

IMPERIAL COLLEGE LONDON
DEPARTMENT OF LIFE SCIENCES

Revealing temporal trends in UK STEM funding using AI

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5874 words
A thesis submitted in partial fulfillment for the degree of
Master of Research at Imperial College London
Submitted for MSc Computational Methods in Ecology and Evolution
August 2023

Declaration

The data of the whole project was given by Flávia Bellotto Trigo (f.bellotto-trigo18@imperial.ac.uk). The author of the report, Hanyi Jiang, is responsible for data processing. The initial version of the code for this project was derived from Flavia. The author of this report, Hanyi, made significant modifications and additions to the code to fulfill the analysis requirements.

Acknowledgement

I would like to express my sincere gratitude to my supervisor, Samraat Pawar and Flávia Bellotto Trigo, Imperial College London for invaluable guidance, expertise and support throughout the duration of the project.

Contents

List of Figures	iv
List of Tables	iv
Abstract	i
1 Introduction	1
2 Methods	3
3 Results	7
4 Discussion	21
References	24

List of Figures

1	Proportional Trends Shifting in Research Landscape	10
2	Changing Subdomain Counts Across Categories Over Time	12
3	Project Counts distribution of Applied Science and Natural Science	14
4	Changing Landscape of Ecology Funding	15
5	Evolution of Funding Trends Across Categories	16
6	Investment Directions within Natural Science (2013-2015 and 2016-2018)	17
7	Allocation of Funding in Natural Science	18
8	While these directions have received consistent financial support, none of them exhibit a clear growth trend.	20

List of Tables

1	Science Takes Center Stage (1973-2024)	7
2	Topic List	8
3	Consistently Funded Research Topics Across Five Phases (2010-2024)	19

Abstract

1 Countries worldwide have always paid continuous attention to and supported scientific research.
2 Based on our daily experience, it seems that fields such as biology or AI have received a lot of
3 attention recently, but this lacks research support. So what does the current scientific landscape
4 look like? And how did it arrive at the current pattern?

5 I take the UK Research and Innovation (UKRI) as a case study to analyze investment
6 directions and structures, aiming to yield profound insights into the funding landscape and
7 its development process. Employing a data-driven approach, I leverage machine learning
8 techniques, particularly the Mallet Latent Dirichlet Allocation (LDA).
9

10 The ultimate discovery underscores a pronounced tendency to allocate funds towards applied
11 and natural sciences, reflecting their paramount significance within the research agenda.
12 During the 20 years of analysis, in each three-year period, more than 80% of the invested
13 projects belong to applied and natural science. 2022-2024, according to incomplete statistics,
14 the two companies received 6,785,877,536 pounds of funding, accounting for 92.15% of the
15 total expenditure funding amount. Furthermore, ecology has consistently received significant
16 attention and continuous funding over the years. During the period from 2016 to 2018,
17 it secured a total funding of £108,990,748. This amount positioned ecology as the second
18 highest-funded field within natural sciences. Nevertheless, the intricacies of these domains
19 have given rise to many specialized orientations. Alternatively, while receiving fewer and
20 comparatively modest allocations in the social sciences domain, public policy occupies a
21 dominant position. Apart from the period between 2010 and 2012, during which business
22 projects also received funding, funds were exclusively allocated to Public Policy within the
23 realm of social sciences in all other years.
24

25 By analyzing the dynamic funding allocation in UKRI, I unveil the ever-evolving priorities and
26 prospects within the funding landscape, revealing the history of scientific development and
27 possible future development trends.
28

1 | Introduction

IN recent years, humankind has faced many daunting challenges, including military conflicts, rising sea levels gradually making some cities disappear, pandemics, noncommunicable diseases, dwindling resources, and so forth, and are also working hard to iterate technology. Countries have reached a record high of almost US \$1.7 trillion in spending on technological innovation and scientific research (FFucation, 2023).

Recently, research remains at the forefront of understanding and addressing these complex problems. The foundation of any successful research project relies on innovative ideas and meticulous execution (Neema and Chandrashekar, 2021). Conducting research, especially in fields like wet laboratory science or large-scale epidemiological studies, demands substantial funding to cover tangible and intangible costs (Schembri-Wismayer et al., 2018). Therefore, even though the process of applying for funding is by no means an easy task and is considerably daunting and time-consuming, with EU research programs, for example, EU research (such as Horizon 2020), application success rates are only around 15% (Schembri-Wismayer et al., 2018), researchers generally opt to seek research funding to ensure the smooth operation of their research projects. Encouragingly, governments, universities, and nonprofit organizations recognize the pivotal role of research and development (R&D) in driving economic growth, job creation, national security, environmental protection, and knowledge expansion (Sargent, 2017).

In 2020, global R&D expenditures reached \$2.352 trillion (Sargent, 2017). The 10 largest R&D-funding countries of 2020 accounted for \$1.999 trillion in R&D expenditures (Sargent, 2017). Such substantial investments highlight the commitment to foster research and innovation. In fact, securing adequate funding is crucial to fueling the relentless pursuit of scientific breakthroughs. For instance, Gush et al.'s findings indicate that funding is correlated with a 6-15% increase in publications and a 22-26% increase in citation-weighted papers for research teams (Gush et al., 2018).

In 2021, The UK government's net expenditure on research and development (R&D), excluding EU contributions, remained at £14.0 billion. Within the UK, research funding takes two primary forms: commercial and non-commercial, with the latter dominating the landscape. Non-commercial funding sources encompass research charities, national academies, various government departments, and the United Kingdom Research and Innovation (UKRI).

Among these organizations, UKRI is UK's most significant public funder of research and innovation, principally funded through the Science Budget by the Department for Business, Energy and Industrial Strategy (BEIS). According to UKRI Annual Report and Accounts

2021-22, they invest more than £8 billion annually to advance our understanding of people and the world around us and deliver benefits for society, the economy, and the environment.

From everyday conversations and the information we gather from online news, we might form a rough perception that the field of science and technology tends to secure a higher frequency of funding for projects. However, these notions are not substantiated and are essentially intuitive assumptions. Moreover, as time progresses, the emergence of novel discoveries continuously challenges or validates our existing beliefs, potentially reshaping the landscape of future funding allocation. This inevitably prompts the question: Can discoveries wield a fresh influence on funding arrangements?

Hence, through a comprehensive analysis of investment patterns, I can uncover the focal points of institutions and gain insights into the developmental trajectories of various specialized domains. Furthermore, this analysis provides a more precise understanding of the rise and fall of various domains and their specific manifestations in terms of funding allocation. Understanding research funding trends carries immense significance for researchers, policymakers, and funding agencies. By unraveling the ever-changing landscape of research investment, people can identify shifts in research priorities and potential areas of innovation. Such insights will empower us to address contemporary challenges effectively and adapt research strategies for future endeavors.

Notably, I seek to address the following key research questions:

1. Evolution of Research Funding Priorities: How have research funding priorities evolved across different disciplines and industries?
2. Emerging Research Areas: What emerging research areas have gained prominence recently, and how do they align with societal needs and technological advancements?
3. Drivers of Fluctuations: What are the driving factors behind fluctuations in research attention to specific themes in different periods?
4. What is the funding trend for ecology and evolution?

I will employ AI-driven methods to process and visualize the data, revealing patterns and connections between funding allocation and significant temporal factors. Monitoring and comprehending shifts in research investment will empower me to effectively tackle current challenges and tailor research strategies for upcoming pursuits.

2 | Methods

MY primary objective based on an extensive dataset encompassing funded projects by UKRI throughout the UK, comprising crucial information such as project titles, abstracts, and corresponding funding amounts. Armed with these comprehensive data, I employed topic analysis methods to ascertain the distinct research domains to which they pertained. This analytical endeavor was intended to discover the evolving landscape of research focus across various disciplines, revealing prominent areas that have garnered substantial support from UKRI-funded programs over the past few decades. By scrutinizing the ever-evolving patterns and dominant themes, I aimed to gain valuable insights into the investment preferences and strategic directions pursued by research funding agencies, particularly UKRI.

Data Preprocessing and Preparation

The available data for analysis consists of UKRI records spanning from 1973 to 2023. The minimum data requirement includes project titles, start dates, titles, abstracts, funding amounts, and all other available project-specific metadata.

