Dissertation

The Potential for Artificial Intelligence Assistance in Funding Research

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Abstract

This dissertation investigates the potential of Artificial Intelligence (AI) in transforming decision-making processes within funding agencies, which include governmental, quasi-governmental, and private organizations that finance research and innovation. These agencies are crucial in directing scientific inquiry and innovation by funding projects that meet their strategic and societal goals. The study seeks to determine how AI can improve the efficiency, transparency, and objectivity of funding allocations, posing the question: "How can AI be effectively integrated into the decision-making frameworks of funding agencies to optimize outcomes?"

The research methodology combines a thorough analysis of AI applications across various sectors with detailed interviews involving stakeholders from funding agencies, AI experts, and funding recipients. This mixed-method approach provides a broad perspective on the current integration of AI and its challenges. The dissertation progresses through several chapters, each offering unique insights into AI's role in funding agencies.

Chapter 2 analyzes the existing processes and challenges within funding agencies, incorporating a landscape analysis and insights from stakeholder interviews to identify areas where AI could offer improvements. Chapter 3 discusses AI's capabilities and applications in sectors like education, healthcare, and finance, examining their implications for funding agency decision-making.

Chapter 4 introduces a strategic AI framework specifically designed for funding agencies, emphasizing the need for transparent algorithms and advanced explainability tools to ensure clear AI-driven decisions and build trust among stakeholders.

The findings highlight AI's potential to enhance the peer reviewer assignment process and optimize proposal management through learning models. The study stresses the importance of combining AI's computational power with human expertise and maintaining ethical considerations. It also points out the necessity for agencies to adapt AI solutions that are sensitive to the changing research landscape and societal needs.

In conclusion, the dissertation argues that AI can significantly improve the effectiveness and fairness of funding decisions when thoughtfully integrated. This research contributes to the discussion on AI applications in public sector decision-making, offering valuable insights for

policymakers, AI developers, and funding agencies. It advocates for leveraging AI's benefits while carefully addressing its challenges to improve public funding mechanisms.

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Chapter 1. Research Funding for the 21st Century

Innovation is widely recognized as a pivotal driver of economic development and prosperity. Studies consistently emphasize the positive correlation between innovation and economic growth, highlighting its potential to boost productivity, create employment opportunities, and foster inclusive economic development (Fagerberg, Srholec, and Verspagen, 2010). According to Lutz Bornmann's analysis, there has been an estimated 8-9% annual growth in research activity levels every 9 years (Bornmann and Mutz, 2015) attributable to various factors such as the competitive nature of innovation and the structure of academic promotion (Rawat and Meena, 2014). Furthermore, the significant role played by funding agencies cannot be understated. These agencies, including public and private entities as well as non-governmental organizations (NGOs), contribute significantly to the surge in research activities by supporting research endeavors. Each funding entity operates with its distinct processes and procedures governing funding allocation and decision-making. This will be discussed in detail in chapter 2.

President Donald J. Trump stated:

> They're giving away approximately, as I understand it recently, more than $32 billion a year, 32 billion. And so, we've been looking at that for a while, and we're going to be having some statements to be made about that. $32 billion a year. It's a lot of money, and we want to make sure it's being spent wisely. [1]

The statement highlights the substantial allocation of public funds towards research and underscores the imperative of ensuring prudent utilization of these funds. However, the complexity and opacity inherent in the decision-making processes within public funding agencies have raised concerns regarding accountability, transparency, and efficiency.

Criticism of the business model of federal funding agencies has stemmed from the lack of transparency and the extended duration required to observe tangible impacts. In 2011, Arizona State University president Michael M. Crow criticized the NIH's "discovery" model and advocated for a multidisciplinary approach with a focus on outcomes beyond academic outputs (Crow, 2011). Amidst the broader landscape of funding innovation, challenges abound, encompassing issues related to selection criteria, evaluation conduct, and desired outcomes. Ensuring fairness and efficacy throughout the decision-making process amidst these challenges is complex. Most notably, reliance on traditional peer review methods introduces potential biases and inconsistencies in evaluating research proposals. Additionally, the opaque nature of decision-making procedures in research funding can impede transparency and accountability,

[1] https://www.latimes.com/business/story/2020-04-20/nih-trump-coronavirus-science

giving rise to concerns about equitable funding distribution and the extent to which intended research outcomes are realized.

Addressing Challenges in Funding Agencies

Building on the recognition of innovation's critical role in economic prosperity, it is essential to delve into the operational intricacies faced by funding agencies. These entities, pivotal in propelling research and development, grapple with a spectrum of challenges that can impede their efficacy and transparency. Through examining processes like peer review and considering both micro and macro-level hurdles, a clearer picture of these impediments emerges.

The peer-review process, while long-standing and esteemed and regarded the gold standard for evaluating research proposals (Lasker, 2018), encapsulates several of these challenges. Despite its intent to uphold scientific integrity, the process often falls prey to issues of bias, inconsistency, and lack of transparency raising concerns about its reliability as a quality control mechanism (Shamseer et al., 2017; Tennant et al., 2017). Instances of data fraudulence and breaches of confidentiality further underscore the vulnerabilities within this system. For example, the U.S. Office of Research Integrity reported that 94% of misconduct cases from 228 identified articles between 1994 and 2012 had issues related to data fraudulence (Steen et al., 2013). In 2017, NIH announced that it would re-review several applications due to violations of confidentiality rules by reviewers. According to the director of NIH's Center for Scientific Review (CSR), a single reviewer reviewed 60 proposals that violated some aspect of the confidentiality rules (Brainard, 2018).

Beyond the monumental task of peer review, funding agencies confront micro-level challenges that affect their day-to-day operations. These include the need for meticulous review of proposals, data validation and analysis, and the logistical complexities of coordinating peer reviews. Such tasks not only demand significant time and resources but also present portals for introducing errors and delays as evidenced by the considerable global expenditure on peer review processes (Cornelius, 2012). One study estimates the worldwide cost of peer review to be around £1.9 billion annually and 15 million hours (Chauvin et al., 2015).

At a broader scale, macro challenges loom, encompassing issues like decision-making transparency, incentive structures for peer reviewers, and the potential for inherent conflicts within the system. These factors collectively influence the strategic direction of research teams and the allocation of funding, with implications for the overall effectiveness and integrity of the innovation funding landscape (Young, 2009).

Considering these multifaceted challenges, the question arises: Can artificial intelligence (AI) offer solutions? With the growing interest in leveraging AI to automate and enhance decision-making processes within funding agencies, it becomes imperative to explore AI's potential to address both micro and macro challenges. While AI offers promising avenues for improving efficiency and objectivity, its integration must be approached with caution with adopters being mindful of the limitations and ethical considerations inherent in deploying AI systems (Yuan et al., 2021; Bolander, 2019).

Dissertation Aim and Scope

In light of the significant role innovation plays in economic growth and the challenges identified within the funding mechanisms that support such innovation, this dissertation seeks to delve into the transformative potential of AI in reshaping the decision-making processes of funding agencies.

Amidst the array of challenges, from operational inefficiencies in peer review systems to broader issues of transparency and accountability, this research will critically examine the potential of AI to offer groundbreaking solutions. This endeavor is particularly timely considering the growing need for more efficient, transparent, and equitable funding mechanisms.

The objectives of this investigation are to:

- analyze the decision-making framework within funding agencies.
- scrutinize the existing challenges within these decision-making processes, pinpointing both micro and macro-level obstacles that compromise efficiency and transparency.
- evaluate the current integration and future potential of AI applications in this context, assessing the effect that AI could have on enhancing decision-making processes.
- consider the practical and ethical implications of implementing AI-enhanced systems, with a focus on addressing risks such as algorithmic bias and ensuring the responsible deployment of AI technologies.

This research aims to map out the landscape of funding agencies and their decision-making procedures, identifying key areas where AI could be most beneficially applied. This includes a thorough examination of AI's role across various stages of the funding process from the initial review of proposals to the assessment of outcomes.

More specifically, the dissertation addresses its main theme by answering several research questions:

- Problem Statement: How can funding agencies enhance their decision-making process by utilizing the potential capabilities of AI?
- Research Question 1: How is the decision-making framework within funding agencies currently structured, and what are its primary characteristics?
- Research Question 2: What challenges and limitations are inherent in the existing decision-making processes of funding agencies?
- Research Question 3: In what ways can the capabilities and applications of AI be harnessed to enhance decision-making processes within funding agencies, and how might AI address specific challenges faced by these agencies?
- Research Question 4: What are the key obstacles associated with the implementation of AI in the decision-making processes of funding agencies, and what strategies can be employed to mitigate these challenges?

Research Methodology

This research will undertake an exploratory approach combining primary and secondary data to address the formulated research questions. The backbone of the analysis will be a literature review that provides a secondary data source for addressing Research Questions 1-4 and establishing the dissertation's theoretical framework.

Primary data collection will encompass a comprehensive landscape analysis examining over 400 funding agencies to identify prevalent practices and challenges. This extensive survey will inform the creation of a shortlist of case studies, selected from the larger data base based on predefined criteria to ensure relevance and diversity, for in-depth investigation within this dissertation. In addition to the landscape analysis, the research included semi-structured interviews with key stakeholders including decision-makers from U.S. public funding agencies and international agencies with experience in AI implementation. Interviews were also conducted with founders of startups offering innovative solutions to the identified challenges in funding agencies. These interviews aimed to enrich our understanding of the intricacies of decision-making processes within these agencies and to explore the potential and current applications of AI in analogous contexts.

In conjunction with the literature review that identified potential AI capabilities applicable within funding agencies and those already employed in other sectors, the landscape analysis extended to investigating the degree to which funding agencies currently utilize software solutions to streamline their operations. This inquiry assessed whether these software tools possess AI functionalities conducive to enhancing decision-making processes. Furthermore, the analysis will include an examination of available commercial solutions that could potentially address existing capability gaps within funding agencies.

In our examination of the current decision-making frameworks within funding agencies, we will identify and assess existing AI capabilities that, while possibly utilized in other sectors, hold potential for implementation in the context of funding agencies. This comprehensive analysis and landscape review of technological solutions is designed to function as a gap analysis. Through this, we aim to pinpoint specific areas within the decision-making process where enhancements are feasible and propose a suite of potential AI-driven solutions tailored to address these identified gaps. Our goal is to offer actionable insights and options for each stage of the decision-making process, leveraging the insights gained from both the landscape analysis and the technological capabilities review.

A key aspect of this project has been developing AI showcases to demonstrate the potential of artificial intelligence to offer innovative solutions to the challenges identified in funding agency processes. Presented in Chapter 5, these showcases will illustrate AI's capabilities, including intelligent proposal-reviewer matching, topic modeling for proposal classification and categorization, enhancing explainability of predictive models, and network analysis to uncover hidden patterns and connections within the review process.

The intention behind these showcases is to demonstrate in practical terms how AI technologies can be applied to enhance specific aspects of the funding agency's decision-making framework, potentially leading to improvements in efficiency, transparency, and overall effectiveness. These showcases have been developed based on the insights gathered from the landscape analysis and stakeholder interviews (Chapters 3 and 4), providing practical examples of how AI can be utilized to improve funding agency operations.

Dissertation Structure

The following chapters of this dissertation will illuminate different aspects of the research questions, progressively building an understanding and providing insights into AI's transformative potential in the realm of research funding.

Chapter 2: Comparative Analysis of Research Funding Agencies directly addresses the first and the second research questions by detailing the existing decision-making frameworks within funding agencies. This will be complemented with insights from stakeholders, enriching the understanding of the first, second, third, and fourth research questions by bringing in perspectives from stakeholders involved in the funding process. This chapter uncovers the real-world challenges and expectations regarding AI's role in improving decision-making efficiency and transparency.

Chapter 3, The Role of Artificial Intelligence: Capabilities, Challenges, and Ethical Aspects, explores the third research question by discussing the capabilities of AI technologies pertinent to the decision-making processes in funding agencies. It also delves into the challenges and ethical considerations involved in AI integration, providing a balanced view of AI's potential and limitations.

Chapter 4: AI Showcases illustrates practical applications and potential solutions to the identified challenges. It showcases how AI can be leveraged to address specific issues within the funding process. This chapter demonstrates AI's practical utility, contributing to answering the third research question.

Chapter 5: Conclusion Synthesizes the findings from the preceding chapters, offering conclusions that directly relate to all four research questions. This chapter reflects on AI's transformative potential in funding agencies, summarizing the study's contributions and suggesting pathways for future research and implementation.

Chapter 2. Comparative Analysis of Research Funding Agencies

This chapter investigates the decision-making processes and challenges within public and philanthropic research funding agencies, focusing on the key question: 'What are the decision-making processes in these agencies, and what challenges do they face?' It provides an overview of methodologies and data collection techniques used to analyze these agencies, primarily from high Research and Development expenditure countries, and delves into the stages of their grantmaking processes, highlighting key challenges faced and potential AI-driven solutions. This discussion sets the stage for a comprehensive examination of global research expenditure trends and the diverse roles played by different funding entities.

