Likewise, proteins derived from various vegetable sources also demand significant water usage. This extensive water consumption, coupled with other costs, escalates expenses and places significant pressure on water resources.

Consequently, protein production is characterized by high variable costs, which prevent the possibility of lowering average costs through scale economies, thus reducing scalability and economic efficiency (The Economist, 2019). Innovative protein production methods can result in substantial new products and processes that address the marginal cost problem by minimizing resource usage and improving efficiency. The role of industrial companies is pivotal in this context. Interestingly, the importance of this efficiency quest is confirmed by the similarities between protein production and traditional energy sector. Proteins serve as energy resources for human bodily functions and are subject to analogous economic principles. It is not surprising, therefore, that several founders of startups in protein production come with experience from the energy sector, such as Glen Courtright of EnviroFlight, a company producing proteins from insects (source: https://www.darlingii.com/es-ES/enviroflight). Addressing the cost of production problem represents an important business opportunity that innovative research led by both large and emerging companies could seize. For instance, data from Pitchbook in 2024 show that since 2020, 902 companies have been established with venture capital or private equity backing, focusing on protein production. The top 10 companies raised a total of USD 1.774 billion in their first financing rounds, with 12.6 % of these companies already filing for patents.

3.1.2. Sustainability perspective

Protein production also presents significant sustainability challenges. As previously discussed, water consumption is a critical issue (UN SDG 6). Additionally, livestock farming is a major contributor to greenhouse gas emissions, particularly CO2 and methane. These emissions exacerbate climate change, leading to long-term economic consequences such as increased natural disasters, reduced agricultural productivity, and higher healthcare costs due to pollution-related illnesses (UN SDG 13).

From a health perspective, the global demand for protein is rising, driven by population growth and increasing affluence. Meeting this demand sustainably is a key challenge (UN SDGs 2 and 3). The OECD has highlighted the dramatic increase in inequality regarding protein availability across countries (OECD/FAO, 2024). In many developing nations, access to affordable and sustainable protein is limited. This disparity not only affects economic development but also has profound implications for public health and social stability. Protein shortages can lead to malnutrition, stunted growth, and impaired cognitive development, particularly in children.

Medical research has demonstrated that insufficient protein consumption, especially among the young, can severely affect muscle mass maintenance (Berrazaga et al., 2019) and significantly impact cognitive skills (Levitsky and Strupp, 1995). The long-term consequences of protein deficiency extend beyond childhood. Adults who suffered from protein malnutrition as children are more likely to experience chronic health conditions, reduced earning potential, and a lower quality of life. Investing in sustainable protein production is, therefore, an investment in the future health and prosperity of the global population. Sustainable alternatives are urgently needed to ensure food security and economic stability.

4. Methodology

Our methodology consists of two stages. First, we identify core scientific areas in protein research using a machine learning analysis of academic articles and then map these areas into patent texts to trace corresponding scientific trajectories. Second, we assess how these trajectories influence forward citations, using them as a proxy for scientific relevance and follow-on innovation (c.f. empirical label IMPACT). It is worth noting that while the scientific map extracted from academic knowledge captures the paradigm's underlying causal logic, our empirical analysis of patent citations and dynamics traces the evolution of technological trajectories, revealing how paradigms materialize, adapt, or fail in the industrial sphere.

4.1. PART I: scientific areas within protein science and their matching in patents

Our objective is to examine the role and the impact of scientific trajectories within industrial research on proteins. This analysis presents a methodological challenge, as patent documents combine legal, commercial, and scientific language, often introducing confounding elements that may obscure underlying technological patterns. To address this, we construct a scientific "map" based on a dictionary of academic-specific terminology (Deng et al., 2019, Rathee et al., 2019). As a first step, we extract relevant scientific terms from a corpus of academic research articles focused on proteins. These publications offer a more precise dictionary that helps isolate the scientific content of patents. Once this scientific map is constructed, we use it as a reference space onto which individual patents are positioned, enabling us to trace and visualize the structure and evolution of scientific trajectories in protein research.

To build this scientific map, we selected academic publications from the top 34 journals classified as Q1 by the Web of Science in the category of Food Science and Technology. A search for the term "protein" between 2000 and 2020 yielded 32,042 articles, from which we extracted titles and abstracts. Only articles with a digital object identifier (DOI) were included, and we retained those with at least one academic or public research affiliation, representing over 97 % of the total dataset. To identify latent topics (i.e., underlying scientific areas) within this corpus, we applied a part-of-speech (POS)-enhanced Latent Dirichlet Allocation (LDA) algorithm. This procedure uniquely classified 28,081 articles (87.6 % of the sample) into four major scientific trajectories. A detailed description of the machine learning approach and the resulting keywords is provided in the Appendix (Fig. A1). The four identified scientific areas are as follows: Scientific Area A represents a broad body of work on animal-sourced protein research; Area B focuses on cellular functions; Area C investigates chemical reactions between amino acids and sugars; and Area D examines physical properties contributed by enzymes, such as emulsion formation and stability. While scientific area A captures a more general research stream, areas B, C, and D delve into more specific biochemical mechanisms. To ensure accurate interpretation of each topic, we consulted a professor with extensive post-PhD experience in microbiology, who validated the scientific coherence of the topics. Table 1 presents descriptive statistics for the four identified scientific areas.

Table 1
Scientific areas emerged from academic research.

Trajectory	Label	# Articles	% over total articles	Average probability of article classification	Interpretation
Scientific area A	Animal-Sourced Proteins	6833	24.3 %	45.4 %	This topic pertains to the composition and quality of food products, with a particular emphasis *on meat and other protein-rich foods*. This research primes the nutritional content of meat, the processing methods used to preserve or enhance meat quality, and especially the composition of proteins, starches, and fats.
Scientific area B	Cellular mechanisms and oxidative stress responses	6654	23.6 %	52.7 %	This topic focuses on *cellular biology*, particularly the mechanisms by which cells respond to various stimuli or stressors. This research analyzes how proteins are involved in cellular responses, such as oxidative stress, gene expression regulation, and protective mechanisms within cells.
Scientific area C	Protein chemistry and bioactive compounds	6309	22.4 %	43.1 %	This topic focuses on *protein chemistry* and the study of bioactive compounds, particularly peptides and other compounds found in milk and other protein sources. This trajectory research delves into the *functional properties of proteins* and peptides, including their roles as antioxidants, their extraction and fractionation methods, and their analysis.
Scientific area D	Protein structure and stability	8265	29.5 %	48.3 %	This topic focuses on the *structural and stability aspects of food products*, particularly those involving emulsions, gels, and other complex mixtures. This research aims at understanding how these components interact to influence the *physical properties of food*, such as texture, stability, and shelf life. This trajectory covers research on the formulation of stable food products, the creation of emulsions (e.g., salad dressings, dairy products), and how different variables like pH and temperature affect these properties.
Not purely classified		3961	12.3 %		

Notes: Article uniquely classified inside a cluster with a threshold probability of 33 %. POS-Enhanced-LDA method. Articles selected in the top 34 journals classified as Q1 by the Web of Science within the category of Food Science and Technology. Our search for the term "protein" between 2000 and 2020.