During the data preprocessing stage, I made various attempts to guarantee the efficiency of information filtering and subject analysis in the subsequent phases. To begin with, I grouped all the available data from 1973 into five-year intervals. Each group consisted of two parts: the title summary, comprising project summaries and project IDs, and the metadata part, encompassing all other project-related details.

However, upon completing the grouping, I encountered an issue with the datasets for 1973-1977, 1978-1983, 1984-1988, and 1989-1993. These groups had very limited data, with the number of projects being less than 100, which rendered them less valuable for meaningful research. Similarly, the number of projects in 1999-2003 did not exceed 1,000. Considering that the actual number of funded projects may be substantially higher than those reflected in the data, I discard data before 2004 and focus solely on projects from 2004 to 2023.

Under such circumstances, to enhance analysis accuracy, I further reduced the time interval and regrouped the data every three years. This adjustment would yield more informative and comprehensive datasets for in-depth subject analysis and allow for a more robust examination of trends and research preferences in recent years.

135 After grouping the data, I started to process the data file formally. I have implemented the
136 following to remove noise in the dataset.

- 137 1. Tokenization: Breaking down raw text into individual words
- 138 2. Removing punctuation and stop words*
- 139 3. Lemmatization: remove inflectional endings only and return the base or dictionary form
140 of a word (Kurt, 2020).
- 141 4. Remove incomplete projects from the dataset to ensure data quality and reliability.
- 142 5. Removes words that appear less than 20 times
- 143 6. Removes words that appear in 80% of the documents

144 *Stop words are common words frequently used in natural language but usually lack practical
145 meaning or have no significant impact on text analysis tasks. Since these words do not usually
146 carry specific semantic information, they are often ignored or removed from the text in tasks to
147 reduce data dimensions, improve processing efficiency, and help focus on meaningful keywords
148 or phrases (Rajaraman and Ullman, 2011).

149 Preparing Topic Numbers for Mallet LDA

150 The current challenge lies in the abundance of unstructured abstracts in the dataset, making
151 extracting relevant and necessary information difficult. To address this, I opted for topic
152 modeling techniques from the field of text mining.

153
154 Topic modeling is a valuable tool in statistics and natural language processing, employing
155 a statistical model to unveil abstract "topics" in a collection of documents. This powerful
156 text-mining approach enables the discovery of hidden semantic structures within the text,
157 offering valuable insights into the underlying themes and concepts in the analyzed documents
158 (Arun et al., 2010). To be more specific, a topic model is a probabilistic model used to discover
159 topics, or latent structures, across a collection of documents (Saxton, 2018). There are many
160 approaches for obtaining topics from a text, such as – Term Frequency and Inverse Document
161 Frequency. Topic modeling encompasses various techniques, including four of the most popular
162 approaches: LDA, Mallet LDA, STM, and HDP (Egger, 2022).

163
164 Latent Dirichlet Allocation (LDA), an unsupervised machine learning approach, was proposed
165 by Blei, David M., Ng, Andrew Y., and Jordan in 2003, which is a powerful algorithm that
166 enables exploring and discovering latent topics within extensive collections of text known
167 as corpora (Chipidza et al., 2022). LDA can infer the topic of each document in the form
168 of probability distribution, so that after analyzing some documents to extract their topic
169 distribution, topic clustering or text classification can be performed according to the topic
170 distribution (Blei, 2012). In LDA (Latent Dirichlet Allocation), the Bag-of-Words model is
171 employed, commonly known as the "bag-of-words" model. In this model, each document is
172 represented as a collection of words, disregarding their order of appearance.

173
174 Mallet LDA and LDA are highly correlated. The MALLET topic modeling toolkit contains
175 efficient, sampling-based implementations of Latent Dirichlet Allocation, Pachinko Allocation,

176 and Hierarchical LDA (McCallum, 2002). According to the experiences of Senol Kurt and the
177 authors of the Gensim tutorial, utilizing the MALLET package (with Python wrapper) to
178 implement the LDA approach for topic generation has been found to produce superior results
179 (Kurt, 2020). Hence, I have adopted the Mallet LDA approach for my project.

180

181 To determine the number of topics for the Mallet LDA model, I employed the `mallet`
182 `evaluate-topics` command to analyze the model's performance across a range of topic
183 numbers, from 50 to 400, with intervals of 50. I used perplexity as the evaluation criterion.
184 Perplexity measures the model's ability to predict unseen test data, normalized by the number
185 of words in the evaluation. The perplexity formula is defined as follows:

$$PP(W) = \left(P(W_1 W_2, \dots, W_m)^{-\frac{1}{m}} \right) \quad (2.1)$$

186 where PP represents perplexity, W refers to the words in the document, and P denotes the
187 probability estimate assigned to the document words. An LDA model with a specific number of
188 topics that yields the minimum perplexity value is considered the optimal model (Neishabouri
189 and Desmarais, 2020).

190

191 Afterward, I utilized the "`mallet run cc.mallet.util.DocumentLengths`" command to calculate
192 the lengths of documents in the test set and saved the results to a file. Following this, I
193 implemented a loop to iterate through different numbers of topics, ranging from 50 to 400
194 with increments of 25. For each topic number, I utilized the "`mallet train-topics`" command
195 to train the topic model, generating three files: the diagnostic file, the inferencer file, and the
196 topics-state.gz file. The inferencer file contains the necessary parameters for inferring topics
197 in new documents, while the topics-state.gz file includes the training data along with all the
198 inferred parameters, which leads to the fact that the inferencer file is much smaller than the
199 topics-state.gz file.

200

201 On the other hand, the diagnostic files contain essential information under each topic number,
202 such as the topic ID and relevant statistical metrics, including word count, probability,
203 cumulative probability, document count, word length, coherence, and more. Among
204 them, the coherence metric measures the semantic similarity between high-scoring words in a
205 topic, providing insights into the quality and coherence of the generated topics (Kapadia, 2022).

206

207 Perplexity is one of the most widely used evaluation metrics for language models. Hence, I
208 leveraged the "`mallet evaluate-topics`" command to assess the performance of the model on
209 the test set and derive its perplexity value. In essence, perplexity focuses on the log-likelihood
210 aspect, providing an indication of how probable new unseen data is when considering the
211 model that was previously learned. In other words, it measures how effectively the model
212 captures the statistics of the held-out data (Kapadia, 2022). A lower perplexity value indicates
213 a higher level of coherence and a better-performing model in representing the underlying
214 patterns of the unseen data (Neishabouri and Desmarais, 2020).

215

216 After the evaluation, I found that the model with 50 topics achieved the lowest perplexity
217 value of -2.277E7. Therefore, I determined that setting the number of topics to 50 for the
218 subsequent topic inferring process would be the most suitable choice.

219

220 Topic Modeling Using Mallet LDA

221 Once the number of topics is determined, which is 50, the process of topic inference begins with
222 the "mallet infer-topics" command. This command utilizes the previously trained inferencer
223 file as input and generates the topic distribution table. In this table, each row corresponds to
224 a project abstract, and each column represents a topic, with the values indicating the degree
225 of association between each abstract and the different topics. This table effectively illustrates
226 the association level between each abstract and the various topics, facilitating subsequent topic
227 analysis and text comprehension.

228
229 Next, I used `xml.etree.ElementTree` to parse the diagnostic information from the XML file
230 generated by Mallet, which contained details about the 50-topic model, allowing me to obtain
231 the specific vocabulary associated with each topic.

232
233 In the penultimate step, I leveraged the power of ChatGPT to gain deeper insights and
234 understanding from the topic-related words obtained in the previous steps. By reading and
235 parsing the XML file containing the diagnostic information of the Mallet-generated topic
236 model with 50 topics, I extracted the specific vocabulary associated with each topic.

237
238 With integrating these topic-related words into ChatGPT, I harnessed its capabilities to derive
239 precise directions and valuable insights based on the given topic words. This fusion of Mallet
240 LDA and ChatGPT enabled me to effectively explore and comprehend the underlying themes
241 and concepts concealed within the extensive collection of abstracts.

243 Topic Analysis and Funding Trends Evaluation

244 As a final step, I comprehensively evaluated the topic distribution table. Each row in the file
245 represents a distinct project, with the subsequent 50 columns containing probabilities associated
246 with different topics. By employing Python's Pandas package, I meticulously analyzed the data
247 on the dominant topic for each project based on the highest probability. Additionally, I derived
248 insights into the distribution of projects across various topics and compiled an overview of the
249 cumulative funding received by projects associated with each topic. This approach provided
250 valuable insights into the thematic landscape and funding trends within the dataset.