Over the past decade, global research expenditure has significantly increased, driven by a range of organizations dedicated to advancing various stages of research, including basic, applied, and translational studies (Research Professional News Intelligence, 2020). In this context, the term 'agencies' refers to entities that specifically fund research activities, encompassing government bodies, private sector firms, non-profit organizations, and academic institutions. Diverse organizations orchestrate this expenditure, aiming to advance knowledge and contribute to the public good. The Organization for Economic Co-operation and Development (OECD) identifies four primary sources of R&D funding: the business enterprise sector, the government sector, the private nonprofit sector, and the higher education sector (Frascati Manual 2015, OECD, 2015).

Government entities have traditionally been the primary funding source for public research to advance scientific knowledge. These entities fund various organizations and individual researchers through block or competitive funding programs. However, the business enterprise sector has also increased its research funding in recent years, accounting for nearly three-quarters of the total expenditure on R&D performance in the OECD area since 2009 (OECD, 2022).

Nonprofit organizations have also played a pivotal role in supporting societal and technological development in developing nations, from implementing existing technologies to developing innovative technological solutions, such as in the case of COVID-19, Human Cell Atlas (Human Cell Atlas). Despite their critical role, funding from private nonprofit institutions represented only 1.4% of all R&D spending between 2015 and 2018 in 37 OECD countries (OECD, 2021).

This study primarily focuses on organizations whose main mission is grantmaking for the public good. We propose a broad categorization of these grantmaking or research funding organizations into two types: A) Government funding organizations and B) Non-Government funding such as Nonprofit or philanthropic organizations, including private and public foundations and charitable organizations.

While grants from government and philanthropic organizations have unique advantages and disadvantages, they face distinct challenges. Increased funding applications and regulatory requirements have placed significant administrative pressure on public funders (United States Government Accountability Office, 2018). Although private grant organizations have fewer compliance requirements, the administrative burden remains high due to less expenditure on operational support (McRay J, 2012).

Adopting grant management software (GMS) has somewhat alleviated the administrative burden for application processing. However, many organizations still rely on emails or hard copies for accepting applications and progress reports (REI Systems, National Grants Management Association & The George Washington University, 2021), and those who use GMS encounter difficulties in checking the originality of research and monitoring the completeness of submissions and research results (Perbangsa et al., 2016).

Several studies have been conducted to understand the review process of grantmaking organizations and the associated challenges. Still, these studies were often limited to a particular geography or agency or were not comprehensive in including both public and philanthropic agencies (van den Besselaar et al., 2018; Demicheli & Di Pietrantonj, 2007). The study by Bresselaar et al. (2018) sought to comprehend the grant selection process through a linguistic analysis of review reports, albeit their analysis was confined to European Union Grants. Similarly, Demicheli et al. (1996) conducted a systematic review of the impact of the review process on the quality of funded projects, encompassing both philanthropic and public organizations. Still, their scope was limited to health-related studies.

Meadmore et al. (2019) surveyed international organizations to understand their past and future approaches to decision-making, but their focus was also restricted to health-related organizations. Studies by Reckling et al. (2010), Mow (2009), and Wieczorkowska et al. (2021) evaluated the decision-making process of regional grant-making agencies and suggested potential modifications to the process.

Several studies have concentrated on understanding elements of the review process, such as external review or peer review (Schroter et al., 2010), review criterion (Abdoul et al., 2012; Falk-Krzesinski et al., 2015; Gallo et al., 2018), or review panels (Coveney et al., 2017; Gallo et al., 2020; Obrecht et al., 2007; Porter, 2005).

A significant body of literature exists on external review, identifying challenges and recommending alternate processes (Bollen et al., 2014; Roumbanis, 2019; Bentley, 2009; Mayo et al., 2006; Dodek et al., 2012; Herbert et al., 2015). This includes challenges with reviewer matching and recommending algorithms for accurate matching (Zhao & Zhang, 2022; Cechlárová et al., 2014; Xu et al., 2010) and methods for calculating reviewer scores (Bayindir et al., 2019).

However, most of these studies are regional and lack a comprehensive comparison of global decision-making processes used by non-profit and public agencies. A holistic view of the decision-making process and the challenges faced could support different organizations in efficient grant management and decision-making.

This chapter aims to provide a comprehensive global perspective on the decision-making processes followed by public and private nonprofit grant-making agencies, the challenges they face, and to identify best practices from other industries for potential applicability. We analyzed a representative sample of 25 public and nonprofit foundations from countries with high R&D expenditures and evaluated their grantmaking processes. The study also examined case studies of these agencies and others to understand grant-making challenges.

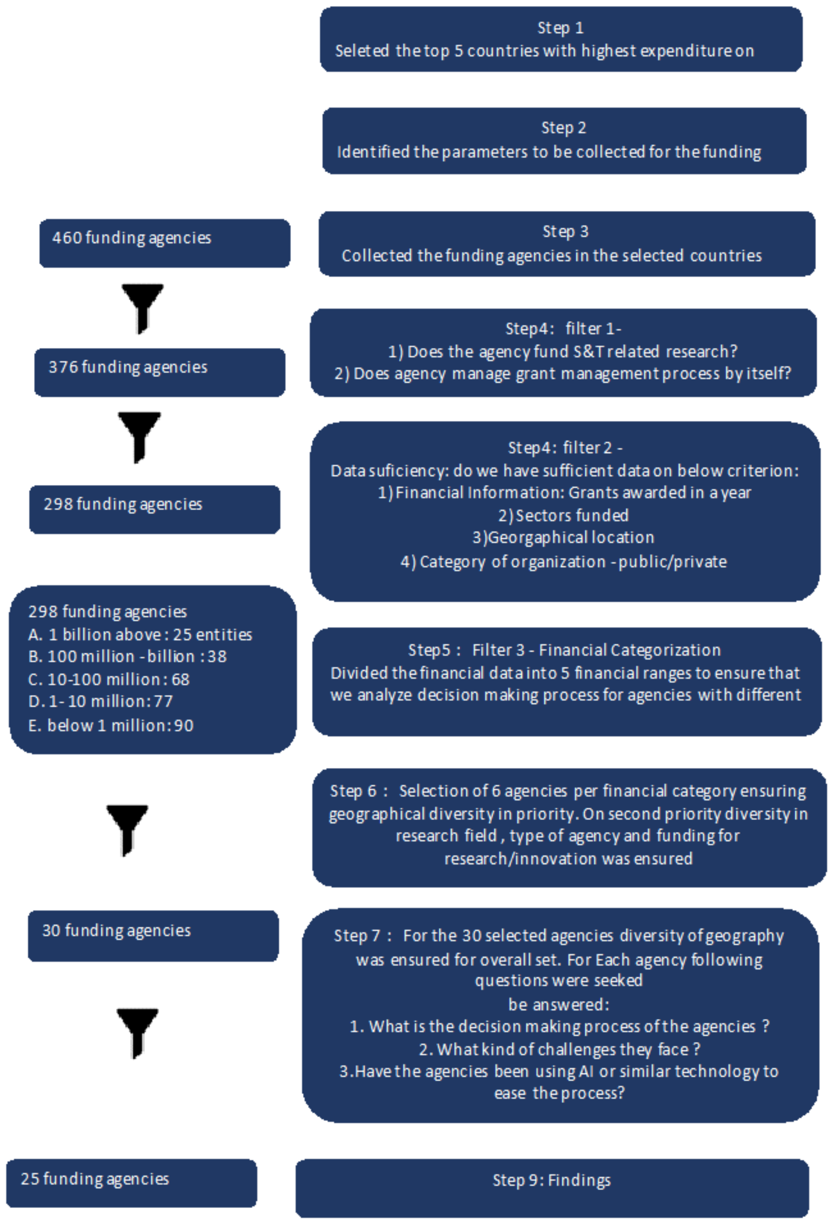
In essence, this chapter seeks to answer the question: What are the decision-making processes in public and philanthropic grantmaking agencies, and what challenges do they face? It progresses through a methodical examination of these processes, the associated challenges, and the exploration of common interventions from other industries, ultimately concluding with insights into the integration of AI within these frameworks.

Methodology and Data Collection

In this section, we aimed to identify regions with a blend of public and nonprofit grantmaking agencies. We assumed nations with the highest R&D expenditure would likely harbor such a mix. To test this hypothesis, we collected data on Gross Domestic Expenditure on R&D (GERD) as a percentage of Gross Domestic Product (OECD, 2020) and GERD per capita (OECD, 2020) from the OECD database. We then selected countries ranked in the top six for both criteria, ensuring representation from major continents - Asia, North America, and Europe. This selection process led us to target the following geographies: Israel, South Korea, China, the US, Belgium, and Sweden.

We then embarked on a digital expedition, shortlisting 460 funding agencies located in in these countries. We applied an inclusion and exclusion criterion to ensure consistency and accuracy in our dataset. We included entities that fund science & technology-related research, innovation, or policy-making activities and manage their grant process internally. We excluded agencies that solely provide funding through contracts, those that fund other nonprofit agencies to manage their grant management process, and agencies that fund only education scholarships without any research project involvement.

Figure 2.1. Methodology for data collection



The first phase of the shortlisting process resulted in 30 funding agencies from a dataset of 460, ensuring diversity on parameters such as the dimension of the funding portfolio, geographical location, type of funder, target technology area, and whether the agency primarily funds research, innovation, or both. Out of the original 460 agencies, 376 met the inclusion criteria. However, identifying agencies for South Korea, China, and Israel proved challenging due to limited English-language search results and website language barriers. Future studies may benefit from using local search engines and translation tools for improved data collection.

We collected parametric information for each agency using the following methodology:

- Dimensions of Funding Agencies' Grant Portfolios: For assessing the dimensions of each agency's funding portfolio, we considered multiple indicators. Primarily, we evaluated the number of awards granted annually by the agency for the fiscal years 2019 to 2022. This data was sourced from public disclosure mechanisms such as annual reports, website disclosures, and IRS reports. Additionally, to capture a broader perspective, various financial metrics were considered. These included terms like 'Obligations for the Year', 'Average Amount Invested in Research', 'Settlement Amount', 'Amount Available for Distribution', and 'Gifts, Contributions, and Grants Paid'. For U.S. public agencies, specific data on obligations were extracted from a government database. This approach allowed for a multifaceted understanding of each agency's funding activities, encompassing both the quantity of grants and the financial scope of their investment in research.

- Type of Funder: In the categorization of funders, we differentiated between two primary types: "Private Non-Profit Funders," encompassing all entities established as nonprofits, such as private foundations and charitable organizations, and "Public Funders," which are entities receiving government funding. Additionally, private organizations not formally established as nonprofit foundations but engaging in grant-making activities under the ambit of Environmental, Social, and Governance (ESG) activities were also included. ESG activities refer to a set of criteria that demonstrate an organization's commitment and impact in three key areas: Environmental (impact on the planet), Social (impact on people including staff, customers, and the broader community), and Governance (how the organization is governed and conducts itself). These activities reflect the organization's values and ethical practices that go beyond mere financial contributions. Incorporating private organizations engaged in grant-making as part of Environmental, Social, and Governance (ESG) activities, despite not being formal nonprofits, is significant as it reflects the evolving dynamics of the funding landscape. This inclusion acknowledges the growing impact of corporate social responsibility and ESG initiatives, highlighting how these entities are increasingly contributing to societal and environmental goals, thus broadening the scope and diversity of funding sources in contemporary research and development efforts.

- Target Technological Focus: In our analysis of funding agencies, we concentrated on the technological sectors they target, acknowledging that their decision-making processes may differ based on the specific area of technological research. This focus was crucial for evaluating the current and potential use of AI tools in proposal evaluation processes. While our research covered agencies funding a broad range of research from basic to applied, we specifically highlighted those funding technological research. We collected this information from the agencies' websites, reviewing their declared funding priorities, mission areas, or areas of technological interest. In instances where agencies did not explicitly focus on a technological domain, their area of research interest was noted as "nonspecific." This categorization was instrumental in understanding the alignment and applicability of automated/AI tools within their decision-making frameworks.

- Nature of Recipient Organizations: In categorizing funding agencies, a critical parameter was the nature of the organizations they primarily support. This categorization helps distinguish between agencies based on the type of research and innovation activities they fund. Agencies primarily supporting industrial innovation, often involving product development and technological advancements, were classified as "Innovation Agencies." In contrast, those focusing on funding academic research, encompassing institutes and individual researchers typically engaged in theoretical or basic research, were termed "Research Agencies." This distinction is crucial as it reflects the varying objectives and outcomes expected by these agencies, shaping their decision-making processes and criteria for funding allocations.

In our initial phase of research, we scrutinized a comprehensive pool of 397 funding agencies that satisfied our inclusion criteria. To delve deeper into their financial characteristics, we stratified these agencies into five distinct financial categories based on their funding portfolios: under 1 million, 1-10 million, 10-100 million, 100 million -1 billion, and above 1 billion dollars. This stratification allowed for a detailed analysis across various types and sizes of funding entities. Within this broad spectrum, a significant subset of 235 agencies, mainly comprising nonprofit organizations, had funding portfolios below 100 million dollars. This finding was crucial for understanding the distribution and focus areas within the larger group. Notably, in the financial range of 100 million to 1 billion dollars, we observed a mix of both nonprofit and public agencies, whereas public funding agencies predominantly dominated the category with funding portfolios above 1 billion dollars. Further refinement led us to a more concentrated group of 89 agencies, which had publicly available data across all the study parameters. This final subset of 89 agencies, drawn from the initial pool of 397, provided a representative sample for our in-depth analysis, capturing diverse operational patterns and decision-making processes among a wide array of funding bodies.