4.2. *Searching for the scientific areas into the patent texts to identify scientific trajectories*

Patents in our sample were drawn from the United States Patent and Trademark Office (USPTO). For the scope of this paper, we selected granted patents of sub-technology class A23J[1] related to the preparation or treatment of proteins or proteinaceous materials for foodstuffs, filed between the years 1990–2015.[2] We deliberately exclude complementary technologies such as 3D printing for food processing to maintain the primary focus in the fields of chemistry, biology, and enzymology. 3D printing operates primarily as a downstream application that is more engineering- and hardware-driven, often involving mechanical and material science. Our final sample consists of 1561 patents. Utilizing the top five keywords from every scientific area, we performed a text frequency analysis on these terms within the titles and abstracts of our sample patents (e.g., Arts et al., 2021; Arts et al., 2018; Balsmeier et al., 2018; Kaplan and Vakili, 2015; Teodoridis et al., 2019). This methodology resembles the process by which an academic scientist, deeply knowledgeable in this field, would interpret and classify a patent related to this technology. Table 2 shows the results of this frequency search. Approximately 77 % of all sample patents were classified into one of the four scientific trajectories derived from academic literature. The remaining 23 % were not assigned to any trajectory, primarily due to our deliberately strict classification criteria. This conservative approach was adopted to minimize Type I error, that is, the risk of incorrectly assigning patents to a trajectory when the epistemic alignment is weak or ambiguous. While we acknowledge that some of the unclassified patents may plausibly belong to one of the defined trajectories, we treat this 23 % as a baseline group of patents without evident scientific origins. The different categories are not mutually exclusive, and 42 % of all patents are assigned to one single trajectory, 27 % to two trajectories, 6 % to three trajectories, and 1 % to all four. Accounting for some patents having more than one scientific area, TRAJECTORY A_ANIMAL is the most frequent category in the data associated with 47 % of all observations, followed by TRAJECTORY D_STRUCTURE with 32 %, TRAJECTORY C_CHEMISTRY with 27 %, and TRAJECTORY B_CELLULAR with 13 %.

Table 2
Patents classified by academic topic.

Panel A: No. of trajectories by patent	Number	Share
Patents not classified	355	23 %
Patents with unique science area	664	43 %
Patents with 2 science areas	423	27 %
Patents with 3 science areas	104	7 %
Patents with all science areas	15	1 %
Total sample patents	1561	100 %

Panel B: Absolute frequency trajectories	No. patents	% of patents
TRAJECTORY A_ANIMAL	739	47 %
TRAJECTORY B_CELLULAR	210	13 %
TRAJECTORY C_CHEMISTRY	429	27 %
TRAJECTORY D_STRUCTURE	504	32 %

Panel C: Co-occurrence of trajectories	TRAJECTORY A	TRAJECTORY B	TRAJECTORY C
TRAJECTORY A_ANIMAL	–		
TRAJECTORY B_CELLULAR	108	–	
TRAJECTORY C_CHEMISTRY	187	75	–
TRAJECTORY D_STRUCTURE	252	70	133

Notes: Patents are classified by searching in the title and abstract the top five keywords from Fig. 1. Patents were selected from the sub-technological class A23J at USPTO.

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[1] https://www.uspto.gov/web/patents/classification/cpc/html/cpc-A23J.html

[2] The filing year 2015 is chosen because, as we discuss below, we count citations only from the grant event of our sampled patents, and we likewise imply that citation patents must have an observed grant event (while considered if the filing date is within the 5-year window). The chosen time window and focus on granted patents minimizes a potential bias from data truncation and legislative changes, such as the American Inventors Protection Act (AIPA). We have also tried a slightly different operationalization, where we sample our patents based on patent grant years no later than 2018, with equivalent results.

4.3. PART II: assessing scientific trajectories on patents' forward citations

4.3.1. Variables & measures

4.3.1.1. Dependent variable. We use the number of forward citations as dependent variable (IMPACT). Patents that receive a higher number of subsequent citations are typically regarded as foundational or pioneering and are therefore widely used as proxies for technological diffusion, knowledge spillovers, and follow-on innovation (Baruffaldi and Simeth, 2020). The number of citations also signal the technological characteristics (Conti, 2014; Fleming and Singh, 2010) and their economic value, such as consumer surplus generated (Trajtenberg, 1990), expert evaluations of patent value (Albert et al., 1991), patent renewal rates (Harhoff et al., 1999), contribution to an organization's market value (Hall et al., 2005), and inventors' assessments of economic value (Gambardella et al., 2008). We count patent citations from the grant event of our sampled patents in a 5-year citation window to avoid data truncation when counting citations.[3]

Moreover, to examine the impact of scientific trajectories on sustainable follow-on innovation (Noailly and Shestalova, 2017) in alternative proteins, we further classify the forward citations of our sample patents into two categories: those linked to the SDGs (IMPACT SDG) and those that are not (IMPACT NON-SDG). This classification is based on a similar text analysis approach previously applied by other works (Ciarli et al., 2021; Confraria et al., 2024), which evaluates whether the abstracts of citing patents align with a sustainability-oriented keyword dictionary developed by *Corporate Knights*[4] (Giarratana and Pasquini, 2022). The most frequent SDGs related to our variable IMPACT SDG are as follows: 9 % SDG 13 (Climate Action), 2.7 % SDG 7 (Affordable and clean energy), 2.1 % SDG_3 (Good health & wellbeing), and 1 % SDG 12 (Responsible consumption).

4.3.1.2. Independent variables of interest. Our core independent variables are the four scientific research areas identified previously via the machine learning POS-LDA enhanced algorithm. Once applied to patents, we label them TRAJECTORIES. Therefore, we have TRAJECTORY A_ANIMAL, TRAJECTORY B_CELLULAR, TRAJECTORY C_CHEMISTRY, TRAJECTORY D_STRUCTURE. For a given patent, the value of 1 is assigned for the different categories if there is at least one keyword associated with the respective scientific area, and zero otherwise. To illustrate qualitatively, Trajectory B centers on system-level biotechnological optimization, where innovations aim to enhance upstream efficiency and sustainability through the integration of metabolic engineering, enzymatic processing, and precision monitoring. A typical example includes the use of microbial fermentation processes optimized via systems biology approaches to increase protein yield while reducing resource intensity. Trajectory C reflects a more specialized approach focused on the engineering of bioactive compounds under tightly controlled processing conditions. Trajectory D encompasses technologies designed to improve the texture, stability, and emulsification properties of food products across a wide range of categories. Examples include the application of modified starches or pectins to enhance freeze–thaw stability and control mouthfeel, making these innovations broadly applicable in both dairy and plant-based formulations.

4.3.1.3. Control variables. We also add a series of control variables at the patent level to reduce potential confounding factors. First, we control for LOG CLAIMS, which represents the number of patent claims at grant (in log), proxying the patent breadth (Marco et al., 2019). We also included LOG BACKWARD CITES as the number of backward citations to other patents (expressed in log), capturing the incremental nature of the patent; NO INVENTORS controlling for the number of patent co-inventors; INVENTOR NON-US as a dummy controlling for the presence of a non-US inventor (as defined by an inventor location abroad), and therefore also considering the institutional context of the innovation system. Furthermore, we control for NO ASSIGNEES as the number of assignees the focal patent is granted to; LOG SCIENTIFIC CITES capturing the number of scientific articles cited by the focal patent to control for a patent's general orientation toward science (Marx and Fuegi, 2020); SIZE PATENT FAMILY as the number of patents that belong to the same DocDB patent family and share a common priority date, which controls for the international scope of patent protection and the potential existence of continuation filings (Harhoff et al., 2003). In addition, we also add a variable to flag whether the patent is a PRIORITY FILING which is defined as the focal patent having a filing date which corresponds to the priority date of the patent family; GRANT LAG as the time distance between the patent filing and grant dates (in years), and PATENT STOCK ASSIGNEE as the (log-transformed) number of total patents in all technological classes granted to the same assignee over time, with an assumed depreciation rate of 15 % (e.g., Hall et al., 2005).