3 | Results

OVER a span of 51 years, from 1973 to 2024, prominent themes have emerged and endured. Notably, biology, chemistry, environmental science, and materials science have consistently dominated the landscape, showcasing their enduring significance.

Table 1: Science Takes Center Stage (1973-2024)

Material Science	Physics	Business	Developmental Biology	Political Science
Medicine	Imaging Techniques	Automotive	Climate Science	Sensor Technology
Epidemiology	Media Studies	Environmental Science	Development	Chemistry
Philosophy	Infrastructure	Neuroscience	Ecology	Climate Science
Microbiology	Particle Physics	Evolutionary Biology	Optics	Quantum Physics
Biochemistry	Statistics	Computer Science	Manufacturing	Agriculture
Healthcare	Machine Learning	Public Health	Networking	Astronomy
Material Science	Biochemistry	Pediatrics	Immunology	Food Science
Education	Oncology	Waste Management	Electronics	Oceanography
Molecular Biology	Modeling	Mathematics	Geology	Surgery

While this analysis provides valuable insights, it’s important to acknowledge that the vast temporal scope might limit the depth of information attained.

I partitioned the metadata into consecutive three-year periods to gain deeper insights into the evolving landscape for a more concentrated exploration of the dominant trends and subjects influencing research and innovation within these specific timeframes. This focused examination of shorter intervals will provide a finer-grained and more intricate viewpoint.

I have made six significant findings by analyzing and consolidating each triennial topic.

1. Sustained Importance: The topics of Environmental Science, Computer Science, Data Science, Ecology, Biology, and Training are consistently present throughout various periods, emphasizing their enduring significance and impact.
2. Transient Topics: Some projects have emerged briefly during specific years, such as video games and supply chain disruptions in 2019-2021.
3. Environment and Sustainable Development: During 2016-2018, there was a pinnacle of concern regarding environmental issues. The prevailing topics of that era were predominantly associated with the environment, including environmental science, earth science, ecology, energy materials, waste management, energy transfer, earth and geology, etc.

4. Data science, computer science, and machine learning have repeatedly emerged at various time intervals.
5. Limited Presence of Social Sciences: Public policy is a prominent funded focus within social science.
6. Certain topics experienced fluctuations in attention across different years. For instance, Particle Physics was prominent in earlier years but waned later.

Table 2: Topic List

2010-2012	2013-2015	2016-2018	2019-2021	2022-2024
Imaging	Machine Learning	Human-Computer Interaction	Problem Solving	Environmental Engineering
Diagnostic Technology	Medical Technology	Healthcare	Agriculture	Medical Science
Computer Science	Automotive Engineering	Transportation	Genetics	Engineering
Neuroscience	Environmental Science	Environmental Science	Particle Physics	Microbiology
Electronics	Neuroscience	Neuroscience	Natural Hazards	Mathematics
Materials Science	Climate Science	Earth Science	Climate Resilience	Sports Science
Environmental Science	Environmental Monitoring	Sensors and Monitoring	Data sensing	Physics
Atmospheric Science	Ecology	Ecology	Quantum Technology	Agriculture
Oceanography	Cell Biology	Cell Biology	Astrophysics	Plant Science
Analytical Chemistry	Fluid Dynamics	Particle Chemistry	Protein Structure	Molecular Biology
Bioinformatics	Cybersecurity	Network Security	Medical Diagnostics	Health Science
Pharmaceutical Science	Plant Science	Agriculture	Soil Ecology	Education
Quantum Physics	Biochemistry	Molecular Biology	Infectious Disease	Environmental Science
Climate Science	Fluid Mechanics	Fluid Dynamics	Wind Energy	Geology
Human-Computer Interaction	Data Analysis	Ecology	Industry Training	Theoretical Physics
Climate Science	Energy Systems	Quantum Science	Pandemic	Climate Science
Automotive Engineering	Chemical Reactions	Materials Science	Modeling	Ecology
Natural Disaster	Genetics	Chemical Reactions	Drug Development	Molecular Biology
Evolutionary Biology	Materials Science	Genomics	Agriculture	Earth Science
Particle Physics	Environmental Pollution	Energy Materials	Sustainable Transport Solutions	Astrophysics
Technology Management	Medical Imaging	Environmental Pollution	Climate Change	Imaging
Fluid Dynamics	Food Science	Imaging Techniques	Stem Cell Development	Data Analysis
Education	Risk Assessment	Agriculture	Biodiversity	Physiology
Geology	Microbiology	Disaster Management	Pollution Monitoring	Molecular Biology
Astrophysics	Virology	Microbiology	Environmental Science	Computer Science
Climate Science	Recycling	Infectious Diseases	Data Analysis	Microbiology
Sensor Networks	Systems Modeling	Waste Management	Immune System	Material Science
Theoretical Physics	Energy Management	Modeling	Machine Learning	Particle Physics
Organic Chemistry	Plasma Physics	Energy Systems	Imaging	Medicine
Materials Science	Astronomy	Plasma Physics	Geology	Astrophysics
Ecology	Aircraft Engineering	Astronomy	Material Design	Engineering
Infectious Disease	Aging	Aerospace Engineering	Public Policy	Geology
Agriculture	Thermodynamics	Aging	Robotics	Health Science
Public Policy	Material Engineering	Energy Transfer	Business	Particle Physics
Cell Biology	Technology Innovation	Material Failure	Cybersecurity	Material Science
Information Technology	Training	Technology	Particle Physics	Environmental Science
Remote Sensing	Mathematics	Training	Drug Discovery	Computer Science
Healthcare	Geology	Mathematics	Material Science	Cell Biology
Ecology	Mathematics	Earth and Geology	Video Game	Chemistry
Computational Science	Computer Science	Statistics	Fluid Dynamics	Mathematics
Climate Modeling	Training	Computer Science	Mathematics	Climate Science
Oncology	Molecular Biology	Vocational Training	Supply Chain	Neuroscience
Molecular Biology	Cancer Research	Genetics	Chemical Synthesis	Public Policy
Plant Breeding	Cardiovascular Diseases	Cancer Treatment	Clean Energy	Data Science
Physiology	Semiconductor Technology	Medical Care	Public Health	Material Science
Genetics	Data Analysis	Optics	Neurology	Control Systems
Systems Biology	Particle Physics	Data Analysis	Aging	Energy Science
Nutrition	Public Health	Particle Physics	Advanced Materials	Environmental Science
Environmental Engineering	Cell Signaling	Public Health	Marine Environment	Hydrology
Product Development	Physiology	Immunity	Ecosystem Biodiversity	Fluid Dynamics

Some data entries in (table 2) are duplicated due to Mallet LDA’s topic analysis, which treats vocabulary for each topic separately. However, similarities in topic direction can lead to duplicated content. I’ve integrated duplicated content in subsequent analyses to ensure accuracy and consistency.

284 Analysis Based on Project Number

285 Building upon the systematic analysis and consolidation of each triennial topic, I conducted
286 an in-depth examination of the prevailing thematic trends. I adopted a categorization
287 framework inspired by Wikipedia's "Outline of Academic Disciplines." This framework
288 systematically classifies endeavors into five distinctive domains: Humanities, Social Science,
289 Natural Science, Formal Science, and Applied Science. Applying this framework gave me a
290 comprehensive perspective through which knowledge's intricate and multifaceted landscape
291 could be thoroughly navigated and understood.

292 Upon thorough analysis, it is clear that UKRI exhibits a pronounced concentration in its
293 project selection, revealing a distinct inclination toward funding projects within Applied
294 Science, closely trailed by Natural Science. Applied science is the use of the scientific method
295 and knowledge obtained via conclusions from the method to attain practical goals (Bunge,
296 1966), which usually have specific commercial objectives related to products, procedures, or
297 services and deal with solving practical problems (Potter and Humiston, 2015). When it comes
298 to natural science, it is entirely grounded in events and phenomena that occur naturally,
299 encompassing two major categories: life sciences and physical sciences. Merriam-Webster's
300 definition of natural science aligns with this, describing it as any scientific discipline concerned
301 with matter, energy, and their interrelations and transformations or with objectively
302 measurable phenomena (Ledoux, 2002).