Table 2.1. The 30 Shortlisted Funding Agencies

Country	Funding Agency	Public/ Private
Israel	Israel Science Foundation	Public
Israel	Israel Innovation Authority	Public
Israel	National Institute for Psychobiology	Private Non-Profit
Israel	The German Israeli Foundation	Public
Sweden	Vinnova	Public
Sweden	Swedish Foundation for Strategic Research (SSF)	Public
Sweden	The Swedish Foundation for Strategic Environmental Research (Mistra)	Private Non-Profit
Sweden	Alfred Österlunds stiftelse	Private Non-Profit
Sweden	The Arosenius Foundation	Private Non-Profit

Country	Funding Agency	Public/ Private
Sweden	Diabetesfonden	Private Non-Profit
Sweden	FOLKSAM Forskningstiftelse	Private Non-Profit
Belgium/Wallonia	FNRS (Fund for Scientific Research)	Public
Belgium/Brussels	Innoviris	Public
Belgium/Wallonia	Research Wallonia Ministry for Public Service (SPW)	Public
Belgium	King Baudouin Foundation	Private Non-Profit
Belgium	Queen Elisabeth Medical Foundation for Neurosciences	Private Non-Profit
Belgium	Belgisch Werk Tegen Kanker – Oeuvre Belge du Cancer	Private Non-Profit
China	National Natural Science foundation of China	Public
China	Tecent Foundation	Private For Profit
South Korea	National Natural Research Foundation of Korea	Public
South Korea	Korea Insitute of Marine Science and Technology Promotion	Public
South Korea	Right Fund	Pub-Private Partnership
USA	Alfred P. Sloan Foundation	Private Non-Profit
USA	American Chemical Society	Private Non-Profit
USA	Andrew W. Mellon Foundation	Private Non-Profit
USA	Bill and Melinda Gates Foundation	Private Non-Profit
USA	Defense Advanced Research Projects Agency (DARPA)	Public
USA	Little Giraffe Foundation	Private Non-Profit
USA	National Institutes of Health (NIH)	Public
USA	National Science Foundation (NSF)	Public

We selected six entities from each financial category seeking to enhance geographical, technological, and agency-type diversity. The final list of the 30 agencies included Israel Science Foundation (Israel), Israel Innovation Authority (Israel), National Institute for Psychobiology (Israel), The German Israeli Foundation (Israel), Vinnova (Sweden), Swedish Foundation for Strategic Research (SSF) (Sweden), The Swedish Foundation for Strategic Environmental Research (Mistra) (Sweden), Alfred Österlunds stiftelse (Sweden), The Arosenius Foundation (Sweden), Diabetesfonden (Sweden), FOLKSAM Forskningstiftelse (Sweden), Fund for Scientific Research (FNRS) (Belgium), Innoviris (Belgium), Research Wallonia Ministry for Public Service (SPW) (Belgium), King Baudouin Foundation (Belgium), Queen Elisabeth

Medical Foundation for Neurosciences (Belgium), Belgisch Werk Tegen Kanker – Oeuvre Belge du Cancer (Belgium), National Natural Science Foundation of China (China), Tencent Foundation (China), National Research Foundation of Korea (South Korea), Korea Institute of Marine Science and Technology Promotion (South Korea), Right Fund (South Korea), Alfred P. Sloan Foundation (USA), American Chemical Society (USA), Andrew W. Mellon Foundation (USA), Bill and Melinda Gates Foundation (USA), Defense Advanced Research Projects Agency (DARPA) (USA), Little Giraffe Foundation (USA), National Institutes of Health (NIH) (USA), and National Science Foundation (NSF) (USA). In Phase II, we collected data for these 30 agencies from their websites, public announcements, and interviews to answer the following research questions:

- What is the agency's decision-making process?
- What kind of challenges do they face?
- What solutions do they use to resolve those challenges?

We found variances in the decision-making process depending on the type of program being considered. While some agencies had a standardized approach across all programs, others varied their decision-making process based on the specific programs. Five of the 30 agencies analyzed did not provide sufficient information on their respective websites regarding the decision-making process used for grantmaking (Alfred Österlunds stiftelse (Sweden), The Arosenius Foundation (Sweden), FOLKSAM Forskningstiftelse (Sweden), Queen Elisabeth Medical Foundation for Neurosciences (Belgium), Korea Institute of Marine Science and Technology Promotion (South Korea)). Therefore, our data is representative of 25 agencies in the set. Building on the foundation laid in the earlier phase II, we recognized the need for a deeper, more nuanced understanding of these elements. The variances observed in the decision-making processes, coupled with the limited information available from some agencies, highlighted the complexity of the landscape we were navigating. This complexity, inherent in the diverse approaches to decision-making and the challenges faced by funding agencies, prompted us to extend our exploration beyond the surface-level analysis.

To enrich our understanding and validate the preliminary insights gleaned from the landscape analysis, we transitioned into a more focused, direct engagement with the practitioners themselves. This move was not merely a shift in methodology but an essential step towards achieving a comprehensive, grounded perspective on the potential integration of AI within funding agency decision-making processes.

Our journey into the realm of primary research was guided by the ethical standards of scholarship and policy analysis. With the approval of the Human Subjects Protection Committee (HSPC) at the RAND Corporation, we embarked on a series of interviews, 17 interviews, with strategically selected participants from within the funding agency ecosystem. This selection was informed by the initial landscape analysis, ensuring that our interviewees were well-placed to provide insightful, firsthand accounts of the decision-making processes within their respective agencies.

The questions posed during these interviews were not arbitrary; they were the culmination of an extensive literature review and the insights from our initial landscape analysis. These questions were designed to delve deeper into the intricacies of current decision-making processes, to uncover the prevailing challenges more clearly, and to explore the avenues for AI integration in a more focused manner. Moreover, these discussions aimed to anticipate the potential hurdles that funding agencies might face in implementing AI-enhanced decision-making frameworks.

Through this extended exploration, we sought to bridge the gap between the theoretical potential of AI in enhancing decision-making processes and the practical realities faced by funding agencies. The thematic analysis presented in this chapter synthesizes the findings from both the literature and the interviews, offering a comprehensive understanding of the subject matter that builds cohesively on the landscape analysis conducted in the previous phases of our research.

To provide a clear and transparent overview of our engagement with the field, we present a table of interviewees below. To respect the confidentiality and privacy of our participants, we have chosen to use generic designations for both the interviewees and their respective organizations. This approach ensures the integrity of our research while safeguarding the identities of those who contributed their valuable insights to our study.

Table 2.2., The List of Interviewees

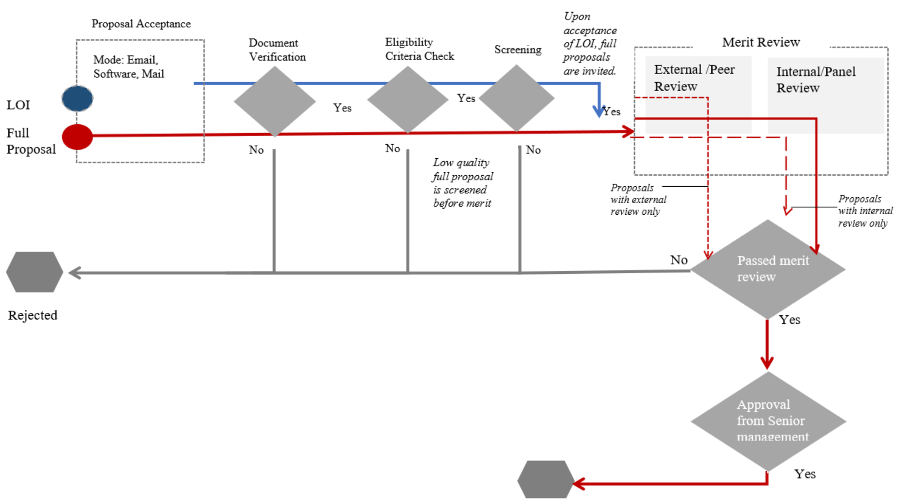
Interviewee Designation	Organization/ Institution
Director	International University, Managing Internal Funds
Vice President of Research	International University
Program Manager	Non- Governmental Organization
Program Manager	Federal Funding Agency (North America)
Manager	Small Funding Agency (North America)
Manager	International University
Manager	International University
Manager	Second Small Funding Agency (North America)
Manager	Third Funding Agency (North America)

Interviewee Designation	Organization/ Institution
Director	International Funding Agency (UK)
Vice President	International Funding Agency (Turkey)
Director	Second International Funding Agency (Sweden)
Program Officer	Federal Funding Agency
Industry Expert and Startup Co-Founder	Startup
Scientist	Startup
Computer Scientist	International Graduate University
Fund Recipient	Think Tank

Comprehensive Analysis of Organizational Decision-Making Processes in Grantmaking

Figure 2.2 delineates the multifaceted decision-making process employed by the organizations within the dataset, which can be broadly categorized into several stages: (1) proposal submission and processing, (2) external or peer review, (3) internal or panel review, and (4) approval and result processing.

Figure 2.2. Decision Making Process Employed by Funding Agencies



The grantmaking process commences with establishing funding programs and issuing solicitations or Requests for Proposals (RFPs), which are predicated on the mission and objectives of the funding organization. RFPs can be structured based on scientific disciplines (one or multiple scientific disciplines can be solicited in a single RFP), applicant type (scholars, junior researchers, experienced researchers), and the scope of technical challenges (Broad challenge, specific challenge). RFPs can be open to a large or small group of institutions and could be time-bound or open throughout the year. Distinctively, private RFPs and direct solicitations are approaches often employed by private organizations, like the Gates Foundation, to target specific applicants aligned with their unique missions and objectives. These private RFPs, unlike public ones, are not broadly advertised and are used to reach a predetermined set of potential applicants. Private RFPs and direct solicitations limit competition and target specific applicants. While private RFPs might accept proposals in narrow technology areas, a few organizations prefer a more passive approach by issuing RFPs in a broader technology sector to accommodate a range of novel ideas. Such RFPs provide a high overview of technologies of interest and include a broad set of guidelines for submission. In certain instances, the guidelines for Requests for Proposals (RFPs) do not specify a fixed budget, leaving room for flexibility based on the project type. This approach indicates that, unlike scenarios where budget constraints are a primary deciding factor, here the proposed budget is not the critical determinant of a proposal's acceptance. Consequently, a proposed budget, tailored to the specific needs and scope of the project, may be accepted. For example, the Gates Foundation, as highlighted by OECD data from 2018-2019, emerged as the most significant philanthropic donor among private funders (OECD, 2018), follows three approaches to identify applicants: 1) issues RFP publicly or privately, 2) accepts Letters of Inquiry for exploring ideas, and 3) engages in direct solicitation by program managers after identifying qualified applicants.

To ensure data sufficiency for our analysis, we considered entities to have sufficient data if the information was available from the proposal submission as several entities did not publicly disclose information on how they established their programs.

Decision Making Process

The decision-making process in funding organizations is profoundly influenced by their scope and the types of research they fund, as revealed through our interviews. A diverse range of approaches is evident, from organizations with a broad, interdisciplinary focus to those with more targeted, discipline-specific agendas. For instance, a vice president of an international university highlighted their institution's comprehensive engagement across disciplines through their internal funding, stating:

> Our university doesn't limit itself to specific disciplines. We strive to push the boundaries in every field, from humanities to technology.

This broad approach contrasts with a program manager from a North American federal funding agency who emphasized a more focused mission:

> Our mandate is clear, to fund research that addresses national priorities within science and technology. Each RFP is crafted with these priorities in mind, ensuring a focused and strategic allocation of resources.

Similarly, the variety of types of research funded further underscores the diversity in funding strategies. An international funding agency director explained their preference for cutting-edge, interdisciplinary research that can address global challenges, highlighting a drive to fund projects that transcend traditional disciplinary boundaries. Conversely, a manager from a small North American funding agency delineated their focus on

> public health initiatives, particularly those that can make a tangible difference at the community level,

showcasing a targeted approach to funding.

This diversity in scope and research focus naturally extends to the stages of the decision-making process, which we will examine in the section below. The steps undertaken by an agency's internal staff reflect the organization's overarching goals and the types of research they prioritize.

Proposal Submission & Processing

At the core of these decision-making processes is the issuance of a call for proposals, a critical step that delineates the research themes and priorities for the funding cycle. A program officer from a federal funding agency in the US highlighted the importance of this stage, stating,

> The call for proposals sets the stage, outlining the research themes and priorities for the funding cycle. It's the starting point from which all subsequent review processes unfold.

This foundational stage is pivotal in shaping the trajectory of the entire funding process, guiding the direction and focus of the research proposals submitted. After the applicant's submission, the internal staff of the agencies in the set conducted a combination of the following processes:

1. acceptance of a proposal
2. document verification & eligibility check
3. screening
4. selecting peer reviewers.

An agency's internal administrative staff primarily conducts these activities.

Acceptance of Proposal

Entities utilized various modalities to accept proposals and designed programs to accept proposals in stages.