To isolate the effect of the identified scientific trajectories and control for unrelated technology heterogeneity, we also insert a series of technology dummies controls. While the A23J subclass is present among all our patents by sampling, we also include dummies for the main CPC group that follows the subclass. Moreover, we also include the number of unique CPC subclasses (considering that many patents have several inventional patent classes in the CPC framework). In this way, we ensure that our machine learning classification into different scientific areas indeed captures distinct scientific trajectory effects above and beyond technology heterogeneity that is well described in the patent class taxonomy.[5] We report descriptive statistics and correlation matrix in Tables 3 and 4, respectively. The list of variable definitions with their respective sources is included in the appendix Table A1.

5. Results

In Table 5, we report the top ten firms by total patent output within the relevant subclass A23J and the distribution of their patents across the four identified trajectories. While many firms are active in multiple trajectories, clear specialization and concentration patterns also emerge. For instance, Burcon Nutrascience Corp. shows activity in animal proteins, cellular and bioprocessing, and protein structure (Trajectories A, B, and D), but is only marginally involved in Trajectory C (protein chemistry). Conversely, Cargill Inc. exhibits a strong presence in Trajectory A and, to a lesser extent, in Trajectories C and D, while remaining largely absent from Trajectory B. These examples illustrate how distinct scientific orientations underpin the organization of corporate

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[3] We consider the filing date of the citing patents in relation to the 5-year window but likewise restrict citing patents to those where a grant event is observed (source: Patentsview citation table, downloaded in July 2024). We also acknowledge some limitations in the use of forward citations as an outcome indicator: citations do not always represent knowledge flows and a true impact on follow-on innovation but may also be the result of different mechanisms. On a technical level, citations can be added by patent examiners without the inventors' awareness of the prior art, citations may originate from follow-on patents by the same firm (self-citations), and they may accumulate at heterogeneous rates over time. Accordingly, we ran our main regressions with adjusted dependent variables, computing the IMPACT, IMPACT SDG and IMPACT NON-SDG excluding examiner added-citations, self-citations, and alterations of the citation time window. Results are robust and available upon request.

[4] Corporate Knights is a media and research company that promotes and certifies SDG objectives in the business sector. They produce widely recognized rankings for companies and business schools, serving as a legitimate indicator of SDG-related activities. Their vocabulary includes keywords which we used as guide to identify patent citations associated with SDGs.

[5] We have also conducted robustness tests with CPC controls in their full granularity by including dummies for the CPC subgroup level. Results remain robust and are available upon request.

Table 3
Descriptive statistics of the sample.

Variable	Obs	Mean	Std. dev.	Min	Max
IMPACT	1561	3.297	4.622	0.000	23.000
IMPACT SDG	1561	0.468	1.001	0.000	5.000
IMPACT NON-SDG	1561	2.808	4.006	0.000	20.000
TRAJECTORY A_ANIMAL	1561	0.473	0.499	0.000	1.000
TRAJECTORY B_CELLULAR	1561	0.135	0.341	0.000	1.000
TRAJECTORY C_CHEMISTRY	1561	0.275	0.447	0.000	1.000
TRAJECTORY D_STRUCTURE	1561	0.323	0.468	0.000	1.000
LOG CLAIMS	1561	2.682	0.702	0.693	4.844
LOG BACKWARD CITES	1561	1.865	1.026	0.000	6.286
NO. INVENTORS	1561	3.065	2.033	1.000	20.000
INVENTOR NON-US	1561	0.621	0.485	0.000	1.000
NO. ASSIGNEES	1561	1.039	0.222	1.000	3.000
LOG SCIENTIFIC CITES	1561	1.151	1.237	0.000	5.659
SIZE PATENT FAMILY	1561	8.388	7.157	1.000	45.000
PRIORITY FILING	1561	0.190	0.392	0.000	1.000
GRANT LAG	1561	3.350	1.960	0.458	13.200
PATENT STOCK ASSIGNEE	1561	2.656	1.907	0.000	8.124

innovation portfolios in the alternative protein domain. Fig. 1 presents a set of box plots, each corresponding to one of the four scientific trajectories, depicting the distribution of forward citations across patents classified as either belonging to the trajectory or not. We observe relevant differences in the median and distributional values for Trajectory B, where patents belonging to the trajectory exhibit higher forward citations, while we observe the opposite finding for Trajectory C.

To further investigate these descriptive patterns, we conducted econometric estimations using Pseudo Poisson maximum likelihood regressions (PPML) (Silva and Tenreyro, 2006; Chen and Roth, 2024) at the patent level, with robust standard errors clustered at the company (patent assignee) level. The baseline scenario occurs when all scientific trajectories are set to zero, corresponding to 355 observations. This group captures innovations that do not strongly align with dominant scientific vocabularies in food science, either because they originate from other technical domains or because their language reflects more proprietary and legally encoded expressions not well mapped by academic discourse. We estimate the following count data model:

$$E\left[IMPACT_p\right] = \exp\left[TRAJECTORY_P + CONTROLS_p + \lambda_c + \delta_t\right] \tag{1}$$

where IMPACT represents the impact of a patent on follow-on innovation (as measured by the citations received within a 5-year time window after grant) for patent p, TRAJECTORY represents a vector for the four science trajectory dummies, CONTROLS represent a vector of control variables, λ_c represents CPC technology fixed effects, and δ_t represents patent filing year fixed effects.

We report our regression results in three different tables. Table 6 displays the results of our main analysis, showing the effects of the different scientific trajectories on IMPACT (Columns 1–3), and specifically the derivative outcomes SDG vs NON-SDGs IMPACT (Columns 4–5). Results in Table 7 explore the possibility of interdependencies between the trajectories and their potential joint effects on the three dependent variables. Finally, Table 8 introduces a dynamic perspective, reporting the findings of the early vs late stages of each scientific trajectory in the timeline and their respective impact on IMPACT (Column 1), IMPACT SDGs and IMPACT NON-SDGs related (Columns 2 and 3 respectively).

Our initial evidence indicates that patents' scientific trajectories capture effects beyond those explained by standard technology classifications. We observe that without technology controls (Table 6, Column 1) and with technology controls (Table 6, Column 2) results remain stable both in terms of economic effects and statistical significance. Our results on the effects of the different trajectories also hold when the full list of controls is included (Table 6, Column 3). More precisely, we observe that TRAJECTORY B_CELLULAR is positively associated with IMPACT ($p < 0.05$), while TRAJECTORY C_CHEMISTRY is negatively

Table 4
Correlation matrix.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)	IMPACT	1.00																
(2)	IMPACT SDG	0.65	1.00															
(3)	IMPACT NON-SDG	0.98	0.49	1.00														
(4)	TRAJECTORY A_ANIMAL	−0.01	−0.05	0.00	1.00													
(5)	TRAJECTORY B_CELLULAR	0.05	0.05	0.05	0.03	1.00												
(6)	TRAJECTORY C_CHEMISTRY	−0.05	−0.06	−0.04	−0.05	0.07	1.00											
(7)	TRAJECTORY D_STRUCTURE	−0.01	0.02	−0.02	0.04	0.01	−0.02	1.00										
(8)	LOG CLAIMS	0.17	0.10	0.17	−0.02	−0.02	−0.05	0.02	1.00									
(9)	LOG BACKWARD CITES	0.16	0.10	0.15	0.00	−0.08	−0.10	0.05	0.16	1.00								
(10)	NO INVENTORS	−0.01	−0.04	0.00	0.00	0.06	0.03	−0.06	−0.02	−0.01	1.00							
(11)	INVENTOR NON-US	−0.20	−0.19	−0.19	0.04	0.04	0.06	−0.06	−0.19	−0.34	0.19	1.00						
(12)	NO ASSIGNEES	0.00	−0.04	0.02	−0.02	0.03	0.03	0.01	−0.01	−0.06	0.12	0.05	1.00					
(13)	LOG SCIENTIFIC CITES	0.05	0.05	0.05	−0.06	0.11	0.13	−0.15	0.07	0.01	0.15	−0.04	0.03	1.00				
(14)	SIZE PATENT FAMILY	−0.01	−0.02	−0.01	0.04	0.06	0.02	−0.05	0.06	−0.05	0.11	0.26	−0.04	0.13	1.00			
(15)	PRIORITY FILING	0.08	0.09	0.06	0.00	−0.08	−0.05	0.05	0.08	0.14	−0.12	−0.36	−0.05	−0.07	−0.22	1.00		
(16)	GRANT LAG	−0.18	−0.07	−0.19	0.00	0.05	−0.02	−0.01	0.03	−0.01	0.11	0.14	−0.01	0.18	0.21	−0.11	1.00	
(17)	PATENT STOCK ASSIGNEE	0.01	−0.03	0.02	0.00	0.03	0.02	−0.07	0.02	−0.01	0.25	−0.01	0.02	0.20	0.05	−0.02	0.00	1.00

Table 5
Top-10 firms by patent frequency and trajectories.