304 These two categories encompass a substantial array of subjects, including Material Science,
305 Environmental Science, Microbiology, and Cell Biology – disciplines often characterized by
306 their intensive need for experimentation and material resources, necessitating substantial
307 funding.

309 Simultaneously, a select subset of Formal Science, such as Mathematics, Statistics, Computer
310 Science, and certain Social Science projects, has garnered funding from UKRI. Regrettably,
311 Humanities have garnered a notably diminished share of funding projects over these 21
312 years, rendering their presence comparatively inconspicuous when compared to the other four
313 categories.

315 The correlation between UKRI's funding patterns and their 2022-2027 strategic priorities
316 provides additional validation for these conclusions. The five strategic focal points,
317 namely "Fostering Sustainable Environmental Practices," "Promoting Global Security and
318 Resilience," "Enhancing Opportunities and Outcomes," "Ensuring Enhanced Health, Ageing,
319 and Wellness," and "Combatting Infectious Threats," closely align with the domains of
320 Applied Science and Natural Science, which have received significant funding. This congruence
321 further underscores UKRI's deliberate strategy to address urgent global challenges and propel
322 pragmatic solutions within these fields.

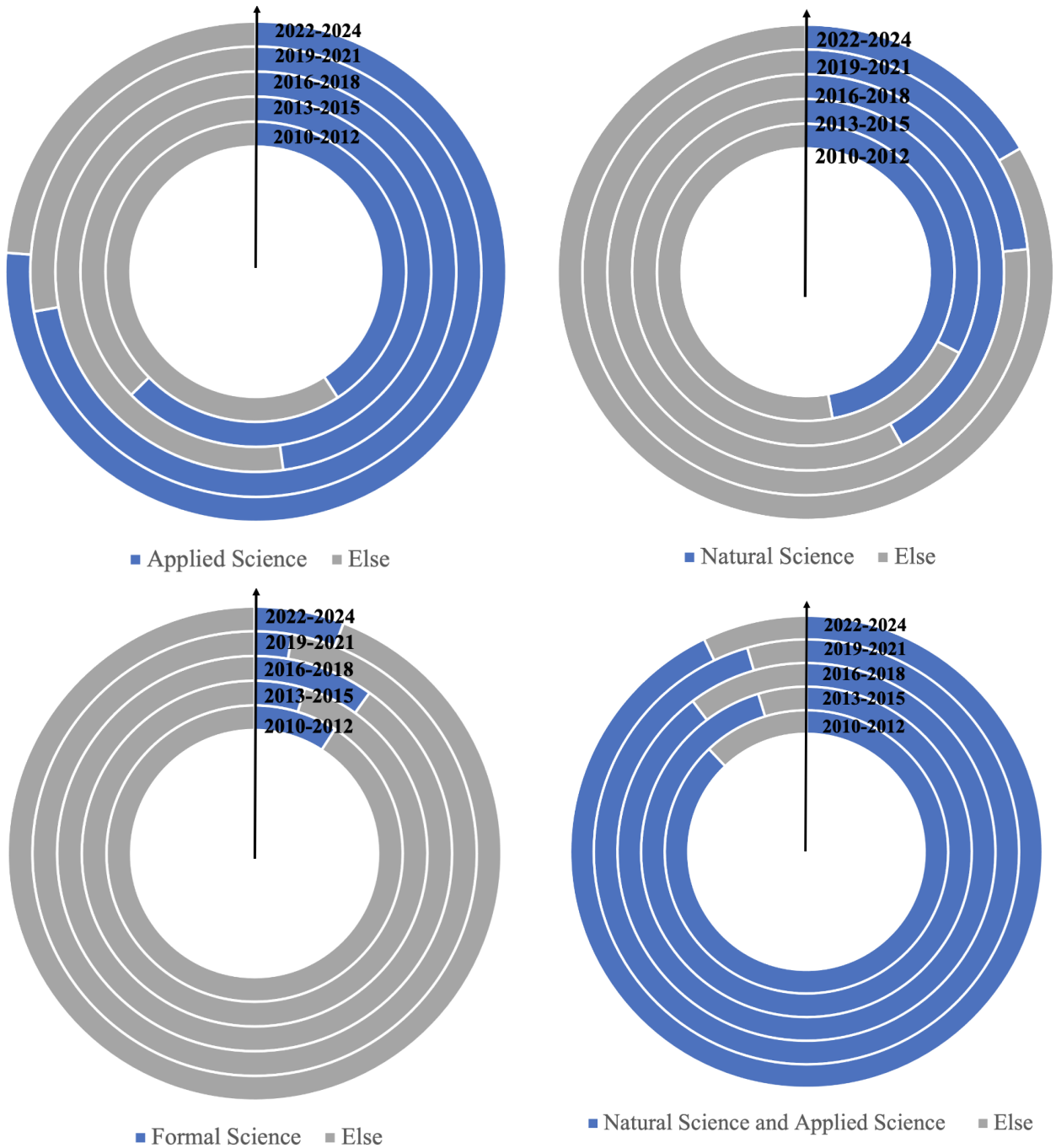


Figure 1: The transition from the inner to the outer circle corresponds to the progression of time from past to present. While the evolution of applied science and natural science exhibits less distinct trends, it is noteworthy that these two domains consistently maintain their status as the most funded areas.

Furthermore, within the realm of social sciences, funding has primarily directed its focus toward public policy. However, the quantity of projects received within the public policy field is comparatively remarkable. Across the periods of 2010-2012, 2019-2021, and 2022-2024, social science has witnessed support solely directed towards public policy. Also, in 2010-2012, 346 projects were funded under the public policy category, surpassing the funding count of any formal science topic and surpassing many themes within the natural science domain. Public policy has emerged as a cornerstone of social science, garnering substantial attention and resources.

Moreover, each triennial interval showcases standout topics that have surged ahead and captured substantial funding. For instance, in 2013-2015, "Automotive Engineering" within the Applied Science category witnessed a staggering 1117 funded projects, a testament to its robust prominence. Similarly, 2016-2018 witnessed a surge of funding in the "Material Science" domain, with an impressive tally of 1253 projects. Notably, 2019-2021 witnessed a crescendo in the "Applied Science - Public Health" category, with a significant surge of 1232 funded projects – a phenomenon that perhaps correlates with the emergence of the COVID-19 pandemic.

From 2022 to 2024, while Applied Science continues to receive the highest number of funded projects, its subdomains have noticeably decreased. The increase in the overall number of funded projects in Applied Science contrasts with the reduction in the diversity of its subdomains, suggesting a tendency toward consolidation within the Applied Science domain. To be specific, 68.75% of the investment directions in applied science for 2022-2024 align with those invested during 2019-2021.