- Submission Modalities: The dataset revealed three main modalities to accept proposals: online software, email, or surface mail. Most entities (80%) employ online software to accept proposals which can either be off-the-shelf or developed in-house. Some entities use email and software, depending on the program. A few public entities such as the Israel Science Foundation, National Science Foundation (NSF), National Research Foundation of Korea (NRF), National Institutes of Health (NIH), and the Defense Advanced Research Projects Agency (DARPA) have made significant investments in developing software solutions. These solutions are actively being utilized across multiple agencies, demonstrating their practical application and utility in enhancing the efficiency and effectiveness of grantmaking processes. However, smaller organizations with more limited funding portfolios tend to rely on off-the-shelf software solutions, which offer greater flexibility and are easier to adapt to the specific decision-making processes of an organization. Several philanthropic organizations such as Right Fund, Alfred Sloan Foundation, American Chemical Society, Oeuvre Belge du Cancer, King Baudouin Foundation, and Andrew W. Mellon Foundation have reported leveraging off-the-shelf software for accepting applications.
- Submission Stages: Depending on program design, entities in the set used a one-stage or a two-stage process to accept proposals. In the latter, applicants must submit a short abstract or letter of intent (LOI) outlining the team's idea and composition. The submission is subject to a technical or eligibility review, and selected applications are asked to submit the full proposals. In contrast, the one-stage process accepts full proposals directly. The two-stage process is often seen to filter the quality of proposals at an early stage, resulting in a lower administrative burden later. However, in a one-stage process, organizations such as the Israel Science Foundation and the National Institute for Psychobiology in Israel conducted technical screening to screen out low-quality proposals before sending them to peer reviewers.

Document Verification & Eligibility Check

Document verification ensures the applicant submits documents in accordance with program requirements. When using online submission software, this document acceptance check is partially fulfilled by automation, and applications will only be accepted when all required documents are submitted, leaving program managers to validate the content of the document. However, when applications are accepted manually or by email, an additional burden of document acceptance is added to the content validation, adding to the agency's administrative burden. We examined the eligibility criteria of representative programs offered by various entities that program managers assessed for content validation. Our analysis included collecting eligibility requirements for 1-2 representative programs per entity, which allowed us to identify a range of eligibility criteria and proposal evaluation parameters, which are as follows:

- Applicant Eligibility
  - Age of Researcher: Certain programs impose age restrictions, targeting either young or senior researchers.

- Educational Qualifications: Many programs necessitate a specific level of education, such as a degree or a particular field of study.
- Experience: Prior research experience, experience as a principal investigator, and project leadership experience are common prerequisites.
- Application History: Some programs consider whether the applicant has previously applied to the program and the outcomes of those applications.
- Affiliation and Employment Status: Some programs mandate institutional affiliation. If the applicant is institutionally affiliated, their employment status (part-time, full-time, consulting) may also be considered. In cases where the applicant is associated with multiple institutions, the percentage of salary collected or the association with the institution that qualifies for funding could also be considered as part of the eligibility criteria.
- Status of Previous Grants: Certain programs consider the status of previous grants (closed/open) received from the funding agency as a preliminary criterion for accepting a new application.
- Number of Applications: A few programs limit the number of simultaneous applications an applicant can submit as a principal investigator.

- Institutional Eligibility
  - Eligibility to Receive Funds: The eligibility criteria for entities to obtain funding are highly contingent on the program and the funding institution. Innovation-based programs often delineate eligibility through a diverse range of factors, including organizational type (e.g., small-to-medium enterprises, multinational corporations, universities, research institutes, and hospitals), legal status, performer type (e.g., manufacturer, supplier, user), and geographical location.
  - Number of Applications per Institution/Entity: Some programs limit the number of applications submitted by a single institution or entity.
  - Geographical Location of Institutions/Entities: International collaboration funding programs have specific eligibility requirements regarding the location of participating institutions. Some programs permit international applicants to participate but restrict the primary applicant to be from a local institution.
  - Team Composition: This criterion refers to the make-up of the research team and could include a combination of factors such as the type of entity leading the project, a minimum number of project parties, and collaboration requirements by entity type. This assessment encompasses considerations like:
    - Type of entity leading the project: A few programs put requirements for the type of entity (Small-to-Medium Enterprises, Multinational Corporations, Hospital, Educational Institutions, etc.) leading the project.
    - number of allowable project parties: Vinnova, for example, in its program for bio innovation, allows a maximum of 3 project parties, with at least two of them being companies based in Sweden.
    - Collaboration requirements by entity type: Programs restrict the entities that can participate in a research project by mandating a particular type of collaboration structure. This could encompass specifications such as the minimum number of universities, research institutions, or companies involved in the project.

- Technical Eligibility: This criterion delineates the type of research to be undertaken and the desired research outcome. Innovation programs frequently specify the nature and outcomes of research required by establishing particular criteria related to the technology advancement required in the project.
- Adequacy of Budget and Estimated Time Frame: While some programs do not specify budget requirements, others define the acceptable budget and timeframe as a qualification for the acceptance of the proposal.

Screening

The screening stage is a critical juncture in the review process, often perceived as a triage mechanism (Bornmann, Mutz & Daniel, 2008) aimed at reducing the administrative burden associated with identifying peer reviewers, thereby enabling both internal and external reviewers to concentrate their efforts on applications of high merit. The present analysis reveals that entities within the set employed two types of screenings to alleviate the load of application review with the specific mode of submission determining the approach adopted. These included (1) screening of complete applications before peer review and (2) screening of Letters of Intent (LOIs) before accepting a full application. Such screening procedures are instrumental in facilitating the efficient and effective allocation of resources, particularly in light of the substantial volume of applications received by funding entities.

Notably, screening complete applications before peer review emerged as an effective strategy for reducing the administrative workload associated with identifying suitable peer reviewers for each application. Of the 25 entities in our dataset, 16 had programs that accepted complete applications, and only three of these, namely the National Institute for Psychobiology, Israel Science Foundation (ISF), and SSF reported conducting technical evaluations before forwarding applications for peer review. The criteria for screening applications were similar to the evaluation criteria used by peer reviewers, such as researchers' suitability for conducting research, scope of project, strategic relevance, potential impact, and intellectual merit.

The screening of LOIs before accepting the full application emerged as another mechanism that reduced the administrative effort of reviewing detailed applications. Eleven of the 25 entities in the dataset designed programs to accept applications in two stages, accepting an LOI at the initial stage and accepting a full application only if the LOI passed an initial merit review. LOIs included a brief description of the proposed project, its methodology, key implementors, budget, and timeframe, and were often evaluated through eligibility criterion checks or scientifically through a merit criterion.

Examples include Right Fund and Israel Innovation Authority which invited applicants for a full proposal if the LOI met the eligibility criterion. Many other organizations evaluated LOI technically through a merit criterion. Five out of 11 entities that evaluated LOIs published criteria publicly. The merit criteria were observed to be similar to those used for the full proposal and include scientific quality, excellence, and methodology; feasibility to achieve goals;

originality, novelty, and innovative nature of the project; intellectual merit; impact on society and sustainable development; project team and partner; and relevance of the project to program priorities.

Selection of Peer Reviewers

The process of selecting peer reviewers is pivotal in ensuring the quality and impartiality of the external review process. Different funding agencies utilize various methods to identify and match experts with relevant expertise to evaluate research proposals. While not all agencies disclose their methods, eight of those entities mentioned the methods utilized for selecting the reviewers, while nine agencies did not publicly disclose their methods. Our findings note the following methods used by agencies to identify peer reviewers:

- Bibliography: A bibliography of the application often serves as a good resource for identifying peer reviewers. The authors of the publications referred to could act as potential reviewers. Israel Science Foundation (ISF) mentions using a bibliography as a method to find peer reviewers.
- Reviewers matching: Many agencies, such as ISF and the German Israeli Foundation, conducted database searches based on the abstract or keywords in the research proposal to identify qualified and relevant reviewers.
- Recommendations: Applicants are often requested to provide names of potential reviewers or to indicate their preference against certain individuals as reviewers. The German Israeli foundation employs a committee of advisors who screen the LOI and recommend three reviewers. Additionally, the NIH solicits recommendations from scientific societies regarding suitable scientists who may serve as reviewers.
- Experts Database: Organizations maintain an expert database that is updated periodically based on the organization's needs. FNRS updates its expert database through its analysis, evaluation, and foresight department, considering the level of expertise needed and ensuring the load of application review with existing reviewers. Similarly, the National Research Foundation of Korea employs its own database called NRF researcher information database and other national databases such as the Korean Researcher Base (KRB), which enlists all researchers in South Korea and other existing review pools to identify relevant reviewers.
- Artificial Intelligence: The implementation of Artificial Intelligence in selecting peer reviewers for grant proposals presents a vast potential in reducing administrative workload and increasing matching relevancy of reviewers. Within our dataset, the National Natural Science Foundation of China (NNSFC) is the only organization that has reported using artificial intelligence to match peer reviewers to the proposals. The AI tool utilized by NNSFC crawls through online scientific literature databases and scientists' webpages utilizing natural language processing to conduct semantic analysis and compare this information with the grant application to recommend a peer reviewer.
- Past Awardees: Successful grant applicants within a given area of scientific expertise are often seen as potential reviewers.

Most often, either an internal team of the agency or a committee selected the reviewers. 11 entities in the dataset mentioned that the selection of peers was performed by internal administration, while in 2 entities (ISF, Oeuvre Belge du Cancer), the selection of the peer reviewers was done by a committee.

External Review

Upon successful navigation of initial steps, including document verification and eligibility checks, proposals enter a merit review stage. The first component of this merit review often involves an external review, where experts external to the funding organization rigorously evaluate each proposal. This peer-driven assessment focuses on the scientific and technical merits of the proposal based on predefined criteria established by the funding agency. Despite being regarded as the gold standard method by the scientific community, peer review has been criticized for its challenges in supporting radical projects and encountering bias (Bollen et al., 2014).

In response to these challenges, some funding organizations have adopted innovative strategies to enhance the fairness and objectivity of the review process. For instance, an international funding agency has implemented an online submission system combined with blinded evaluations. The vice president of this agency explains,

> After issuing a call for proposals, we ensure a blind review by external referees, focusing solely on the merit and potential impact of the research.

This approach aims to safeguard against biases by concealing the identities of both the applicants and the reviewers, thus emphasizing the content and quality of the proposals over the reputation or affiliations of the proposers.

Furthermore, the issue of bias in reviewer selection, particularly the difficulty in finding suitable national referees for specialized topics, has been acknowledged. The Vice President of an International Funding Agency points out the complexities associated with this task, noting,

> Finding appropriate national referees for narrow subjects can be challenging, and there's a risk of personal conflicts influencing the process.

This recognition underscores the importance of adopting more inclusive and diverse strategies in reviewer recruitment, ensuring a broad and balanced perspective in the evaluation process. By addressing these challenges head-on, funding agencies strive to maintain the integrity and effectiveness of the peer review process, ensuring that it continues to serve as a cornerstone in the allocation of research funds based on merit and potential impact.

Table 2.3. Review processes followed by organizations.

Organization Name	Accept Full proposals or LOI.	Merit review process			Program Considered
		Preliminary merit Screening* on Full Proposal/LOI	Peer review	Panel review*	
Israel Science Foundation	Full Proposal	Yes (*Panel members screen full proposals for peer review)*	Yes	Yes	Israel Science Foundation has four modes for review and review process changes according to programs.
	Full Proposal	No	No	Yes	Programs that follow a Joint review process, e.g., The Joint Canada-Israel Health Research Program
	Full Proposal	No	No	Yes	Programs that follow review by technical committee only, e.g., New-faculty equipment grants
Israel Innovation Authority	LOI	No	No	Yes	Followed by a Joint innovation program, e.g., the Uruguay-Israel R&D Cooperation Program
	Full Proposal	Yes *(Internal Administration does examination & writes an opinion on the full prop)*	No	Yes	Followed by Local Innovation Program, e.g., Government-tech track: digital innovation in the public sector
National Institute for Psychobiology	Full proposal	Yes *(Full Prop reviewed by the scientific advisory board for peer review)*	Yes	Yes	General Process
The German Israeli Foundation	LOI	Yes (*LOI reviewed by the panel members)*	Yes	Yes	Program: GIF Nexus - Solo and Collaborative Track:
Vinnova	Full proposal	No	Yes	Yes	Program: Bio-innovation: Enabling Technologies and processes for bio-based products
SSF	Full Proposal	Yes	Yes	Yes	General process for framework programs
MISTRA	Full Proposal	No	Yes	Yes	Program: A Sustainable Blue Economy for Sweden