PATENT ASSIGNEE	FIRM LOCATION	UNIQUE PATENTS	TRAJECTORY			
			A	B	C	D
BURCON NUTRASCIENCE (MB) CORP.	CA	64	15	26	2	17
NESTEC S.A.	CH	57	32	13	23	18
FUJI OIL HOLDINGS INC.	JP	35	17	7	11	18
SOLAE COMPANY LLC	US	28	14	4	6	9
CARGILL, INCORPORATED	US	24	13	0	4	6
SNOW BRAND MILK PRODUCTS CO.	JP	19	15	3	9	11
DSM IP ASSETS B.V.	NL	19	5	1	9	1
KRAFT FOODS HOLDINGS, INC.	US	18	7	3	11	7
ABBOTT LABORATORIES	US	17	10	1	4	4
NOVO NORDISK A/S	DK	15	6	1	9	3

associated with IMPACT ($p < 0.05$). The shift to TRAJECTORY B_CELLULAR (i.e., from 0 to 1) increases the predicted value of our dependent variable by 27.8 %, whereas TRAJECTORY C_CHEMISTRY is associated with a 19.7 % decrease in predicted IMPACT.

When we distinguish our dependent variable based on citations classified as sustainability-relevant (IMPACT SDG, Table 6, Column 4) versus those that are not (IMPACT NON-SDG, Table 6, Column 5), we find broadly consistent patterns across models. In both cases, TRAJECTORY B_CELLULAR shows a positive and statistically significant effect ($p < 0.05$ and $p < 0.10$, respectively), while TRAJECTORY C_CHEMISTRY remains negatively associated with forward citations ($p < 0.05$ and $p < 0.10$, respectively). Notably, beyond more pronounced statistical significance, also the magnitude of the coefficients tends to be larger for the SDG-related citations, reinforcing the idea that some trajectories are more salient in sustainability-oriented follow-on innovation. Interestingly, TRAJECTORY A_ANIMAL, linked to traditional protein production, exhibits a significant negative relationship only with IMPACT SDG ($p < 0.05$), suggesting that this trajectory may be less aligned with sustainability-oriented innovation. The economic interpretation of the marginal effects on SDG IMPACT suggests that the predicted value of the dependent variable increases by 41.6 % with a shift to TRAJECTORY B_CELLULAR, while it decreases by 31.3 % for TRAJECTORY C_CHEMISTRY and by 22.1 % for TRAJECTORY A_ANIMAL. The remaining TRAJECTORY D_STRUCTURE is not statistically significant with any of the models considered.

In Table 7, we explore whether interdependencies exist between the scientific trajectories, and accordingly, introduce interaction effects between them. Most combinations do not yield statistically significant results, indicating limited evidence of systematic complementarities between them. An exception is the interaction between TRAJECTORY C_CHEMISTRY and D, which is positive and significant at the 10 % level (Column 3), suggesting a potential joint effect. This interaction becomes stronger and statistically significant ($p < 0.05$) when we focus on sustainability-oriented citations (IMPACT SDG, Column 5), while it remains non-significant for citations unrelated to sustainability (IMPACT NON-SDG, Column 6). Given the increased multicollinearity introduced by interaction terms, and the resulting instability in coefficient estimates, we interpret these results with caution and refrain from drawing strong conclusions. Future research could further explore the possible synergistic relationship between TRAJECTORIES C_CHEMISTRY and D_STRUCTURE, particularly considering their differential effects on sustainability-oriented versus general innovation outcomes.

Finally, since trajectories are intrinsically dynamic, Table 8 introduces a temporal dimension, splitting each trajectory into Early and Late periods, using 2003 as the dividing year. We again analyze the three

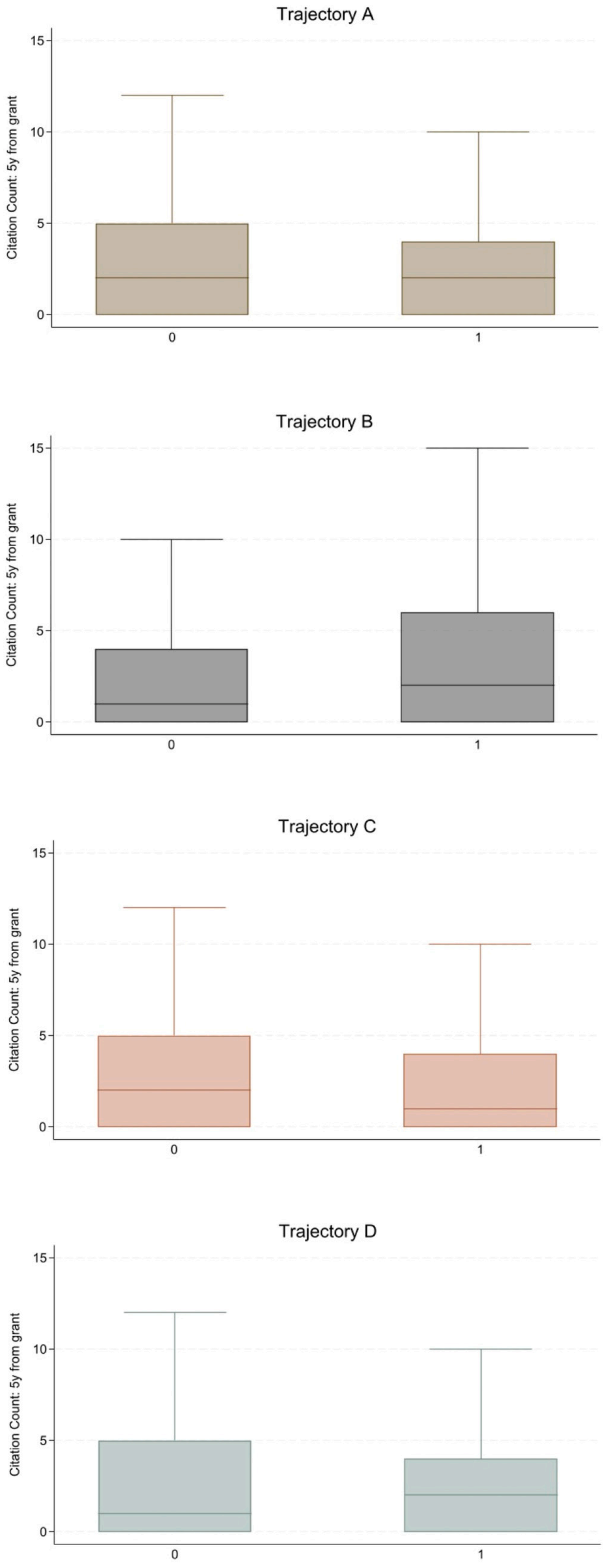

Fig. 1. Forward citations (IMPACT) across scientific trajectories.