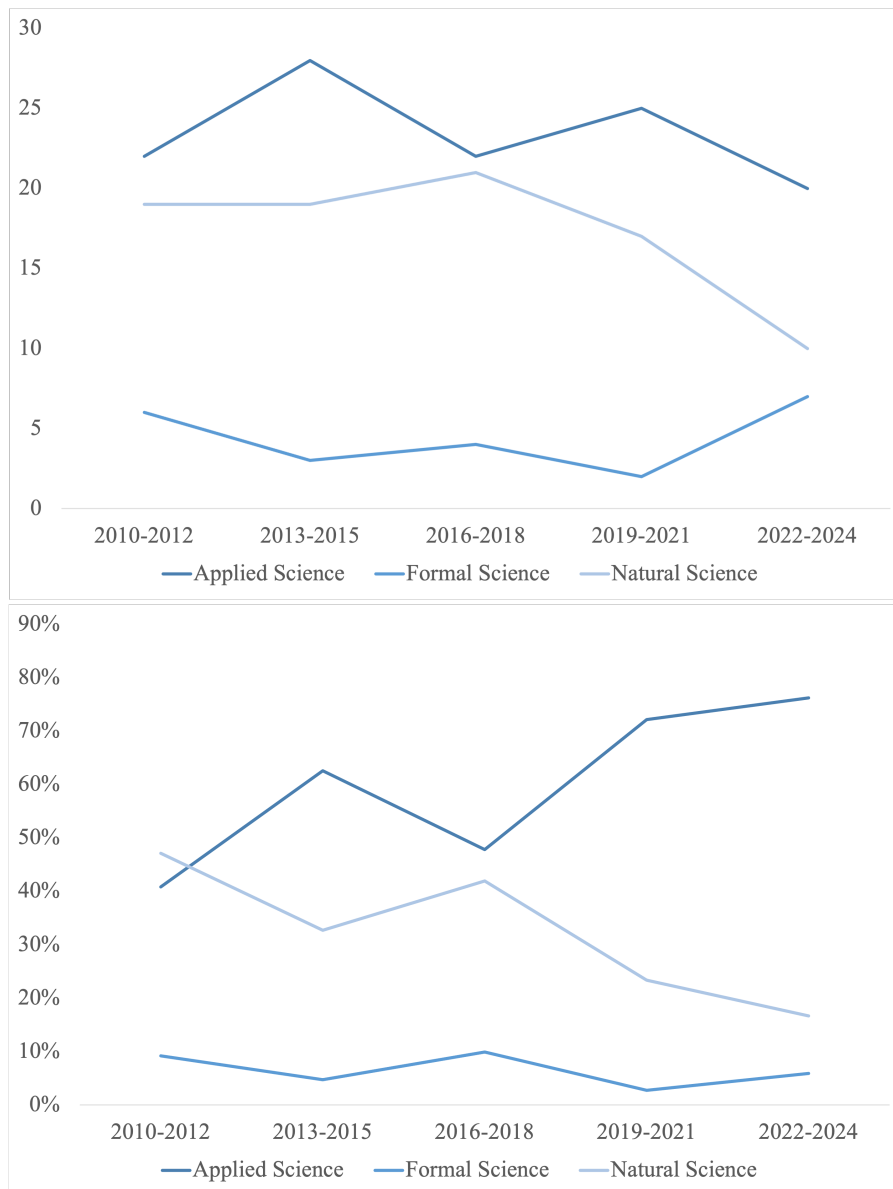


Figure 2: The upper figure showcases shifts in the count of funded subdomains within each category. The lower figure portrays the ratio of the number of funded subdomains normalized by the total project count.

Despite minor fluctuations in the proportional distribution of project counts across various categories, a consistent trend emerges over the 21-year period. Applied Science and Natural Science have consistently maintained a notable advantage, collectively accounting for over half of the funded projects. Formal Science, particularly Mathematics and Statistics as foundational disciplines, have exhibited a consistent presence with a smaller yet stable number of funded projects. In contrast, Social Science received minimal funding during 2013-2015, rendering its contribution negligible and thus not represented on the line graph for visual clarity.

Funding for Applied Science projects shows an overall upward trend, whereas Natural Science projects exhibit an overall downward trend, and Formal Science projects maintain relatively stable funding allocation. Hence, it can be inferred that Applied Science has, to a certain extent, encroached upon the funding allocation that might have originally been directed toward Natural Science.

362 The number of subdomains within Applied Science and Natural Science has notably decreased,
363 indicating a trend toward consolidation in both domains. I have created a heatmap for detailed
364 analysis to gain more insight into these subdomain dynamics.

365

366 In comparison to the period between 2019 and 2021, a significant influx of funding in the realm
367 of natural sciences has been directed toward environmental and material science from 2022 to
368 2024. However, no prominent research directions have been identified within applied science.

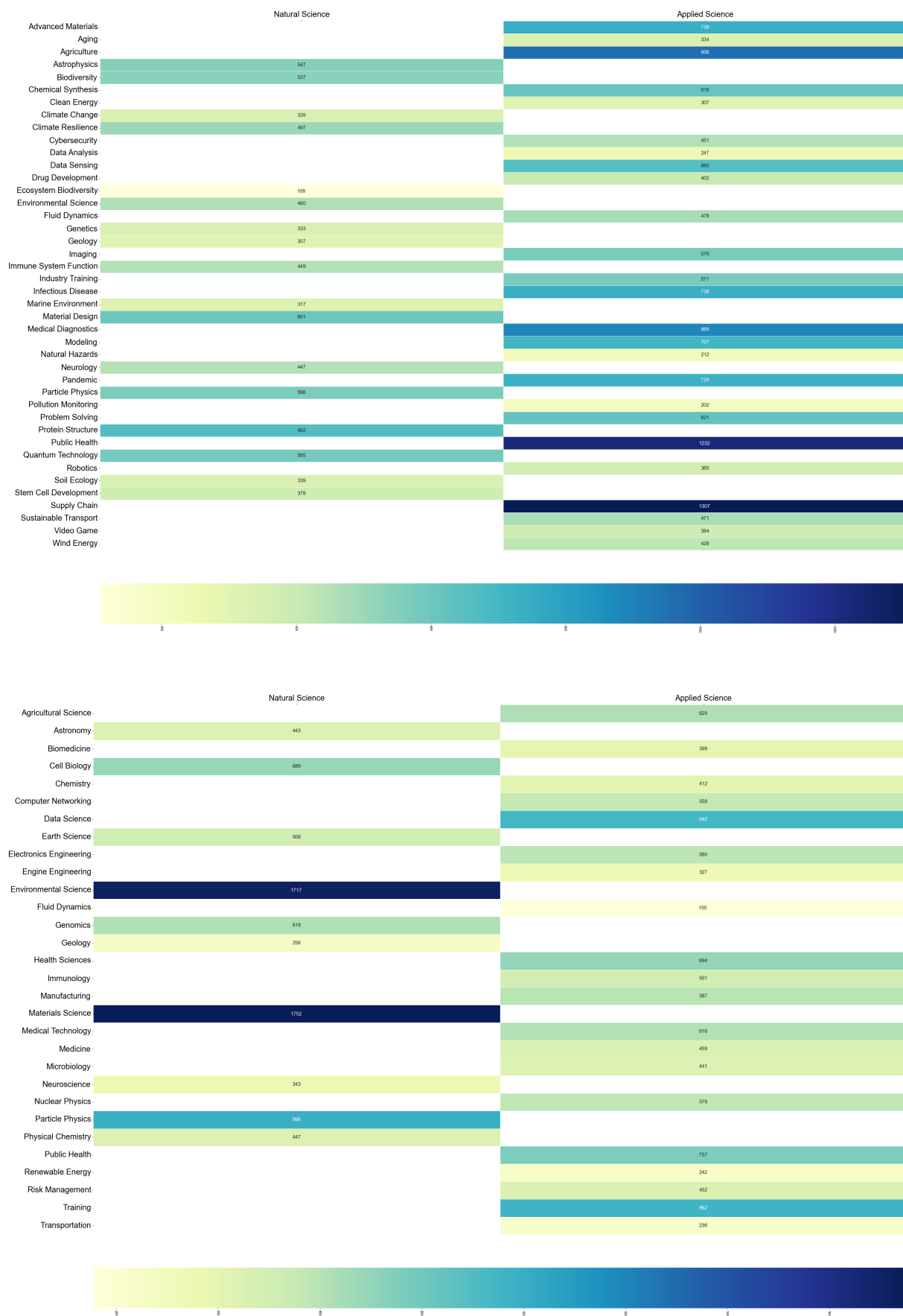


Figure 3: A huge amount of funding is directed towards Environmental Science and Materials Science.

369 An aspect worthy of attention is the sustained inclusion of ecology within the funded projects
370 list, maintaining a prominent position throughout each three-year interval.