Organization Name	Accept Full proposals or LOI.	Merit review process			Program Considered
		Preliminary merit Screening* on Full Proposal/LOI	Peer review	Panel review*	
					Experts who perform external reviews are on the panel
Diabetesfonden	Full Proposal	No	No	Yes	General process for all programs
FNRS	Full Proposal	No	Yes	Yes	General process for all programs
Innoviris	Full Proposal	No	Occasional	Yes	Program: Prospective research, Proof of concept, R&D projects
Research Wallonia Ministry for Public Service (SPW)	LOI	Yes *(LOIs are reviewed by administration)*	Occasional	Yes	
King Baudouin Foundation	Full proposal	No	No	Yes	Program: Fund Alphonse & Jean Forton and the Belgian CF Association muco.be
Oeuvre Belge du Cancer	Full proposal	No	Yes	Yes	Program: Fundamental, Translational & Clinical Research 2022
	LOI	Yes *(LOIs are screened by a scientific committee)*	Yes	Yes	Program: Organ saving treatment and improvement of quality-of-life Grants 2022
NSFC	Full proposal	No	Yes	Yes	General process for all programs
Tecent Foundation	Full proposal	No	Yes	Yes	New Corner Stone Investigator Program
National Research Foundation of Korea	Full proposal	No	Yes	Yes	General process for all programs
Right Fund	Full proposal	No	Yes	Yes	
Alfred P. Sloan Foundation	LOI	Unclear if the review is done on merit criterion	Occasional	No	General process for all programs
American Chemical Society	Full Proposal	No	Yes	Yes	Program: Petroleum Research fund
Andrew W. Mellon Foundation	LOI	Yes *(Administrative Staff reviews LOIs)*	No	No	General process for all programs. The internal staff reviews LOIs and invites applicants to submit full proposals. Program staff works with the applicant to develop a full proposal.
Bill and Melinda Gates Foundation	LOI	Yes *(Administrative Staff reviews LOIs)*	Occasional	Unclear	Program: Global HPV Burden Study
	LOI	Yes *(Administrative Staff reviews LOIs)*	Occasional	Yes	Program: Solutions learning implementation grant

Organization Name	Accept Full proposals or LOI.	Merit review process			Program Considered
		Preliminary merit Screening* on Full Proposal/LOI	Peer review	Panel review*	
Little Giraffe Foundation	LOI *(no full proposals are accepted)*	No	No	Yes	Program: Neonatal Research Initiative
DARPA	LOI	Yes *(Program manager reviews LOIs)*	Occasional	No	General process
NIH	Full Proposal	No	Yes	Yes	General process
NSF	LOI/Full Proposal	Yes (for screening LOIs in some programs)	Depending on program	Depending on program	General process

In our dataset, 21 entities explicitly mentioned using external review in their decision-making process, including 12 public and nine nonprofit private entities. It was observed that organizations utilizing a scientific committee or jury for review either omitted external review or considered it occasionally, depending on the need. Entities such as the Israel Science Foundation (ISF), Israel Innovation Authority, Diabetesfonden, Innoviris, King Baudouin Foundation, and Little Giraffe Foundation did not send proposals for external review, instead predominantly conducting panel reviews by scientific committees. Philanthropic agencies such as the Gates Foundation and the Sloan Foundation and public entities like DARPA and SPW allowed program managers to evaluate the need for peer review depending on the budget and complexity of the project.

The external review criteria were similar to those adopted for the screening of Letters of Intent (LOIs) before accepting full proposals. Many entities in our dataset did not define the review criteria and used a combination of the criteria below for the merit review. Consistent with the systematic review by Hug et al. (2020), our dataset confirms the utilization of core peer review criteria such as originality, academic relevance, and plausibility/soundness across grant proposals. These criteria predominantly evaluate the project's objectives and the research methodology's robustness. However, our analysis further extends these dimensions to include criteria specific to innovation programs. This encompasses assessing the potential for commercialization, scalability, or technological exploitation of research outcomes, reflecting a broader scope of evaluation that captures both the intellectual merit and the practical impact of proposed research endeavors. This extended set of criteria underlines the multifaceted nature of grant evaluations, accommodating the diverse aims of research and innovation funding agencies.

Scientific Quality and Excellence

All entities in the dataset considered the evaluation of the idea's scientific merit to be a primary criterion, evaluated in terms of its originality and approach. The originality of the research idea, often referred to as "novelty of research idea" or "originality and innovativeness of research," refers to the value addition of proposed research over prior knowledge. The intellectual merit of the proposed research includes the evaluation of a scientific approach to solving a research problem. The entities in the dataset define the criterion in various forms. For example, the National Science Foundation (NSF) defines this criterion as evaluating the research project's potential to advance knowledge and understanding in a field of study. ISF mentions evaluating proposals on the suitability of the systematic approach and chances of success, while the American Chemical Association evaluates if the research is testable and hypothesis-driven. Additional criteria, such as the degree of interdisciplinarity, were also noted by organizations such as the Swedish Foundation for Strategic Research (SSF).

Feasibility to Achieve Goals

The feasibility of achieving expected outcomes is a holistic evaluation of the project plan, budget, and experience of the project team.

- The overall project plan is evaluated for its clear articulation and planned activities or workflows. Reviewers evaluate the approach to see if the planned activities are relevant to achieving the anticipated outcome and if it is realistic with respect to budget and planned activities. For example, Vinnova evaluates the proposals on how technology readiness levels (TRLs), market readiness levels (MRLs), and sustainability readiness levels (SRLs) are described along with their movement of these parameters during the project and whether the planned activities contribute to the achievement of expected results. DARPA and ISF evaluate if the technical risks in the approach have been identified and potential mitigation efforts are defined and feasible.
- Project Team and Collaborators: Most entities within the dataset indicated that evaluating a team's suitability for conducting research was a significant aspect of their review process. This evaluation encompasses an analysis of the team's composition, the individual experience of team members, their historical accomplishments (both scientific and entrepreneurial), international exposure, and the ability of the project lead and the organization to manage the project's plan, budget, and timelines. The assessment determines whether the team possesses the complementary expertise necessary to implement the project's planned activities. The evaluation of team members' experience is conducted through a review of their publications, academic records, resumes, proven track records supporting similar work, and other documents provided with the application. In the context of innovation programs, the involvement of the user or owner of the technology in the project team is deemed favorable. The 'technology owner' is distinct from the 'user,' who would utilize the technology post-commercialization or licensing. The involvement of the 'technology owner' is critical, as they have the in-depth knowledge and vested interest in the technology's development and potential applications. Certain agencies also anticipate a plan to manage gender diversity within the team. For instance, Vinnova mandates a balanced gender distribution within the team

and an equitable distribution of power and influence in terms of work tasks and roles within a 40/60 percentage range. Moreover, they evaluate the extent to which the 'technology owner' is integrally involved in the project, ensuring that the research trajectory is likely to lead to impactful commercialization or practical application of the technology.

- Budget and Timeframe: The project is also evaluated based on the rationale and feasibility of executing the proposed plan within the stipulated budget. DARPA incorporates cost realism as one of the evaluation factors, assessing whether the proposed costs align with the technical and management approach and are consistent with the applicant's scope of work. The costs provided must be detailed, and the budget should ideally reflect the realistic effort required to complete the project. Entities such as the National Natural Science Foundation of China (NNSFC), Right Fund, American Chemical Society, and German Israeli Foundation have mentioned evaluating the rationality of the plan for the adequacy and utilization of funds. Reviewers also assess the approach concerning the timelines for project realization, determining whether the milestones are appropriate or aggressive and whether a rationale supports them in the case of aggressive timelines.

Societal Impact and Potential for Commercialization, Scale-up, or Exploitation

Researchers are often asked to provide a commercialization or exploitation plan for the proposed research. The proposed project is expected to have the potential to move up in the value chain. For applied research projects, their potential for commercialization is evaluated, while for innovation projects, depending on their expected TRL level, the potential for further scale-up is evaluated. Vinnova, in its innovation programs, evaluates the proposal for its plan to make a clear shift in TRL, MRL, and SRL levels. SSF retains 4% of the grant for exploitation efforts and evaluates the proposal on its vision to utilize the research results in Sweden in the medium to long term.

Strategic Relevance

Agencies evaluate research projects on their ability to drive their program missions and priorities. Many agencies issue programs for technological priorities, so evaluation ensures the proposed research falls within its priorities. Vinnova and SSF evaluate the research projects for their strategic relevance, where proposed research should provide solutions to important application problems or enable future applications, products, or services.

Panel Review

Following the external review, or in some cases as an independent assessment, a panel review is conducted. The panel typically consists of 3 – 10 members possessing diverse backgrounds, who rate the applications in comparison to each other based on a predetermined criterion. The members rank the proposals according to merit relevance to the agency’s mission and recommend the decision to the higher management. They may consider the external evaluation, program managers’ evaluation, and their professional evaluation of the application.

The program manager assists the panel by providing a summary of applications and peer review ratings, managing conflicts of interest among the panel members, highlighting any red flags, training the panel members on the review process, and ensuring that each application is provided a thorough review. The program manager can provide a recommendation but will not provide the rating. The board of directors chairs the panel in the case of many foundations or is led by a program director or center director in the case of public funding organizations.

Twenty-one entities in the dataset mentioned using panel review in their decision-making processes. In comparison, three entities (Alfred P. Sloan Foundation, Andrew Melon Foundation, and DARPA) did not mention using panel review. The program managers in such entities instead worked with the potential applicant to develop a full proposal. They had more discretion in making a recommendation based on the external review results. In entities such as the Gates Foundation, the utilization of panel reviews is not a fixed protocol but is adapted to suit the nature and requirements of each specific funding program. Entities in which a panel review was followed by an external review evaluated and ranked proposals based on comments from the external review and aligned the proposal with the organization's funding strategy and budget. NIH conducts a special review during this stage for the proposals that have requested $1 million or more in direct costs and considers other factors such as portfolio balance, programmatic priorities, IC priorities, and availability of funds. Meanwhile, for entities that opt not to use an external review, proposals are evaluated by an internal review panel. This panel uses a set of criteria similar to those that would be employed in an external review to ensure a consistent and thorough assessment of each submission.

Agencies followed varied guidelines and processes for running the panels. In MISTRA, experts who conducted the external review were later invited to do the panel review. In others, an external review was conducted by a set of experts different from that of a panel review. Israel Science Foundation, National Institute of Psychobiology- Israel, German Israeli Foundation, Swedish Foundation for Strategic Research, and Oeuvre Belge du Cancer involved panel members at an early stage. The panelists conducted a preliminary review for screening Letters of Intent (LOIs) for peer review. They convened a second time to review the evaluation from peer review and recommend the final decision. Few Several entities, such as FNRS, NNSFC, and King Baudouin Foundation, maintained panels in various fields, with members appointed for fixed terms. The applicant chooses the panel or scientific committee to evaluate the application based on the field. Panel reviewers from NIH and NSF reported receiving 20 to 100 proposals before the meeting and are assigned as primary or secondary reviewers on 6-8 proposals. Reviewers took 15 – 60 hours to read and write reviews (Porter, 2005).

Entities in the set were observed to follow different types of reviews depending on the program requirements.

- External review: Several programs within NSF, Alfred Sloan Foundation, Bill and Melinda Gates Foundation, and DARPA utilized external review as the primary mechanism for evaluating the application's merit. Program managers in such programs make recommendations based on the ratings provided by external reviewers.

- Panel review: Certain programs of ISF, Israel Innovation Authority, Mistra, Diabetesfonden, Innoviris, King Baudouin Foundation, Little Giraffe Foundation, and NSF solely relied on panel review to evaluate the proposal's merit. NSF reported that multidisciplinary proposals may undergo multiple panel reviews. The panel in such programs recommends proposals to be awarded.
- Combination of external and panel review: Several programs in the entities in our dataset followed an approach that utilized external review followed by panel review for decision making.
- Internal review: In a few programs of NSF and Andrew Melon Foundation, the evaluation of application merit is done solely by program managers without the involvement of external and panel reviewers.

Amidst these varied methodologies, achieving consensus among reviewers, particularly in panel settings with diverse expertise, poses a significant challenge. The director of an international funding agency encapsulates this challenge by stating,

> We aim for consensus in the group, but the diversity of backgrounds can make this challenging.

This statement underscores the inherent complexities of balancing varied perspectives within the decision-making process. The diversity of reviewer backgrounds enriches the evaluation with a broad spectrum of insights. Still, it complicates the attainment of a unanimous decision, reflecting the nuanced and multifaceted nature of assessing research proposals.

Table 2.4. Overview of Grant Evaluation Processes and Criteria Across Entities

Category	Details
Entities Using External Review	21 entities, including 12 public and 9 private nonprofit entities
Entities Omitting External Review	ISF, Israel Innovation Authority, Diabetesfonden, Innoviris, King Baudouin Foundation, Little Giraffe Foundation
Entities Allowing Managerial Evaluation	Gates Foundation, Sloan Foundation, DARPA, SPW
Common Review Criteria	Originality, academic relevance, plausibility/soundness, potential for commercialization, scalability, technological exploitation
Scientific Quality & Excellence	Primary criterion across entities. Variability in definitions, e.g., NSF focuses on advancing knowledge, ISF on systematic approach and success likelihood, American Chemical Association on testability and hypothesis-driven research.
Feasibility to Achieve Goals	Assessed via project plan clarity, team suitability, and budget/timeframe feasibility. Specifics like Vinnova's evaluation on TRLs, MRLs, SRLs, DARPA's and ISF's technical risk and mitigation assessment.
Societal Impact & Commercialization	Evaluated based on the project's commercialization plan and its potential for value chain movement. Entities like Vinnova assess shift in TRL, MRL, and SRL levels. SSF focuses on research utilization in Sweden.
Strategic Relevance	Projects assessed for alignment with agency missions and priorities, with entities like Vinnova and SSF evaluating strategic relevance in terms of solving application problems or enabling future applications.