Table 6
Main regressions results.

	(1)	(2)	(3)	(4)	(5)
	IMPACT			IMPACT SDG	IMPACT NON-SDG
TRAJECTORY A_ANIMAL	−0.103	−0.111	−0.104	−0.251**	−0.084
	(0.086)	(0.084)	(0.081)	(0.122)	(0.085)
TRAJECTORY B_CELLULAR	0.245**	0.223**	0.246**	0.348**	0.220*
	(0.109)	(0.109)	(0.107)	(0.150)	(0.112)
TRAJECTORY C_CHEMISTRY	−0.210**	−0.238**	−0.220**	−0.377**	−0.185*
	(0.092)	(0.095)	(0.095)	(0.151)	(0.098)
TRAJECTORY D_STRUCTURE	−0.087	−0.047	−0.073	0.033	−0.094
	(0.084)	(0.084)	(0.077)	(0.115)	(0.081)
LOG CLAIMS			0.281***	0.173*	0.295***
			(0.066)	(0.095)	(0.067)
LOG BACKWARD CITES			0.137***	0.100*	0.135***
			(0.039)	(0.054)	(0.040)
NO INVENTORS			0.006	−0.004	0.004
			(0.024)	(0.035)	(0.024)
INVENTOR NON-US			−0.310***	−0.574***	−0.275**
			(0.113)	(0.143)	(0.115)
NO ASSIGNEES			−0.044	−0.476	0.014
			(0.138)	(0.352)	(0.136)
LOG SCIENTIFIC CITES			0.103**	0.109**	0.105**
			(0.042)	(0.052)	(0.045)
SIZE PATENT FAMILY			0.016***	0.015	0.017***
			(0.005)	(0.010)	(0.005)
PRIORITY FILING			−0.055	0.051	−0.082
			(0.074)	(0.140)	(0.074)
GRANT LAG			−0.081***	−0.029	−0.087***
			(0.021)	(0.033)	(0.023)
PATENT STOCK ASSIGNEE			−0.018	−0.053	−0.011
			(0.022)	(0.035)	(0.022)
CONSTANT	1.392***	1.244***	0.458	−0.618	0.200
	(0.098)	(0.157)	(0.324)	(0.563)	(0.329)
TECHNOLOGY DUMMIES	NO	YES	YES	YES	YES
FILING YEAR DUMMIES	YES	YES	YES	YES	YES
Observations	1561	1561	1561	1561	1561

Note: pseudo Poisson ML, robust standard errors clustered at firm level in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

dependent variables, IMPACT, IMPACT SDG, and IMPACT NON-SDG, to capture potential differences in how trajectories evolve over time. The results suggest that the effect of scientific trajectories on follow-on innovation and diffusion is not constant over time. In particular, the effect of TRAJECTORY B_CELLULAR is more pronounced in the early period, although once sustainability related impact is considered, the coefficient estimates between early and late periods are very similar. We also observe differences in timing for TRAJECTORY C_CHEMISTRY, where we observe the negative impact presented in the main analysis predominantly in the late period, especially for non-sustainable impact. Finally, TRAJECTORY A_ANIMAL exhibits a negative impact in the late period for sustainability-related impact, consistent with the idea that animal-based solutions are increasingly difficult to reconcile with sustainability-related innovation.

6. General discussion

6.1. Results interpretation of scientific trajectories

This study sheds light on a central question for sustainability-oriented industrial policy: how do scientific trajectories influence the direction and societal value of innovation? In the case of alternative proteins, a field shaped by acute environmental, nutritional, and geopolitical challenges, we demonstrate that scientific foundations vary significantly in their ability to produce broad technological spillovers and contribute meaningfully to the SDGs.

A central insight emerging from our findings is that the role of science differs markedly depending on the underlying logic of the trajectory. Trajectories grounded in codified, conceptual knowledge structures (e.g., Trajectory B) support broader recombination, cumulative spillovers, and longer-term diffusion (e.g., higher number of forward citations). In contrast, trajectories rooted in specialized or application-bound knowledge (e.g., Trajectory C) tend to remain locked into narrow domains. These distinctions are particularly important when evaluating the potential of each trajectory to generate sustainability-oriented innovation. This distinction reflects underlying differences in knowledge generality (Arts and Veugelers, 2015; Arora and Gambardella, 1994), where abstract and cross-applicable knowledge facilitates wider exploration, while context-specific knowledge tends to reinforce localized exploitation. Moreover, scientific trajectories embedded in cumulative epistemic structures - those with stable vocabularies, modularity, and disciplinary maturity - are more likely to sustain innovation over time (Bonaccorsi and Vargas, 2010). Such trajectories also create larger “adjacent possibles” (Katila and Ahuja, 2002), expanding the design space and enabling more diverse experimentation. In contrast, knowledge locked into narrow use-cases often faces diffusion barriers, limited absorptive capacity, and low combinatorial flexibility (Cohen and Levinthal, 1990).

To better understand the underlying causal mechanisms driving these differences, we turn to the scientific content embedded in each trajectory. Trajectory A, focused on animal-based protein research, has no significant effect on overall spillovers and exhibits a negative association with SDG-related outcomes. This suggests a declining relevance for sustainability agendas, as societal and regulatory pressures shift toward lower-impact alternatives. The marginalization of this trajectory reflects a broader demand push pattern in which older paradigms lose

Table 7
Interdependencies of scientific trajectories.

	(1)	(2)	(3)	(4)	(5)	(6)
	IMPACT				IMPACT SDG	IMPACT NON-SDG
TRAJECTORY A_ANIMAL	−0.091	−0.105	−0.108	−0.099	−0.284*	−0.081
	(0.105)	(0.082)	(0.081)	(0.106)	(0.146)	(0.110)
TRAJECTORY B_CELLULAR	0.248**	0.236*	0.243**	0.248*	0.322*	0.230*
	(0.107)	(0.136)	(0.107)	(0.133)	(0.187)	(0.137)
TRAJECTORY C_CHEMISTRY	−0.220**	−0.220**	−0.322***	−0.322***	−0.640***	−0.269**
	(0.095)	(0.095)	(0.124)	(0.124)	(0.201)	(0.128)
TRAJECTORY D_STRUCTURE	−0.054	−0.078	−0.150	−0.135	−0.165	−0.145
	(0.110)	(0.086)	(0.091)	(0.127)	(0.172)	(0.133)
TRAJECTORY A x D	−0.041			−0.027	0.062	−0.018
	(0.145)			(0.144)	(0.228)	(0.151)
TRAJECTORY B x D		0.029		−0.010	0.060	−0.036
		(0.180)		(0.181)	(0.284)	(0.192)
TRAJECTORY C x D			0.310*	0.309*	0.686**	0.261
			(0.170)	(0.175)	(0.287)	(0.182)
LOG CLAIMS	0.280***	0.281***	0.278***	0.278***	0.170*	0.292***
	(0.066)	(0.066)	(0.066)	(0.066)	(0.093)	(0.067)
LOG BACKWARD CITES	0.138***	0.137***	0.133***	0.134***	0.090*	0.132***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.055)	(0.039)
NO INVENTORS	0.006	0.006	0.006	0.006	−0.003	0.004
	(0.024)	(0.024)	(0.024)	(0.024)	(0.035)	(0.024)
INVENTOR NON-US	−0.310***	−0.311***	−0.305***	−0.305***	−0.567***	−0.270**
	(0.113)	(0.113)	(0.112)	(0.112)	(0.140)	(0.115)
NO ASSIGNEES	−0.044	−0.044	−0.032	−0.032	−0.435	0.023
	(0.138)	(0.138)	(0.137)	(0.137)	(0.347)	(0.135)
LOG SCIENTIFIC CITES	0.103**	0.102**	0.102**	0.102**	0.105**	0.105**
	(0.043)	(0.042)	(0.042)	(0.042)	(0.051)	(0.045)
SIZE PATENT FAMILY	0.016***	0.017***	0.017***	0.017***	0.017*	0.017***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.010)	(0.005)
PRIORITY FILING	−0.056	−0.054	−0.048	−0.049	0.065	−0.077
	(0.074)	(0.074)	(0.073)	(0.074)	(0.138)	(0.075)
GRANT LAG	−0.081***	−0.081***	−0.078***	−0.078***	−0.021	−0.085***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.033)	(0.022)
PATENT STOCK ASSIGNEE	−0.018	−0.018	−0.018	−0.018	−0.055	−0.011
	(0.022)	(0.022)	(0.022)	(0.022)	(0.035)	(0.022)
CONSTANT	0.454	0.459	0.482	0.478	−0.574	0.218
	(0.322)	(0.324)	(0.322)	(0.320)	(0.549)	(0.327)
TECHNOLOGY DUMMIES	NO	YES	YES	YES	YES	YES
FILING YEAR DUMMIES	YES	YES	YES	YES	YES	YES
Observations	1561	1561	1561	1561	1561	1561