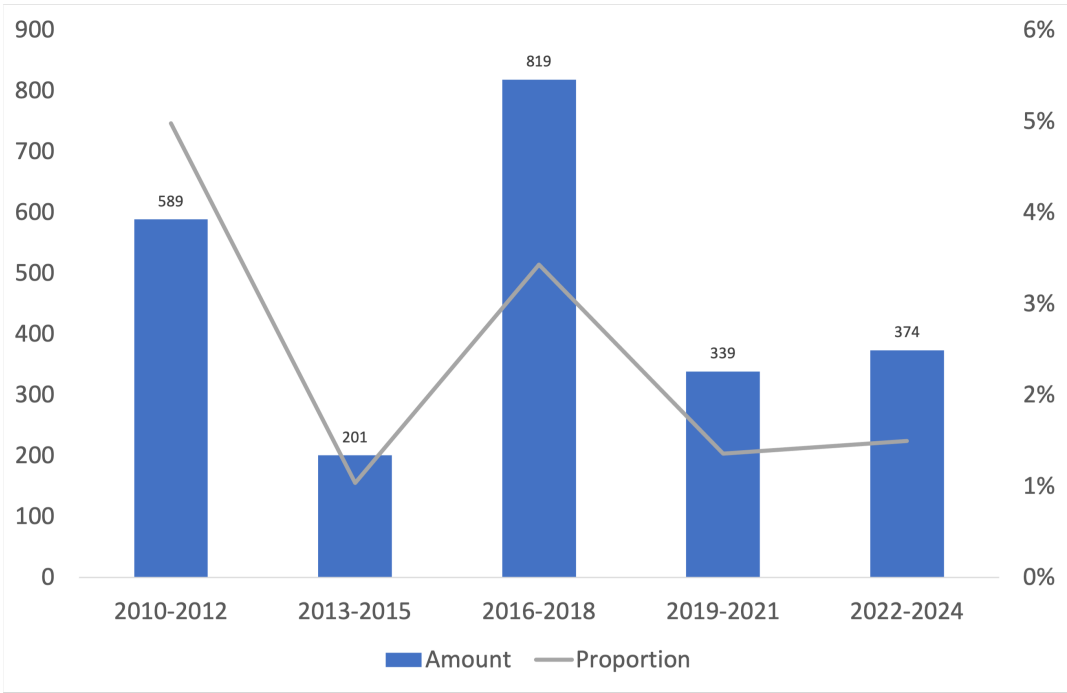


Figure 4: Ecology has consistently secured funding for several hundred projects during each triennial period.

371 In contrast, evolutionary biology has not received funding at a high frequency, with only 203
372 projects receiving funding between 2010 and 2012. Subsequently, the number of funded projects
373 related to this field has remained notably low across the entire dataset.

374 Overall Analysis Based on Funding Amount

375 In addition to project count, the amount of funding allocated to projects in different domains
376 can also indicate the level of attention and popularity within each respective field. The
377 funding received by projects across various domains reflects the extent of emphasis and interest
378 dedicated to those domains, thereby providing valuable insights into their prominence and
379 significance.

380
381 Over the past two decades, there has been a noticeable upward trend in the funding
382 amounts provided by UKRI. Specifically, the funding amounts for the periods 2010-2012,
383 2013-2015, 2016-2018, 2019-2021, and 2022-2024 have been £3,150,014,803, £5,859,873,507,
384 £7,314,254,625, £7,507,960,726, and £7,285,275,813, respectively. It is important to emphasize
385 that the funding amount for 2022-2024 is based on data up to 2022 rather than being the
386 most up-to-date information. Consequently, a substantial number of projects have not yet
387 been included in the analyzed data, resulting in a seemingly reduced figure. Furthermore,
388 numerous projects are still in the application phase, including cases like the "Knowledge
389 transfer partnerships (KTP): 2023 to 2024 round four," where the allocation of the £9,000,000
390 funding remains pending.

UKRI continues to invest more in "applied science" and "natural science." While the proportions of these two categories of projects have changed over time, their combined total has consistently remained above 80%. Notably, during 2013-2015 and 2016-2018, this proportion reached an astonishing 96%. This trend highlights the significant importance UKRI places on these areas and underscores the greater need for research funding for projects within these domains. It also indicates that, to a certain extent, they have reallocated funding from other category projects.

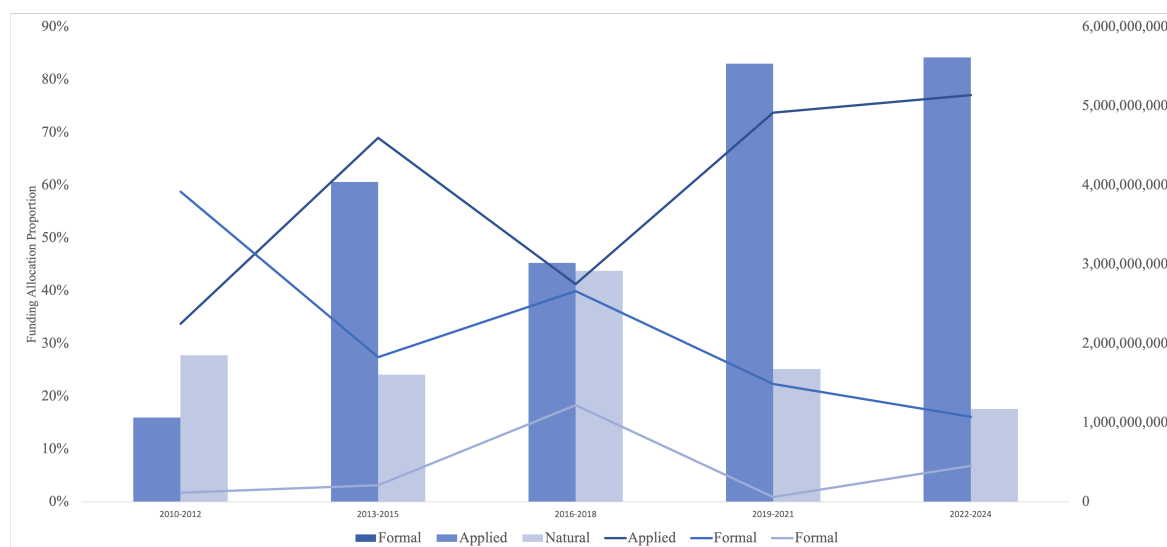


Figure 5: Applied Science continues to exhibit an upward trajectory in funding amounts, maintaining the highest proportion of funding allocation.

Upon closer examination of each three-year interval, in each interval, UKRI's focus within the natural sciences field has continuously evolved. For instance, From 2013 to 2015, UKRI allocated substantial funding towards Energy Systems and Technology Innovation, providing support amounting to £512,227,820 and £406,407,200, respectively. However, of even greater significance is UKRI's evident keenness towards the health and longevity of humanity. Cell Biology received a substantial grant of £48,791,642, while Aging research secured £310,492,126, and Public Health initiatives were granted £185,898,579. Further, considerable support was extended to Medical Technology with £83,056,741 in funding, and Cardiovascular Diseases research obtained £65,710,644, among numerous other related projects. This demonstrates UKRI's concerted efforts to drive advancements in diverse fields critical to human well-being.

However, a notable shift in focus occurred during 2016-2018, as UKRI redirected its attention towards environmental concerns. During this period, natural science topics that received the highest funding included Energy Systems with £112,236,139 and Environmental Pollution with £358,116,908, encompassing Earth Science with a funding allocation of £163,914,390. This phase witnessed a substantial increase in funding for numerous environmental protection and sustainability initiatives. Similarly, in the subsequent interval of 2019-2021, UKRI continued this trend by allocating £127,302,749 to Wind Energy, £94,358,531 to Clean Energy, and a substantial £155,449,671 to Marine Environment projects.