Category	Details
Panel Review	21 entities mentioned using panel review, with procedures varying. Some entities like Alfred P. Sloan Foundation, Andrew Melon Foundation, and DARPA might not use panel review but prefer managerial discretion. NIH has special considerations for large funding requests.
Review Types and Processes	Varied across entities: NSF, Alfred Sloan Foundation, and others use external review; ISF, Israel Innovation Authority, etc., rely on panel reviews; combinations or internal reviews are also present. The process complexity reflects the diverse nature of grant evaluations, balancing intellectual merit and practical impact in decision-making.
Challenges in Consensus	Highlighted by the diversity of backgrounds in panel settings, affecting unanimous decision-making. This complexity underscores the nuanced nature of assessing research proposals.

Approval and Result Processing

The multifaceted review process, encompassing both external/peer review and internal/panel evaluations, concludes with the formulation of recommendations for funding. These recommendations then advance through one or two tiers of approval within the funding organization before applicants are informed of the decisions. The authority accountable for endorsing the decisions of the review group varied among the entities in the dataset. It encompassed a board, council, jury, committee, director general, Chief Executive Officer, or government representative. The board serves as the final approving body in the National Institute for Psychobiology, German Israeli Foundation, Swedish Foundation for Strategic Research (SSF), Mistra, Diabetesfonden, Queen Elisabeth Medical Foundation for Neurosciences, Oeuvre Belge du Cancer, American Chemical Society, and Andrew Melon Foundation. A few organizations were observed to have multiple levels of approval. For instance, in the Israel Science Foundation (ISF), the review committee forwards the recommendation to the academic board, which subsequently presents it to the academic council. Similarly, in Vinnova, the program manager communicates the decision from the panel to the director, who further conveys it to the director general. In the case of Innoviris and Service Public de Wallonie (SPW), a minister or secretary of state responsible for scientific research serves as the final approving body.

The emphasis on collective decision-making is echoed by a project manager from an NGO who underscores the collaborative nature of these decisions:

> No one person is making a unilateral decision; these are really based on a breadth of reviews and perspectives to really capture the best thinking.

This sentiment reaffirms the value of incorporating a wide range of insights and evaluations, ensuring that funding decisions reflect comprehensive expert opinions and a collective commitment to supporting the most promising and impactful research initiatives.

Challenges with the current process

A comprehensive literature review and web-based exploration were undertaken for each entity within the dataset to identify any reported challenges within the grant management process. It was discerned that most entities within the dataset did not publicly disclose any challenges. However, a few challenges were identified by the King Baudouin Foundation in Belgium and the National Natural Science Foundation of China (NNSFC), elaborated upon below. Evidence of such challenges noted in the literature referred to:

Database Management

The King Baudouin Foundation reported a challenge of lack of integration across its programs in 2006 (King Baudouin Foundation, 2006). Each program operated independently, creating over 2300 nonstandard databases by individual staff members using different formats. This led to a high volume of duplicate organizations and contacts. The organization required an online system tailored to its needs, which could further integrate the requirements of all programs. This challenge was resolved by creating a customized solution in partnership with MicroEdge (King Baudouin Foundation, 2006). The increase in funding applications over the years has also resulted in an increase in outputs such as proposals, outcomes, patents, publications, etc., which has further posed a challenge for funding agencies to gain a higher view of their funding portfolio and assess impact. In an interview with decision-makers and program staff in US federal agencies, program officers expressed the need for tools to view the funding portfolio in broader terms and allow for a drill-down capacity (Vorvoreanu et al., 2015).

Review System

The NNSFC noted several issues with the peer review system (Chen et al., 2021).

- Increased administrative burden of finding reviewers due to high volume of applications: The number of proposals received yearly at NNSFC has been increasing, with more than 280K applications in 2020, which increased the load on administrators and reviewers (Chen et al., 2021). This challenge is observed worldwide in many agencies. For instance, in 2019, the National Science Foundation (NSF) reviewed 41,024 competitive full proposals (NSF, 2019). A study on stakeholder views of peer reviews of the National Institute of Health Research (NHIR) UK reported the time and effort required to identify reviewers as its biggest challenge (Turner et al., 2018). Another survey of 57 international public and private organizations in the field of biomedical research reported declined review requests, late reports, administrative burden, difficulty finding new reviewers, and reviewers not following guidelines as frequent or very frequent challenges (Schroter et al., 2010). The administrative burden of the process was reported to have increased over the past five years (Schroter et al., 2010). According to a grant-in-review report based on a survey of 4,700 researchers worldwide, funders spend 2-6 hours finding peer reviewers for an application (Publons, 2019). A program manager would invite at least three reviewers to secure one reviewer. It was also found that 50% of the reviewers declined a proposal for review because they were too busy with other commitments (Publons, 2019).

Funders often maintain a pool of peer reviewers, which makes finding reviewers easy, as the funders trust the reviewers with quality reviews, ensure avoiding conflicts of interest, and reduce the need to train the reviewers. However, with an increasing number of applications yearly, funders find it difficult to identify reviewers without a conflict of interest and with relevant expertise to evaluate proposals. In Publon's survey, it was found that 40% of the researchers rejected the request for review because the proposal did not fit with their expertise (Publons, 2019). Due to the need to find reviewers, program managers often allocate proposals to peer reviewers who might not be qualified experts to comment on the proposals. Peer reviewers in such scenarios may reject the proposal or could accept the proposal and provide a bad-quality review. Finding the right expert might require looking out of the internal pool of peer reviewers, which adds to the administrative burden on the funders.

Our discussions with key stakeholders from funding agencies provided a more nuanced view of the challenges associated with the reviewer selection process. A director from an International Funding Agency highlighted the significant effort involved in recruiting reviewers who are both willing and capable of delivering high-quality assessments, stating,

> Identifying and ensuring the commitment of quality reviewers is a time-intensive and often imprecise part of our process.

This challenge is compounded by the need for these reviews to be not just completed but of high quality, underlining the complexity of the issue at hand.

Adding another layer to this complexity, an NGO Program Manager brought attention to the lack of incentives for reviewers, which is a notable gap in the current ecosystem. The reliance on the goodwill of reviewers to contribute their expertise without tangible rewards was underscored by their observation:

> Currently, we don't offer incentives for reviewing, relying on reviewers' willingness to contribute to the scientific community.

- Reviewers Fatigue: The increase in applications results in a burden not only on administrators but on reviewers too. At NNSFC, a decrease in review quality was observed due to an increase in the number of applications per reviewer, with a few experts reviewing more than 50 applications (Chen et al., 2021). This issue has been noted with other funding agencies worldwide. According to a study by Aczel et al., it was found that the total time reviewers globally worked on peer reviews was over 100 million hours to publication peer reviews in 2020 alone, equivalent to over 15 thousand years (Aczel et al., 2021). The estimated monetary value of the time US-based reviewers spent on reviews was over 1.5 billion USD in 2020. For China-based reviewers, the estimate is over 600 million USD, and for UK-based, close to 400 million USD. This has increased "reviewers' fatigue" and decreased the quality of reviews provided by reviewers (Aczel et al., 2021).
- In our exploration of the challenges facing funding agencies during the peer review process, a recurring theme emerged from both our literature review and interviews: the lack of clear norms and guidelines for review. The NNSFC report found that the

evaluation received from reviewers lacked norms and guidelines for review (Chen et al., 2021). Often, the criteria for review are not clearly defined to the reviewers; hence, it was left at the reviewer's discretion to select their definition of the review criterion. In an interview with panel members of the European Research Council, the members pointed out the lack of specification, applying criteria, and choosing indicators as a challenge. This ambiguity sometimes caused proposals that met the unstated criteria to be perceived unfavorably, even though reviewer comments did not necessarily justify such negative assessments. (van den Besselaar et al., 2018). Further compounding these challenges are the nuanced biases and operational inefficiencies identified through our interviews. The influence of institutional prestige was acknowledged by representatives across the spectrum of funding agencies, with a small funding agency manager noting the bias towards well-known universities:

> Seeing that someone works at X or Y or Z, you know, immediately kind of brings them to the top of the pile.

This institutional bias risks overshadowing meritorious proposals from less renowned entities, thereby limiting the diversity of research that receives funding.

Another concern raised by interviewees was the impact of existing relationships, often referred to as the "Old Boys' Network." A small funding agency manager and an NGO project manager highlighted this dynamic, where ongoing interactions with funders can advantage previous recipients. The former described a cycle where initial funding facilitates regular contact with funders, potentially biasing future funding decisions towards these established connections.

Lastly, the lack of comprehensive evaluation tools was a significant barrier to effective decision-making. A small funding agency manager lamented the reliance on basic proposal reviews and previous relationships rather than on more sophisticated evaluation mechanisms: "It's mostly based on evaluating the proposal and any former relationship with the researcher, rather than any major tool that could help them." This deficiency underscores the urgent need for enhanced tools and methodologies to ensure that funding decisions are made based on the merit and potential impact of the proposed research.

- The review system does not support evaluating innovative and disruptive projects that China aims to fund: As noted by NNSFC, literature has also documented this concern as a significant challenge to the review process. Although peer review is considered a critical component of the process, it does not support the risk-taking element of novel and unconventional ideas, thereby discouraging scientific progress (Hug & Aeschbach, 2020).

Other potential challenges

Portfolio Monitoring and Impact Assessment: Program managers necessitate sophisticated knowledge management systems that effectively monitor ongoing projects and support comprehensive impact assessment. While current systems provide basic functionalities for searching and filtering projects, they lack advanced monitoring and analytics features. These advanced features are crucial for understanding the broader impacts of funded projects, including their scientific, societal, and economic contributions. The ability to visualize data trends, project progress, and outcomes in real time would significantly enhance the capacity for informed decision-making and strategic planning, thereby addressing a critical gap in current grant management practices (Vorvoreanu et al., 2015).

Evolution and Adaptations in Response to the Challenges

In response to the challenges identified within their operational frameworks, funding agencies have embarked on a journey of evolution and adaptation. This dynamic response is characterized by a shift from traditional methods to the adoption of advanced technological solutions and innovative practices. A significant step in this evolution has been the modernization of grant management systems. As articulated by a director of an international funding agency, the move away from "outdated technology" has been pivotal in addressing the inefficiencies and inflexibility that hampered older systems, marking a crucial step towards enhancing operational efficiency.

The journey towards digital transformation is exemplified by adopting platforms like Salesforce, which has revolutionized how agencies operate. A manager from a small funding agency recounted the initial hurdles of this transition, noting,

> The transition was challenging, but the long-term benefits in operational streamlining and funding diversity tracking were undeniable.

This reflects a broader trend towards digitalization, aiming to streamline operations and improve the management of diverse funding portfolios.

Leadership changes within these organizations have often served as a catalyst for embracing technological advancements. Reflecting on the transformative impact of new leadership, a program manager highlighted,

> The new presidency marked the beginning of a more technology-embraced era in our processes.

This underscores the significant influence that visionary leadership can have in steering organizations towards more technologically integrated solutions to overcome traditional challenges.

Some organizations have opted to maintain a degree of consistency in their grant management processes while acknowledging the need for updates. A director from one such agency admitted,

> Our methods have served us well since 1994, but the recognition that we must update our approaches to stay relevant is clear.

This highlights the delicate balance between preserving what has been effective and adapting to remain competitive and relevant in a rapidly evolving landscape.

Even incremental adjustments within these frameworks have been shown to impact the effectiveness of grant management processes significantly. A vice president of an international funding agency observed,

> Subtle but strategic adjustments, especially in our dealings with commercial partners, have significantly smoothed our operations.

This illustrates how minor modifications, thoughtfully implemented, can facilitate substantial improvements, underscoring the ongoing commitment of funding agencies to refine and enhance their operations in response to both internal challenges and external pressures.

Insights and Solutions from Grant Management and Scholarly Publishing

Having delineated the challenges encountered in the current grant management process, including issues related to database management, the review system, and portfolio monitoring, it becomes imperative to explore innovative solutions and best practices that can address these hurdles. The following section embarks on this journey by presenting strategies and insights gleaned from both the grant management sphere and the scholarly publishing sector. Given the shared challenges, particularly around the peer review processes, an examination of how these sectors have adapted and innovated offers valuable lessons for enhancing operational efficiency and effectiveness in grant management. By drawing parallels and learning from these domains, we can uncover actionable solutions that not only mitigate the challenges identified but also propel the grant management process towards a more streamlined and impactful future.