Note: pseudo Poisson ML, robust standard errors clustered at firm level in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

legitimacy and institutional support when they no longer align with sustainability norms (Malerba, 2002).

Trajectory B, in contrast, exemplifies the influence of codified science as a foundational infrastructure. With technologies like precision fermentation and bioprocessing, it shows both early and persistent influence, particularly in sustainability-linked domains. Its strong SDG performance stems not only from its scientific abstraction, but from the ability of these technologies to address multiple sustainability pressures simultaneously, reducing methane emissions, minimizing land and water use, and supporting scalable protein alternatives (FAO, 2023; OECD/FAO, 2024). This mirrors what Confraria et al. (2024) describe as mission-oriented innovation trajectories, scientific domains that evolve in alignment with grand societal challenges and exhibit structural readiness for translation into SDG-relevant outcomes. Moreover, platform technologies like bioprocessing serve as enablers within sustainability transitions, as they can be recombined across product lines and sectors without substantial reconfiguration, which is an essential feature when addressing complex environmental goals (Nill and Kemp, 2009). Trajectory C is negatively associated with forward citations, particularly with SDG-related patents. Its focus on enzyme-enabled functionality and nutritional enhancement reveals a more engineering-driven structure, one in which knowledge is narrowly applicable and embedded in market-specific or proprietary solutions.

Reinterpreted through Dosi's (1982) lens, Trajectory B exemplifies a science-push trajectory, closely aligned with a well-defined technological paradigm. Its core technologies, such as precision fermentation and bioprocessing, derive from codified scientific principles and maintain a clear causal structure linking underlying mechanisms to functional outcomes. Because this knowledge base is highly codified, modular, and abstract, it can be easily recombined and transferred across application domains, generating visible spillovers in the citation network even before full economic translation occurs. The capacity of these technologies to address multiple sustainability pressures simultaneously, reducing emissions, minimizing land and water use, and enabling scalable protein alternatives, illustrates how a trajectory situated close to its paradigm can foster systemic spillovers across the innovation landscape.

By contrast, Trajectory C embodies more demand-pull dynamics, where inventive activity is guided by concrete trade-offs in product performance and market application. Knowledge in this trajectory tends to be context- and organization-specific, often embedded in tacit problem-solving routines. As a result, it becomes progressively distant from its paradigm, characterized by local optimization rather than exploratory expansion. The narrow spillover profile and negative association with SDG-related citations suggest that its problem-solving heuristics exhibit high appropriability but low transferability, confining learning within firm or sectoral boundaries. This weaker

Table 8
Early vs late trajectories stage.

	(1) IMPACT	(2) IMPACT SDG	(3) IMPACT NON-SDG
EARLY TRAJECTORY A_ANIMAL	−0.020	−0.142	−0.011
	(0.090)	(0.148)	(0.091)
LATE TRAJECTORY A_ANIMAL	−0.282*	−0.470**	−0.238
	(0.166)	(0.198)	(0.183)
EARLY TRAJECTORY B_CELLULAR	0.309***	0.333*	0.295**
	(0.117)	(0.196)	(0.123)
LATE TRAJECTORY B_CELLULAR	0.077	0.381*	0.006
	(0.179)	(0.221)	(0.183)
EARLY TRAJECTORY C_CHEMISTRY	−0.103	−0.328*	−0.064
	(0.096)	(0.169)	(0.099)
LATE TRAJECTORY C_CHEMISTRY	−0.527***	−0.442	−0.534***
	(0.185)	(0.278)	(0.192)
EARLY TRAJECTORY D_STRUCTURE	−0.026	0.105	−0.055
	(0.086)	(0.149)	(0.089)
LATE TRAJECTORY D_STRUCTURE	−0.144	−0.101	−0.141
	(0.149)	(0.183)	(0.159)
LOG CLAIMS	0.270***	0.164*	0.285***
	(0.064)	(0.094)	(0.065)
LOG BACKWARD CITES	0.134***	0.097*	0.132***
	(0.038)	(0.054)	(0.039)
NO INVENTORS	0.010	−0.003	0.008
	(0.023)	(0.035)	(0.023)
INVENTOR NON-US	−0.317***	−0.581***	−0.281**
	(0.110)	(0.141)	(0.112)
NO ASSIGNEES	−0.046	−0.464	0.009
	(0.136)	(0.350)	(0.134)
LOG SCIENTIFIC CITES	0.103***	0.114**	0.105**
	(0.039)	(0.050)	(0.042)
SIZE PATENT FAMILY	0.017***	0.015	0.017***
	(0.005)	(0.010)	(0.005)
PRIORITY FILING	−0.050	0.056	−0.077
	(0.075)	(0.138)	(0.076)
GRANT LAG	−0.084***	−0.025	−0.092***
	(0.022)	(0.034)	(0.024)
PATENT STOCK ASSIGNEE	−0.021	−0.058*	−0.014
	(0.022)	(0.035)	(0.022)
CONSTANT	0.500	−0.599	0.244
	(0.323)	(0.562)	(0.328)
TECHNOLOGY DUMMIES	YES	YES	YES
FILING YEAR DUMMIES	YES	YES	YES
Observations	1561	1561	1561

Note: pseudo Poisson ML, robust standard errors clustered at firm level in parentheses.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

citation profile does not necessarily signal a negative heuristic in Dosi's sense but may instead reflect a strategic orientation toward protecting application-specific knowledge, shifting emphasis from paradigm expansion to downstream economic capture.

Taken together, the contrast between Trajectories B and C illustrates a fundamental duality of innovation systems: science-push trajectories remain close to their paradigms and promote systemic knowledge diffusion, whereas demand-pull trajectories become increasingly contextualized, channeling innovation toward proprietary advantage at the cost of reduced codification and higher tacitness. These differences in codification have important implications for the absorptive capacity of third parties. Trajectory B's conceptual and codified knowledge structure enables higher potential and realized absorptive capacity, allowing firms to more easily identify, assimilate, and apply external knowledge (Cohen and Levinthal, 1990; Zahra and George, 2002). Its modularity and generality support cumulative learning and systemic recombination. By contrast, the tacit, firm-specific character of Trajectory C limits transformative capacity, making it harder for firms to recontextualize and scale such knowledge in SDG-relevant applications. As pointed out by Gruber et al. (2013), engineering-driven inventions tend to be rooted in firm-specific problem solving, often lacking the generalizable abstractions that facilitate diffusion across domains. Moreover, as van der Have and Rubalcaba (2016) argue, sustainability innovation depends not just on novelty, but on the capacity of knowledge to travel, scale, and support structural transformation, conditions that narrowly embedded innovations are less likely to meet., as trajectories with more codified, transferable knowledge facilitate broader technological learning and adoption across the system.