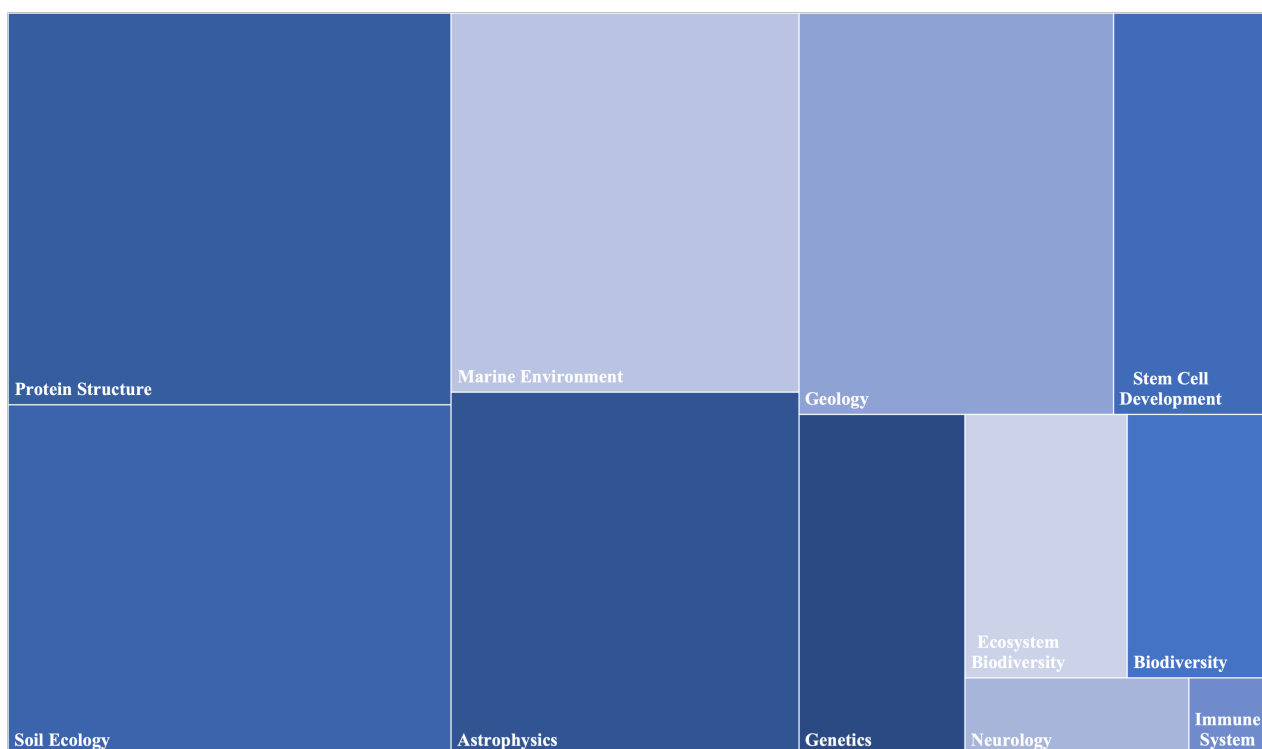
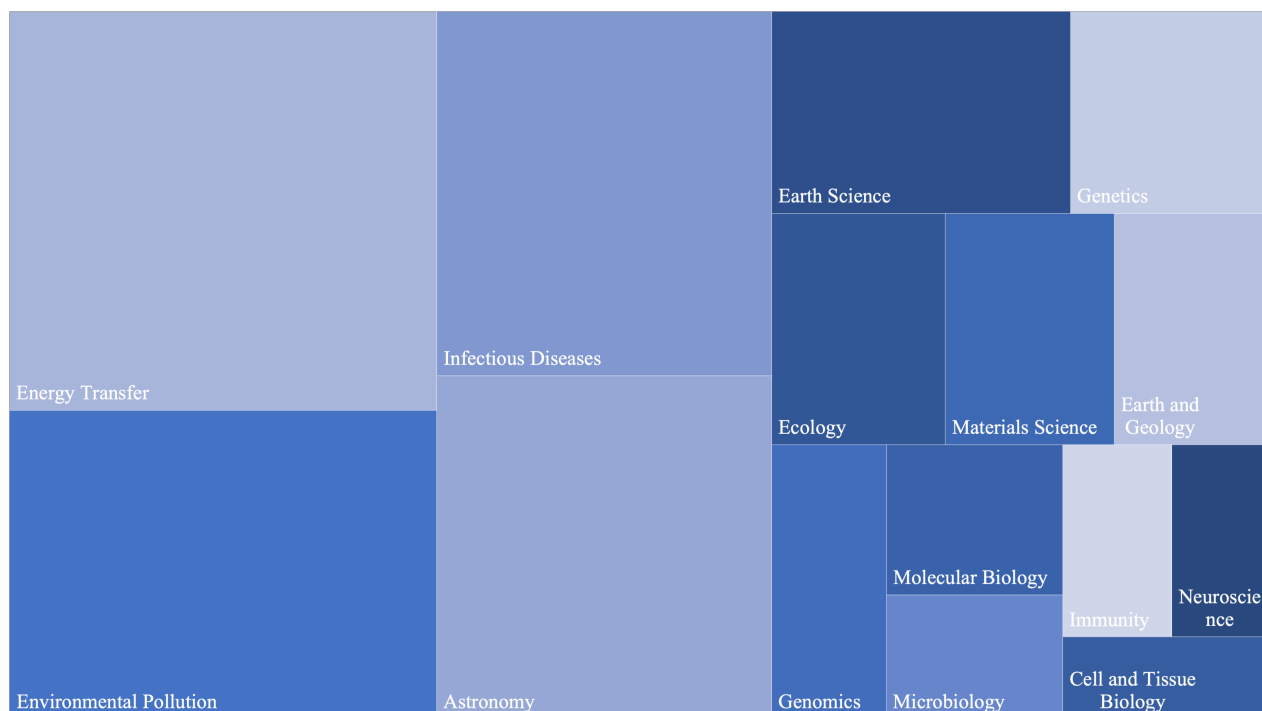


Figure 6: Within the Natural Science category, the field of Life Science consistently received a relatively higher amount of funding compared to Physical Science.

420 Natural science can be further categorized into two main divisions: life science and physical
 421 science. Life science refers to disciplines like biology or human anatomy, essentially
 422 encompassing the scientific study of all living organisms on Earth. On the other hand, physical
 423 science encompasses the remaining natural sciences, including fields like chemistry and physics,
 424 as well as areas unrelated to life (Ledoux, 2002).

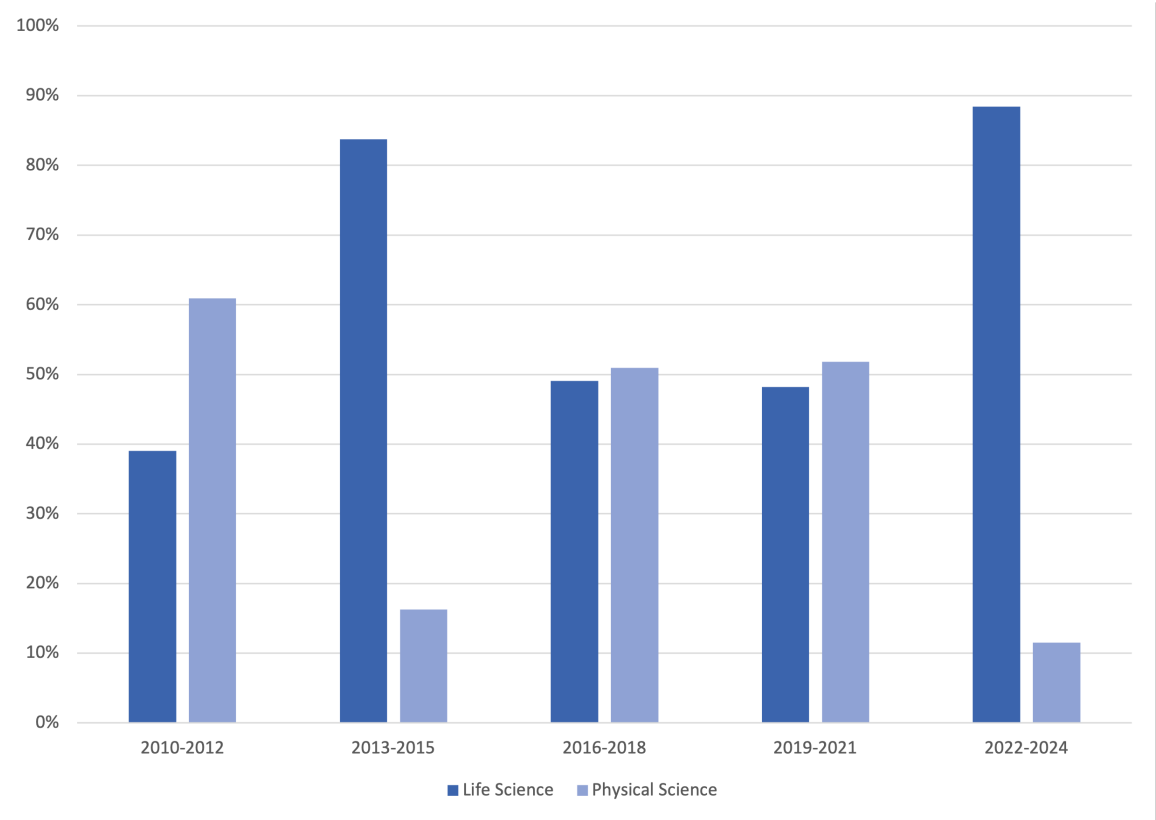


Figure 7: UKRI does not show a clear preference for either life science or physical science within the category of natural science.