- This section presents strategies adopted by the National Natural Science Foundation of China (NNSFC) alongside insights from scholarly publishing that could inform improvements in grant management. Funding agencies and the publishing sector share common challenges, notably in peer review processes. By examining how these sectors have navigated similar issues, we can identify actionable solutions that grantmaking entities might adopt to enhance their operational efficiency and effectiveness.
  Incentivizing Reviewers: The peer review system, prevalent in publishing and grantmaking, is currently overburdened. Funders have devised various strategies to incentivize researchers for peer review, such as providing monetary rewards, sending acknowledgments or thank you emails, and publishing the names of reviewers in the funders' annual reviewer list. However, a significant number of funders do not provide any form of incentivization. A survey of 4500 researchers conducted by Publons revealed that 22% of researchers reported receiving no incentivization at all. Most researchers (75%) reported receiving thank you emails as a form of recognition, while 22% received monetary recognition. Despite the various forms of recognition, only 44% of researchers expressed satisfaction with their recognition. Due to the lack of effective incentives to encourage researchers to review, many reviewers are unwilling to dedicate significant time to review applications and produce quality reviews. According to the Publons survey, researchers recommend more explicitly recognizing peer review contributions as the primary encouragement for researchers to engage in peer review. Many academic journals utilize review recognition mechanisms such as recognition via ORCID IDs, the

Publons reviewer database, Elsevier's reviewer recognition platform, and other initiatives to provide more explicit recognition. However, in the case of grant peer review, there is no explicit mechanism to provide recognition due to sensitivities around the confidentiality of novel and unpublished research. Funders rely on sending thank you emails as a form of recognition (Enago Academy, 2023).

Considering the inefficiencies created on the program managers' side due to the lack of proper incentives for grant peer review, program managers should have tools at their disposal to support the efficient identification of peer reviewers who are experts and provide quality reviews. One such solution is providing a specialized search for peer reviewers and providing reviewers' reliability metrics – including metrics on how likely reviewers are to accept the proposal, creating a count of the quality of past reviews provided, providing researcher qualifications (H-Index), etc. This allows the program manager to select the reviewers likely to accept the review efficiently. The NNFSC in China recently implemented a "Responsibility, Credibility, Contribution" (RCC) supervision and evaluation system. Upon reviewing the proposals responsibly and making concrete contributions to the research work, reviewers receive a Credit in the form of an RCC score. Reviewers build their reputation and RCC score over time. The NNFSC would prioritize reviewers with a high RCC score (Enago Academy, 2022).

- Software Support in Finding Reviewers: The scholarly publishing sector has employed numerous off-the-shelf software solutions that assist in finding peer reviewers for a particular area. These solutions include Jane, Reviewer Finder, Taylor and Francis reviewer locator tool, Publons Reviewer connect, Flow Cite author services, Web of Science Reviewer Locator, and Elsevier- Find a reviewer with Scopus, among others. Additionally, open databases of reviewers such as DiversifyEEB, Early Career Reviewer Database, Potential Plant Peer Reviewer Database, and 500 Women Scientists are also available. These solutions hold great potential for use in grantmaking. Most of these solutions rely on the existing database of authors who publish in their journals; however, for grantmaking agencies, data privacy policies result in a lack of any global repository of funding data. Hence, there is a smaller dataset compared to publications. Dimensions AI is a software solution that attempts to create a global funding dataset. With 6 million grants from 637 funders worldwide, it supported finding grant peer reviewers. However, checking conflicts of interest remains a significant challenge which is currently conducted manually. Several AI-based solutions for the publishing industry support identifying peer reviewers and checking conflicts of interest. For example, EVISE, an AI created by Elsevier, can suggest publishing peer reviewers based on content, communicate with other programs to evaluate scientific performance and identify conflicts of interest among reviews (Kousha, K., & Thelwall, M. (2023)). Similarly, the UNSILO peer review finder API has been integrated by many journals (Kousha, K., & Thelwall, M. (2023)). Frontiers, an open science publishing platform, has developed an AI tool called AIRA (Artificial Intelligence Review Assistant) to recommend reviewers and detect potential conflicts of interest. The software was developed during COVID-19 to increase the processing of proposals for COVID-related research. It is currently used for publishing and grant peer reviews (Kousha, K., & Thelwall, M. (2023)).

Several funding agencies have worked on creating an internal AI tool that assists in finding reviewers. For example, in 2019, the National Natural Science Foundation of

China (NNSFC), piloted an AI tool that could crawl through online scientific literature databases and scientists' personal webpages utilizing natural language processing. It uses semantic analysis to compare this information with grant applications and recommend a peer reviewer. With an increase in applications by 10 percent a year in the past five years, NNSFC's annual applications are now six times that of the US National Science Foundation. The agency has a huge task: finding several peer reviewers for each application annually. To increase the turnaround time, NSFC piloted the AI tool with the early version of the tool, finding at least one reviewer for nearly 44,000 panels (David Cyranoski, 2019). The Russian Science Foundation (RSF) has also developed a set of tools to ease the review process. It already has automatic application checkers which can highlight application inconsistencies and reduce irrelevant applications for the program manager. It has also created an AI tool to automatically select peer reviewers for each application. In 2018, the tool was piloted in a competition with the AI selecting three peer reviewers each for 1300 proposals. Panel coordinators had the liberty to make changes if they were unhappy with the selection. AI significantly reduced the time program managers spent on reviewer selection. However, there is still a lot of potential to improve. Currently, the tool identifies the conflict of interest of a peer reviewer by checking if the peer reviewer is an applicant in the competition or if they share the same organization. As a next step, the algorithm would need to enhance the identification of conflicts of interest by understanding complex relationships among the researchers (RSF Press Office, 2018). The Research Council of Norway also utilizes AI in Grant Management, particularly for assigning peer reviewers and mapping research outputs to its portfolio of thematic priorities (Frauke Rohden & Ingrid Helene Johnsen, 2022). In a recent effort to improve efficiency in the processing of applications, the National Institutes of Health (NIH), the largest funder for health in the United States, worked with Leidos to implement two software– Assisted Referral Tool (ART) and Science Similarity Detection (SSD) using artificial intelligence. ART can process 9,400 grant applications monthly, leading to an 80% reduction in the clerical workload associated specifically with recommending peer reviewers for each NIH application. On the other hand, SSD supports reviewers by identifying similarities among grant applications, thereby helping to prevent redundancy in the review process by highlighting potentially overlapping or duplicate submissions (Checco et al., 2021).

- Preliminary Screening of Inferior Applications: Artificial Intelligence (AI) algorithms have been trained to provide evaluative ratings for publication reviews, thereby assisting editors in making informed decisions. Automated peer-review systems can conserve reviewers' time by identifying substandard studies early and providing a rating analogous to a human reviewer's peer-review rating (Thelwall et al., 2022). Despite the numerous challenges that need to be surmounted before AI can supplant humans, at the current juncture, it can serve as a supplementary opinion to peer reviewers in both publishing and grantmaking, thereby aiding in the reduction of administrative burden.
- Guaranteeing Quality Reviews from Reviewers: "Meta-reviewing," a process of reviewing reviews, is a widely researched topic in academic publishing but remains largely unexplored in grantmaking. Ramachandran et al. developed software that provides feedback to reviewers on their assessment of authors' submissions using text mining and natural language processing techniques. The software employs metrics such

as review content type, relevance, coverage of submission, tone, volume, and plagiarism (Ramachandran et al., 2017).

Following our exploration of actionable solutions derived from grant management and scholarly publishing, we now shift our focus to a frontier teeming with potential: the integration of Artificial Intelligence (AI) within funding agencies. This next section, grounded in the insights shared by our stakeholders, delves into the nuanced landscape of AI's current and future role in enhancing decision-making processes. The conversation around AI in this context emphasizes augmentation over replacement. An industry expert and startup co-founder passionately advocates for AI as an augmentative tool capable of scrutinizing publications, analyzing proposals, and suggesting potential reviewers. He highlights the critical need for transparency in AI models to circumvent the issues associated with opaque 'black box' systems.

> I think it's possible, for sure. And I think most of the challenges are going to be of an organizational nature,

they note, spotlighting AI's function as an enhancer of human capabilities rather than their replacement.

A project manager at a small funding agency reflects on AI's utility in streamlining grant management processes. From keyword extraction to administrative task automation and trend identification, they argue that AI applications could

> significantly reduce the manual workload and enhance our operational efficiency.

This broad potential of AI across different operational dimensions illustrates its capacity to impact grant management profoundly.

Data analytics and reviewer selection represent another area where AI's precision could be highly beneficial. With access to extensive data repositories, funding agencies could employ AI to derive insights from submissions, discern trends, and more accurately match proposals with reviewers.

> We are trying to identify reviewers; we maybe could have some kind of AI mechanism that we could train a bit well,

suggests a director at an international funding agency, pointing to the sophisticated capabilities AI could offer in refining the reviewer selection process.

Nevertheless, integrating AI into grant management processes is not devoid of challenges. For instance, the preliminary screening and risk assessment stages introduce both opportunities and potential pitfalls. While AI could streamline the categorization of proposals, thereby alleviating the workload on executives, there exists the risk of proposals being strategically tailored by researchers to exploit AI's selection criteria. This complexity underscores the nuanced challenges funding agencies must navigate in the adoption of AI-driven processes.

Furthermore, AI's capability to identify global trends and align funding initiatives with an agency's ethos provides a strategic edge. Directors from various international funding agencies share their experiences experimenting with AI for portfolio analysis, identifying strengths, gaps, and global trends, thereby showcasing AI's role as an operational tool and strategic asset.

As funding agencies stand on the cusp of this AI-driven transformation, the collective insights from stakeholders highlight a landscape brimming with promise. The integration of AI into grant management processes not only aims to tackle longstanding challenges of efficiency and objectivity but also to forge new pathways for strategic alignment and global impact. However, it is crucial to address the complexities and potential hurdles that accompany the integration of Artificial Intelligence (AI) into decision-making processes. Insights from stakeholders across a broad spectrum of organizations emphasize the need for a nuanced approach to incorporating AI technologies. These insights underline the importance of careful planning and adaptability in the face of emerging challenges.

The integration of AI into established grant management processes, for instance, may necessitate significant adjustments. This includes not only the redefinition of workflows but also the potential hiring of specialized staff to oversee AI-driven operations. Highlighting this challenge, a program manager at a small funding agency remarked,

> Integrating AI might require rethinking our current approaches and potentially hiring new personnel to effectively manage these AI-enhanced systems.

This comment reflects the broader issue of ensuring that organizations are adequately prepared for the transformative impact of AI.

Furthermore, the acceptance of AI within the research community and concerns about bias in AI systems represent significant hurdles. An international funding agency director pointed out the dual challenge of ensuring AI's fairness and gaining trust:

> Care must be taken to ensure AI systems do not inadvertently encode biases, particularly regarding institution types. Moreover, gaining acceptance for AI's place in peer review from the research community remains a substantial hurdle.

This illustrates the critical balance between leveraging AI's capabilities and maintaining ethical standards.

Another area of concern is the challenge of effectively processing unstructured data with AI. An industry expert from a startup emphasized the need for bespoke AI solutions, stating,

> AI's efficacy can be limited by unstructured data, necessitating models that produce meaningful insights tailored to the specific needs and contexts of funding agencies.

This highlights the importance of developing AI tools that are both sophisticated and adaptable to the unique demands of grant management.

Organizational inertia and resistance to change also pose barriers to AI adoption. A project manager at a small funding agency illuminated the internal challenges, noting,

> Introducing new technologies like AI can encounter resistance, particularly in environments averse to change, highlighting the need for clear directives to embrace new tools.

Crucially, maintaining a balance between AI recommendations and human judgment remains a pivotal concern. The vice president of an international funding agency emphasized AI's role as a support tool, stating,

> AI should be viewed as a supportive utility, offering recommendations to aid program managers in making more informed evaluations while not diminishing the value of human insight.

Echoing this sentiment, a program manager from an NGO highlighted the irreplaceable value of the human perspective,

> The integration of AI should not overshadow the critical role of human insight and judgment, which bring irreplaceable value to the management of funding processes.

Together, these insights stress the importance of complementing AI's analytical power with human intuition and creativity, ensuring that AI serves as an enhancer rather than a replacement in the decision-making process.

These insights from stakeholders illuminate the multifaceted challenges associated with AI integration into funding agency decision-making processes. While AI offers promising solutions to enhance grant management, addressing these challenges requires careful planning, open dialogue, and a commitment to balancing technological innovation with the indispensable human elements of the funding ecosystem.

Author's Insight: Navigating AI Integration in Funding Agency Operations

In my analysis of the funding agency landscape, I was struck by the glaring underutilization of AI capabilities. Remarkably, among the myriad of organizations surveyed, only the National Natural Science Foundation of China (NNSFC) purports to use AI for peer review matching. Yet, details about the algorithms employed or the efficacy of these models remain shrouded in mystery, revealing a significant gap in transparency and understanding within the sector.

This gap echoes in the sentiments of the scientific community, as revealed through my interviews. A notable resistance to AI integration stems from its perception as a 'black box', an enigmatic tool whose decision-making processes are neither clear nor comprehensible to its human users. This resistance was particularly poignant in a discussion where the opacity of current peer review processes, ironically similar to the criticized 'black box' nature of AI, was highlighted. The preference for human judgment, however flawed, over the unfamiliar mechanics of advanced AI algorithms underscores a deep-seated mistrust and a fundamental challenge in advocating for AI adoption in this field.