Trajectory D alone exerts limited influence, but its positive interaction with Trajectory C reveals a potential synergy. This pattern may reflect a form of cross-domain knowledge integration, whereby system-level formulation capabilities (D) enhance the practical deployment of molecular innovations developed in C. As Cattani and Malerba (2021) note, such layered integration allows niche breakthroughs to scale and diffuse more effectively. This dynamic could indicate a process of path creation through mutual reinforcement (Garud and Karnøe, 2003), in which distinct innovation efforts co-evolve and jointly enable novel applications. It also aligns with the view that sustainability-oriented innovation often depends on complementary combinations of knowledge types to transform technical advances into viable, accepted products (Fleming and Sorenson, 2004). While our evidence points in this direction, it remains tentative, and further research is needed to substantiate the nature and scope of these cross-trajectory complementarities.

Importantly, we also find that the timing of a trajectory's influence matters. While some trajectories show immediate impact on follow-on innovation, others emerge more gradually, reinforcing the idea that scientific contributions unfold across different stages of maturity and alignment with societal needs (Sorenson and Fleming, 2004; Confraria et al., 2024). These temporal dynamics are consistent with the notion that the alignment between a knowledge trajectory and evolving societal priorities can shift, requiring reconfiguration, integration, or support to regain relevance.

6.2. *Qualitative case examples*

These quantitative results are further supported by illustrative firm-level examples, which provide external validation of the empirical patterns observed across trajectories. This mix-method approach reinforces the empirical validity of our results and supports our distinction between systemic science-based knowledge and market-bound technical solutions. Table 9 presents illustrative firms aligned with Trajectories B, and C. DeLaval and Tate & Lyle, both operating in Trajectory B, exemplify how platform-like innovations such as enzymatic feeding systems or fermentation-based ingredients can support a stream of sustainability applications. DeLaval and Tate & Lyle develop foundational technologies, such as enzymatic precision feeding, oxidative stress control, and fermentation-based ingredient extraction, that serve as enablers for follow-up innovations. For example, DeLaval integrates artificial intelligence with enzyme-based precision feeding systems to enhance dairy efficiency and reduce methane emissions, directly aligning with SDGs related to climate action and sustainable food systems. Similarly, Tate & Lyle leverages fermentation technologies to create modular, scalable inputs used across a range of clean-label food applications. These innovations reflect the modularity, generality, and upstream recombination potential associated with Trajectory B, characteristics consistent with its strong and persistent association with SDG-related patent citations. These examples further illustrate how firms embedded in upstream trajectories contribute not only through product development but also by reconfiguring platform ecosystems around scalable, low-

Table 9
Illustrative case examples for trajectory B and C.

Trajectory	Scientific Focus	Application Logic	Illustrative Firms	Why the Firm Is Interesting	Empirical Impact on SDG-Related Innovation
B – Cellular mechanisms and oxidative stress responses	Metabolic and enzymatic control, precision fermentation, oxidative stress mitigation	Enables upstream efficiency, process modularity, and foundational biotechnology for alternative proteins	DeLaval Tate & Lyle	*DeLaval* applies enzymatic feeding and AI monitoring to increase milk yield while reducing methane and antibiotics. *Tate & Lyle* combines enzymatic protein extraction with fermentation to produce scalable clean-label ingredients.	Strong positive impact, especially in early-stage SDG-related citations. These patents are foundational and widely reused due to their codifiability and alignment with systemic sustainability goals (e.g., GHG reduction, circularity).
C – Protein chemistry and bioactive compounds	Engineering of bioactive peptides, enzymatic reactions (e.g., Maillard), nutrient-specific functionality	Enables formulation of functional foods, health-enhancing compounds, and high-value nutritional customization	Novonesis Morinaga	*Novonesis* leads global enzymatic markets, yet its patents tend to remain confined to specific industrial uses. *Morinaga* produces lactoferrin, HRB probiotics, and postbiotics for metabolic health—scientifically rich but narrowly diffused.	Negative association with SDG-related citations, particularly in later stages. These innovations are highly specialized, firm-specific, and often protected by trade secrecy, limiting spillovers.

emission alternatives, precisely the kinds of systemic enablers emphasized in the sustainability transition literature (Owen et al., 2021; Otero et al., 2022).

Trajectory C, focused on protein chemistry and enzymatic reactions (e.g., hydrolysis, peptide design, and Maillard processes), is represented by Novonesis and Morinaga. Both firms are global leaders in enzyme-enabled functional ingredients, developing bioactive compounds such as lactoferrin and postbiotics. While these innovations are technologically advanced, they are typically embedded in product-specific formulations, and thus most probably tightly controlled proprietary processes. This aligns with the observed lower citation diffusion in our analysis, particularly for SDG-related patents, reflecting a more downstream, context-dependent innovation strategy that limits broader spillovers. Novonesis, for instance, dominates global enzyme markets, but its patents are rarely reused beyond narrow industrial contexts, supporting our finding that trajectory C tends to remain commercially bounded. Similarly, Morinaga's lactoferrin and postbiotic products enhance health outcomes but are confined to proprietary health-focused applications, making them scientifically deep but limited in epistemic and technological generality. The strategies of these firms also illustrate how narrow application scope and market exclusivity, although potentially effective for product performance, may restrict the role of such innovations in broader systems change to a critical distinction in assessing alignment with SDG goals (Pandza and Ellwood, 2013).

7. Conclusions

This paper investigates how science informs sustainability-oriented innovation (van der Have and Rubalcaba, 2016; Confraria et al., 2024; Ciarli and Ràfols, 2019) by mapping the influence of distinct scientific trajectories embedded in corporate patents (Dosi, 1982; Cattani and Malerba, 2021). Focusing on the domain of protein production, we combine supervised and unsupervised text analysis to construct a scientifically grounded classification of trajectories, linking academic language to patented inventions. In doing so, we identify four core trajectories and assess their differentiated contributions to follow-on innovation, particularly with respect to citations from sustainability-related patents (SDG-aligned). Our findings highlight, on one hand, the importance of revealing the inner logic of scientific trajectories and, on the other, challenge the assumption that science uniformly enhances innovation outcomes. Instead, we demonstrate that the influence of science is contingent on the structure, maturity, and epistemic logic of the underlying trajectory. Some trajectories generate broader diffusion and SDG alignment, while others remain locked into specialized use cases with limited spillovers especially those characterized by lower codifiability and strong contextual embeddedness, consistent with engineering-driven paths (Gruber et al., 2013; Levinthal and March, 1993).

These results reinforce the conceptual value of viewing science as a map (Fleming and Sorenson, 2004), not merely as a source of inputs, but as a framework that shapes how firms formulate problems, design search strategies, and identify opportunities for recombination. They also provide clear evidence of the connection between scientific paradigms and technological trajectories (Dosi, 1982), showing how trajectories organize industrial R&D by delimiting the search space (Gruber et al., 2013; Levinthal and March, 1993; Katila and Ahuja, 2002) and thereby influence both the direction and scalability of innovation. Moreover, our findings indicate that the temporal dynamics of trajectories matter for both impact and sustainability orientation, underscoring the evolving interdependence between scientific knowledge and innovation outcomes (Malerba, 2002; Pel et al., 2020). This epistemic structuring becomes particularly salient in sustainability transitions, where firms operate under conditions of deep technological uncertainty and escalating environmental urgency.