426 The data for the years 2022-2024 has provided further intriguing insights. UKRI’s investment
427 strategy during this period continues to favor natural science and applied science, reflecting
428 a continued emphasis on these domains. Funding for specific sub-disciplines such as Public
429 Health, Computer Science, Fluid Dynamics, and Ecology has also been sustained. However,
430 due to the incompleteness of data for 2023 and 2024, with several projects still in the
431 application phase, a comprehensive analysis of the funding trends for this period has not been
432 conducted. This highlights the dynamic nature of research funding and the ongoing evolution
433 of priorities within the funding landscape. Further investigation into these recent trends may
434 unveil new dimensions of research support and shed light on emerging directions.
435

436 **Evolution of Funding Amounts in Specific Disciplines**

437 Continuing our investigation, I delve into the intriguing landscape of disciplines that have
438 consistently secured funding over time. While these disciplines have remained on the funding
439 roster, the allocated amounts have fluctuated, possibly influenced by the specific financial
440 requirements of projects during each period. By delving into these nuances, we aim to discern
441 the intricate patterns underlying funding variations and shed light on the evolving priorities
442 within various domains.
443

Table 3: Consistently Funded Research Topics Across Five Phases (2010-2024)

Imaging	Genetics	Computer Science	Environmental Science
Pharmaceutical Science	Particle Physics	Fluid Dynamics	Education
Geology	Ecology	Public Health	Materials Science

Compared to the Natural Science and Applied Science categories, which have prominently led in the number of funded projects and the allocated amounts, the domains of Social Science and Formal Science exhibit a more stable array of funded research directions. Within Formal Science, fields such as Theoretical Physics and Computer Science have consistently secured funding, reflecting their enduring significance.

On the other hand, Natural Science and Applied Science have encompassed a diverse spectrum of funded research domains. Notably, this diversity includes areas like Environmental Science, Ecology, Pharmaceutical Science, and various branches of Biology. Biology has emerged as a dynamic focal point, manifesting a rich tapestry of funded sub-disciplines over the past two decades. These encompass a myriad of specializations, such as Cell Biology, Molecular Biology, Microbiology, and more.

Furthermore, "Public Policy" stands as a distinctive current within the realm of Social Science, representing a significant recipient of funding. Notably, within the broader landscape of Social Science, "Public Policy" consistently demonstrates a relatively higher probability of securing funding. This prominence underscores this field's vital role in shaping and informing societal decisions, governance, and strategies.

Indeed, the disparity in funding amounts across various domains does not inherently reflect the differing levels of emphasis by UKRI. The allocation of funds is largely influenced by the financial requirements of individual projects. Certain research fields necessitate substantial financial investments due to the costs associated with experimental equipment, while other domains, such as purely theoretical research, might have relatively lower demands for resources.



Figure 8: Changing Fortunes in Science Funding

469 Despite continuous funding support from UKRI over 21 years, there is no discernible consistent
 470 pattern in funding amounts for these research directions. Each direction has experienced
 471 significant fluctuations in funding levels. Notably, most projects within natural science have
 472 consistently received funding around or below 200,000,000. This suggests that while natural
 473 science projects contribute to the overall funding pool, the allocation per individual direction
 474 remains relatively modest. Within this context, it is worth highlighting that ecology has
 475 consistently outperformed other directions in terms of funding amounts, indicating promising
 476 prospects for the field.

477

4 | Discussion

VARIOUS factors guide the decisions different countries make regarding science funding allocation. The anticipated outcomes of this project's research are evident in many cases. Many disciplines within the natural and applied sciences rely heavily on funding, with substantial investments required for experimental materials and equipment. Moreover, the results generated within these two domains are more readily applicable, yielding greater economic advantages.

In contrast, formal sciences and many social science disciplines lean towards advancing our fundamental understanding of nature rather than providing information directly applicable in practical contexts (Shaw, 2022). This propensity often results in fewer institutions funding research due to limited immediate tangible benefits. Apart from economic considerations, funding decisions are increasingly subject to external pressures. The demand for societal relevance may influence expert panel perceptions of research quality. Some researchers even express concerns that institutional assessments such as the "Research Excellence Framework" in the UK could adopt criteria that ultimately become ineffective substitutes for gauging research quality (Meirmans et al., 2019).

In this context, fields such as public health, computer science, ecology, fluid dynamics, biology, and pharmaceutical science have emerged as popular and well-funded domains, and the factors driving this sustained support are multifaceted. Firstly, in the post-pandemic era, the prominence of public health, pharmaceutical science, and biology can be attributed to their widespread societal demand and profound impact. Particularly, research in public health encompasses human well-being and disease prevention, directly influencing overall societal health and quality of life. Simultaneously, against the backdrop of escalating environmental pollution and climate change concerns, research in environmental science, ecology, materials science, and sustainable energy holds crucial significance for environmental preservation and ecological equilibrium. Additionally, computer science plays a pivotal role in digitization, exerting substantial influence on technological innovation, information technology, and data analytics.

Moreover, the research and applications within these fields directly address numerous real-world challenges. Especially in the current era of advanced artificial intelligence, computer science is a foundational discipline underpinning the profound development of emerging fields. As a fundamental scientific field, the continuous funding support for fluid dynamics further underscores the UK's commitment to international competitiveness and influence.

515 In addition, the research has also yielded some unforeseen outcomes. For instance, the
516 substantial investments made by UKRI in the environmental and renewable energy sectors
517 during 2016-2018, as well as the stark contrast between the increasing number of projects
518 receiving investments in the applied science domain and the diminishing investments in certain
519 specific subfields. The heightened focus on environmental concerns during this period could be
520 attributed to the historical milestones of 2016, marked by record-breaking global temperatures,
521 diminished polar ice, rising sea levels, and escalating ocean heat content. The persistence of
522 extreme weather events and climatic conditions into 2017 drew global attention, potentially
523 influencing UKRI's decision-making processes.

524
525 Furthermore, the aggregated nature of investments in the applied science domain might
526 reflect UKRI's inclination towards channels that have been previously funded. Continuous
527 investments in domains such as Medical Technology, Agricultural Science, and Immunology
528 may signify positive developments in these fields, suggesting ongoing advancements or the
529 likelihood of breakthrough progress in the near future.

530
531 Furthermore, with the rapid development of artificial intelligence and platforms like ChatGPT
532 in recent years, the pervasive impact of AI across diverse sectors of the internet has garnered
533 widespread attention. The dynamic evolution of AI technologies and modeling techniques is
534 noteworthy. It is reasonable to anticipate a potential increase in funding or the number of
535 projects in AI, modeling, and related fields.

537 Limitation

538 Certainly, given the incompleteness of data for the years 2022-2024, it is essential to
539 acknowledge that the current analysis comes with limitations and potential biases stemming
540 from pending projects still in the application phase. However, from my perspective, the
541 emphasis on addressing environmental pollution and promoting public health has been
542 consistently evident. As a result, fields related to environmental concerns and various branches
543 of biology remain focal points for funding allocation.

545 Conclusions

546 In the intricate landscape of science funding allocation, the decisions made by different
547 countries are guided by a complex interplay of factors. This study unveiled various trends
548 and considerations that shape funding distribution across different scientific domains. Notably,
549 funding allocation is multifaceted, influenced by societal demands, economic advantages, and
550 research relevance. While applied and natural sciences often garner substantial funding due to
551 their practical applications and economic benefits, formal sciences and certain social science
552 disciplines focus on advancing fundamental understanding rather than immediate practicality.

553 Public health, computer science, ecology, fluid dynamics, and pharmaceutical science have
554 emerged as well-funded and impactful domains. The pandemic has underscored the importance
555 of public health and pharmaceutical research, while environmental concerns and technological
556 advancements have driven investments in ecology, sustainable energy, and computer science.

557 In conclusion, science funding allocation is a dynamic process influenced by many factors. The
558 trends identified in this study reflect a balance between societal needs, economic considerations,
559 and research objectives. With its ever-changing challenges and opportunities, the evolving
560 scientific landscape will continue to shape funding priorities and drive innovation in the years
561 to come.

562 Data and Code Availability

563 The original dataset for this project can be obtained from
564 <https://www.dropbox.com/scl/fo/x85cc5gxk8uxu5x1c5lpz/h?rlkey=5ryaw51zilehxhisyah7prt4udl=0>.
565 The corresponding source code is available at <https://github.com/hyjiang0120/MappingFunding>.

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