From a policy perspective, our findings suggest that the evaluation of public science should move beyond traditional metrics of academic output to consider its capacity to shape industrial innovation paths. This is particularly crucial in sustainability-intensive sectors, where the alignment between scientific abstraction and industrial application can determine the success of long-term transitions. Moreover, our approach offers an empirical strategy to assess how different research directions either reinforce or constrain sustainability objectives over time, an insight relevant for funding agencies and mission-oriented policy frameworks (Confraria et al., 2024). Our approach also offers a novel toolkit for innovation strategy. By classifying patents through science-based dictionaries, we extend beyond conventional patent citation analysis and highlight the role of language, vocabulary, and epistemic framing in advancing and diffusing innovation (Kaplan and Vakili, 2015; Cattani et al., 2018; Falchetti et al., 2022; Cutolo and Ferriani, 2024). This framework enables firms, investors, and policymakers to visualize where innovation is scientifically grounded and where strategic recombination may unlock additional value. However, this study has several limitations. First, we focus exclusively on USPTO data, which may not fully capture global patterns of sustainability innovation or regional differences in regulatory pressures. Second, while our patent-level focus improves consistency, it abstracts from firm-level strategies and organizational routines that may further shape trajectory evolution. Finally, the classification of SDG-related patents through keyword matching, while validated, may not fully capture the complexity of sustainability intent.

Future research should expand this framework across sectors and countries to test the generalizability of trajectory-based patterns.

Comparative studies could examine whether similar forms of alignment and misalignment emerge in sustainability-critical domains such as renewable energy, circular materials, or decarbonized mobility. Fieldwork involving interviews or ethnographic studies with inventors could further illuminate how firms interpret and operationalize scientific knowledge. Introducing country-level regulatory contexts and patent system variations would also offer insight into the institutional contingencies of scientific trajectories (Gentile et al., 2023; Miguelez and Moreno, 2018; Dechezleprêtre et al., 2015). Finally, linking trajectory patterns to firm-level outcomes, such as profitability, ESG performance, or strategic valuation, could help bridge epistemic structure with organizational impact, clarifying how science translates into both innovation and value creation.

CRediT authorship contribution statement

Marco S. Giarratana: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Martina Pasquini:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Markus Simeth:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this paper the authors used ChatGPT in order to proofread the text. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

On behalf of all authors of the manuscript, the corresponding author declares to not have any potential competing, conflicting, or non-financial interests related to this paper.

Appendix A

Unsupervised (POS)-enhanced Latent Dirichlet Allocation (LDA) Algorithm.

To uncover the latent topics (i.e., the research trajectory) within this large corpus. we implemented a part-of-speech (POS)-enhanced Latent Dirichlet Allocation (LDA) algorithm. This algorithm classifies each word as a noun. adjective. verb. or adverb before eliciting topics. By analyzing the co-occurrence of words. LDA helps uncover hidden topics that reflect the collective themes present in each body of text (Blei et al., 2003). LDA operates on the premise that documents can be represented as probability distributions across latent topics. which themselves are probability distributions over words. Each topic is characterized by a unique distribution of words. and each document represents a mixture of a limited number of these topics. with every word in the corpus linked to these topics. In our analysis. we excluded common stop words. our search terms. and generic keywords frequently found in scholarly articles. such as "study." "research." "results." and "analysis." among others. The list of journals and stop words is provided in the appendix. The LDA analysis identified a list of prominent topics within the document corpus. assigning a probability vector to each document that suggests the relative presence of these topics. In accordance with the probabilistic framework of LDA. we applied a probability weighting threshold of 33 %. calculated as the mean plus one standard deviation of the sample average. to assign articles to specific topics. It is important to note that a probability of 25 % for each topic would suggest an equal likelihood of an article being classified under all four topics. Utilizing this threshold. our analysis of four distinct topics. Optimized based on perplexity and coherence scores. resulted in the unique classification of 39,334 articles. accounting for 87.69 % of the entire sample. The remaining articles comprised 6.16 % that were unclassified and 6.15 % that were classified under two topics simultaneously.

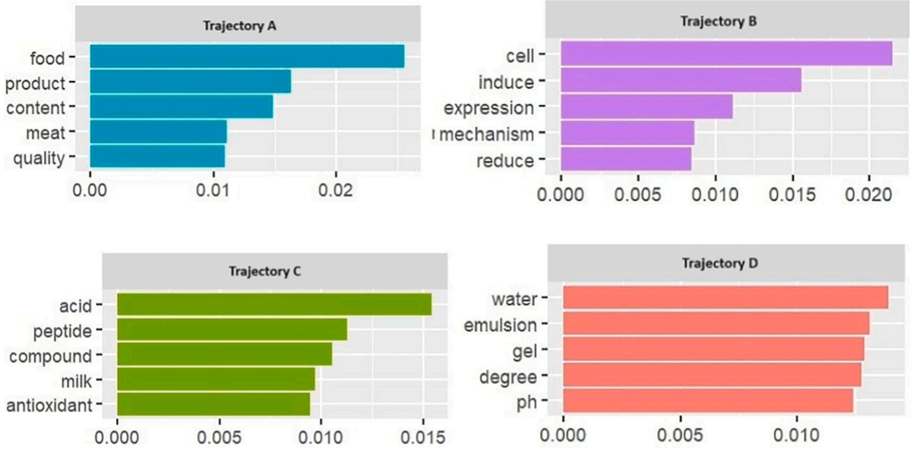

Fig. A1. Top recurring keywords for each trajectory.

Notes: Most frequent word by topic according to POS-Enhanced-LDA method. X axis. word probability

Table A1
Definition and measures of the variables.

Variable	Definition	Data Source
IMPACT	Number of citations received within 5-years from the patent's grant date	Patentsview
IMPACT SDG	Number of citations received (within 5-years from grant). where citing patents include SDG terms	Patentsview & Corporate Knight
IMPACT NON-SDG	Number of citations received (within 5-years from grant). where citing patents do not include any SDG terms	Patentsview & Corporate Knight
TRAJECTORY A_ANIMAL	Dummy equals to 1 whether the focal patent is associated with the scientific area A (animal-based protein innovation) identified by the machine-learning algorithm	WoS
TRAJECTORY B_CELLULAR	Dummy equals to 1 whether the focal patent is associated with the scientific area B (innovation of metabolic engineering. enzymatic processing. and precision monitoring) identified by the machine-learning algorithm	WoS
TRAJECTORY C_CHEMISTRY	Dummy equals to l 1 whether the focal patent is associated with the scientific area C (engineering of bioactive compounds) identified by the machine-learning algorithm	WoS
TRAJECTORY D_STRUCTURE	Dummy equals to 1 whether the focal patent is associated with the scientific area D (improve the texture. stability. and emulsification properties of food products) identified by the machine-learning algorithm	WoS
LOG CLAIMS	Number of claims at patent grant (in logs)	Patentsview
LOG BACKWARD CITES	Number of backward citations (U.S. granted patents) (in logs)	Patentsview
NO INVENTORS	Number of co-inventors listed on the patent.	Patentsview
INVENTOR NON-US	Dummy variable that takes the value of one if the patent has at least one co-inventor located outside the U.S., zero otherwise	Patentsview
NO ASSIGNEES	Number of patent assignees	Patentsview
LOG SCIENTIFIC CITES	Number of references to scientific documents (in logs).	Matt Marx webpage & Patentsview
SIZE PATENT FAMILY	Number of patents that belong to the same patent family than the focal patent. as defined by the DocDB standard.	Patstat
PRIORITY FILING	Dummy variable that takes the value of one if the patent's filing date is equivalent to the priority date of the patent family. and zero otherwise	Patstat
GRANT LAG	Time lag (in years) between the patent's filing and grant dates.	Patstat
PATENT STOCK ASSIGNEE	Number of cumulative patents of the patent assignee. computed by the perpetual inventory method. with 15 % discount rate (in logs).	Patentsview

Data availability

Data will be made available on request.

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