Interestingly, one interviewee illuminated an aspect of AI application that I had previously overlooked, likely due to my perspective being anchored in the funding agencies' viewpoint. The conversation opened my eyes to how small funding agencies could leverage AI to surmount the resource-intensive demands of grant application processes. Unlike their well-resourced counterparts, these smaller entities often lack the extensive support staff that can alleviate the administrative burden on researchers, allowing them to concentrate on the scientific essence of their proposals. AI, in this context, emerges as a potential equalizer, offering to streamline the administrative overhead and democratize access to funding opportunities.

Despite the prevalent challenges and skepticism surrounding AI's integration into funding processes, the status quo of grant allocation is far from ideal. The current business model is beset with inefficiencies, characterized by extensive time and financial expenditures. AI's robust capabilities in data recall, processing, and analysis present a viable solution to these challenges. It could enhance operational efficiencies within funding agencies, manage the influx of proposals, verify applicant eligibility, streamline reviewer matching, evaluate funding impact, and more. These are not mere administrative tasks but critical components of a strategic funding ecosystem where AI can play a transformative role.

Moreover, the inability to reproduce peer review outcomes consistently highlights a fundamental issue in the existing framework, further bolstering the argument for a more scientific, objective, and quantifiable approach. AI stands at the frontier of this transformation, offering tools to navigate the complexities of funding processes, from risk assessment to strategic alignment and impact evaluation.

In conclusion, the journey towards AI integration in funding agencies is fraught with challenges, yet it is a path laden with potential for transformative change. Agencies that approach AI adoption with an open mind, ready to navigate its intricacies and leverage its capabilities, are poised to gain a significant advantage. By cultivating a more scientific, objective, and efficient funding model, these forward-thinking entities can lead the way in revolutionizing the grant allocation landscape

Conclusion

This chapter has illuminated the intricate review processes employed by public and philanthropic research grantmaking organizations, outlining a multi-stage journey from proposal submission to final approval. Through an examination of various modalities for accepting applications, the preliminary screening to filter low-quality submissions, and the comprehensive assessment of proposals via internal, external, and committee reviews, we've delved into the operational nuances of these organizations. While it's challenging to generalize the preference for specific review processes among public or philanthropic entities based on this study's sample, insights suggest that the choice often hinges on the project's budget and complexity. Notably, the exploration revealed that while only a few agencies publicly acknowledge the challenges they face, such as the administrative burden of reviewer selection and the inadequacy of current review systems to assess innovative projects, these hurdles are significant.

To further enrich our understanding of these systems, we incorporated interviews with stakeholders from the funding agencies' ecosystem. These discussions provided valuable insights into the operational challenges and the potential for innovative solutions, such as Artificial Intelligence (AI), to address these issues. Despite the nascent adoption of AI in grant management, its widespread application in scholarly publishing to enhance review processes underscores AI's untapped potential in the grantmaking domain. This chapter underscores the critical need for grant management agencies to explore AI solutions, which promise to streamline operations and significantly mitigate administrative load.

The next chapter will explore AI's prospective roles within the realm of public and private research funding entities. By leveraging insights from stakeholders and examining AI's current applications in related fields, we aim to uncover the most promising opportunities for AI integration into grant management processes, setting the stage for a future where AI and human expertise collaborate to foster innovation and efficiency in research funding.

Chapter 3: The Role of Artificial Intelligence in Research Funding Decision-Making: Capabilities, Challenges, and Ethical Aspects

Building upon our analysis presented in Chapter 2, which delved into the intricate decision-making processes and the multifaceted challenges faced by funding agencies, this chapter transitions into exploring the transformative potential of Artificial Intelligence (AI) in redefining these processes. Chapter 2 highlighted key issues such as the administrative burdens of proposal evaluation, the subjective nature of decision-making, and the need for enhanced efficiency and transparency within funding agencies. It also underscored the diverse methodologies employed by these agencies in managing grant proposals and the subsequent challenges that arise, setting a solid foundation for the introduction of AI as a viable solution.

As we pivot to Chapter 3, our focus shifts towards harnessing the capabilities of AI to address the challenges identified previously. The advent of AI technologies offers promising avenues for not only streamlining the operational aspects of funding agencies but also elevating the objectivity and fairness of their decision-making processes. This chapter aims to elucidate the role of AI in augmenting the effectiveness of funding agencies, thereby fostering a more dynamic, equitable, and efficient ecosystem for research funding.

In this chapter, we embark on a multidimensional exploration of the convergence between Artificial Intelligence (AI) and decision-making processes within funding agencies. Section 3.1 delves into the historical and contemporary insights of AI, tracing its evolutionary trajectory and its symbiotic relationship with decision theory, setting the stage for its application in modern decision-making contexts. Section 3.2 expands our horizon to a sectoral exploration, showcasing AI's transformative impact across various domains, with a particular focus on its role in managing uncertainties, a critical component of funding agencies' decision-making frameworks. Moving forward, Section 3.3 addresses the inherent challenges and considerations of integrating AI into these processes, including pivotal issues like data privacy and algorithm bias. In Section 3.4, we navigate the technological landscape, highlighting the current adoption of AI tools and technologies within funding agencies and identifying potential areas for enhanced AI integration. Finally, Section 3.5 synthesizes these insights, proposing a strategic roadmap to bridge the decision-making divide in funding agencies through targeted AI capabilities, thereby fostering a more efficient, transparent, and equitable funding ecosystem.

Artificial Intelligence and Decision Theory

The field of Artificial Intelligence (AI) represents a profound intersection of computational ingenuity and human-like cognition encompassing capabilities such as learning, reasoning, problem-solving, perception, and language comprehension. Originating with the coining of the term "Artificial Intelligence" by John McCarthy in 1956 at the Dartmouth Conference, AI has since evolved into a multifaceted discipline with both specialized and generalized applications (McCarthy et al., 1955).

AI's historical trajectory can be delineated into two broad categories: narrow AI, designed for specific tasks such as facial recognition or internet searches, and general AI, aspiring to replicate the full spectrum of human intellectual capabilities. The current landscape is dominated by narrow AI with applications ranging from voice recognition to recommendation systems (Russell & Norvig, 2010).

The evolution of AI has been characterized by alternating periods of fervent progress, termed "AI summers," and subsequent disillusionment and funding reduction, known as "AI winters." The inaugural AI summer of the 1960s and 1970s witnessed pioneering programs like ELIZA and SHRDLU, which laid the groundwork for natural language processing (Weizenbaum, 1966; Winograd, 1972). However, the limitations of these early endeavors precipitated the first AI winter by the mid-1970s.

A resurgence in the 1980s, driven by the development of expert systems, was subsequently curtailed by the high costs associated with these systems leading to another AI winter. The current AI summer, ignited in the late 1990s and early 2000s, has been fueled by advances in machine learning and the proliferation of "big data." These innovations have catalyzed progress in speech recognition, image processing, and natural language processing, culminating in applications from web search to autonomous vehicles (Heaton, J. (2018)).

A notable milestone in AI's contemporary landscape is the emergence of large-scale language models such as GPT-3 by OpenAI. Trained on extensive text data, these models exhibit human-like contextual relevance and coherence proficiently executing tasks ranging from query answering to poetry creation and beyond. The underlying transformer algorithm has revolutionized natural language processing and raises critical ethical considerations (Brown et al., 2020).

Simultaneously, decision theory, also known as choice theory, has evolved as a multidisciplinary field that scrutinizes the decision-making process. With roots in economics, psychology, philosophy, mathematics, and statistics, decision theory's development spans centuries. Its foundational concepts, such as expected value and utility, were formulated by mathematicians like Blaise Pascal, Pierre de Fermat, and Daniel Bernoulli (Pascal & Fermat, 1654; Bernoulli, 1738).

The 20th century saw an acceleration in decision theory's development, with seminal works by John von Neumann, Oskar Morgenstern, and Leonard J. Savage providing mathematical underpinnings for decision-making under uncertainty (Von Neumann & Morgenstern, 1947; Savage, 1972). Decision theory's applications permeate various domains, including economics, business, medicine, and public policy.

The convergence of AI and decision theory offers a compelling nexus for enhancing decision-making processes. AI systems can leverage decision theory principles to optimize predictions, outcomes, and uncertainty management. Techniques such as decision trees, Bayesian decision theory, and multi-criteria decision-making (MCDM) are instrumental in complex decision-making scenarios including resource allocation and strategic planning (Russell & Norvig, 2010).

Sectoral Exploration of Artificial Intelligence in Decision-Making

Artificial Intelligence (AI) has emerged as a transformative force in various sectors, exhibiting profound proficiencies in decision-making and the amplification of organizational performance. AI's computational prowess and analytical methodologies have been pivotal in augmenting human cognitive functions, especially in multifaceted scenarios. This section is dedicated to an overview of AI's competencies, emphasizing its role in uncertainty management, performance enhancement at organizational and procedural levels, and refining existing processes to bolster automation, information dissemination, and transformative impacts. The discussion is grounded in reviewing relevant scientific literature, providing an understanding of some of the AI's capabilities and potential for future applications.

Building on the foundational insights into AI's broad capabilities, it's instructive to delve into specific sectoral applications to understand how this technology is reshaping traditional paradigms and addressing complex challenges. In the educational sector, for instance, AI transcends the conventional bounds of automation to offer tailored learning experiences, automated assessments, and dedicated support mechanisms that cater to the unique needs of learners. This nuanced application of AI in education has sparked a rich dialogue about its wider implications and ethical dimensions, highlighting the importance of transparent and explainable AI systems that can inform and drive forward the innovations in AI-enhanced educational practices (Tuomi, 2018; Zhang & Aslan, 2021; Baltrušaitis, Ahuja, & Morency, 2018; DiMitri et al., 2017; Giannakos et al., 2019; Cukurova, 2019).

In Finance, AI's potential to significantly enhance the effectiveness of trading strategies is rooted in its ability to analyze vast quantities of data and generate predictions. Through the intricate processing of large data sets, AI is capable of discerning patterns and trends that might remain elusive to human traders. This concept has been empirically validated in studies such as the one conducted by Dulhare et al. (2022), which explored the regulatory development of cryptocurrencies for trading through deep learning techniques, and the research by Ye et al.

(2017), which focused on the creation of sustainable trading strategies by employing directional changes with high-frequency data.

In healthcare, AI's role extends to enhancing patient care and organizational workflows, marking a significant advancement in medical diagnostics and treatment outcomes. For example, the application of deep convolutional neural networks (CNNs) in diagnosing skin cancer illustrates AI's diagnostic capabilities, which align closely with those of expert dermatologists. This breakthrough highlights AI's potential in medical diagnostics and suggests its capacity to extend expert care beyond traditional clinical settings, potentially offering universal access to critical healthcare services (Esteva et al., 2017).

The exploration of AI in managing uncertainty further highlights its utility in complex decision-making environments. Through predictive analytics and decision support tools, AI facilitates a more informed and strategic approach to decision-making, addressing various types of uncertainty and enhancing situational awareness in challenging contexts (Campello & Kankanhalli, 2022; Wu and Shang, 2020; Skaug and Busch, 2022).

These sectoral examples illustrate AI's significant impact on decision-making and organizational performance, reinforcing its role as a powerful adjunct to human cognition in data-rich environments. By integrating AI into organizational processes, entities across various sectors can achieve greater efficiency, foster innovation, and enhance their adaptability, ultimately empowering them with strategic insights for more informed decision-making (Jarrahi, 2018).

The insights gleaned from these sectoral applications of AI not only showcase its diverse capabilities but also set the stage for exploring its potential integration into the decision-making processes of funding agencies. As the discussion transitions to the specific challenges and considerations within the funding context, these examples underscore the importance of adopting a nuanced approach to leveraging AI, ensuring that funding decision-making is enhanced through innovative, data-driven methodologies.

Challenges in AI-Driven Decision Making

Integrating Artificial Intelligence (AI) into various fields holds great promise, but it also presents several challenges, such as those related to data privacy. These challenges include individual privacy rights, ethical use of data, compliance with legal regulations, and developing strategies to ensure privacy.

Navigating Data Privacy in AI Implementation

AI systems, characterized by their reliance on extensive datasets, are frequently entangled with privacy concerns, especially in sensitive sectors like healthcare. Using patient data in AI applications poses risks of inadvertent disclosure of personal information if not carefully managed (Mittelstadt & Floridi, 2016). Data privacy has evolved considerably with the advent of

AI, extending its scope from protecting personal information to encompassing responsible and ethical data usage in line with legal standards (Banciu & Cîrnu, 2022). Instances of privacy breaches in AI systems, such as potential leaks in AI-powered healthcare systems, have been documented (Reddy, 2021).

For funding agencies, the importance of ensuring data privacy in research-related AI applications has been increasingly emphasized. This is partly driven by heightened awareness of ethical data handling, leading to stricter requirements for data privacy (Mascalzoni et al., 2019)

To effectively address data privacy concerns in AI, a blend of technical and organizational strategies is required:

- Technical Measures: Techniques like differential privacy, which allows for publicly sharing information about a dataset without revealing individual details, can be employed (Dwork & Roth, 2014). Emerging solutions such as 'Cryptonets' deep learning networks trained on encrypted data, offer confidentiality throughout the entire process (Gilad-Bachrach et al., 2016). These are deep learning networks trained on encrypted data, and they even make encrypted predictions that can be decrypted only by the owner of a decryption key thus ensuring complete confidentiality throughout the process. Decentralized 'federated' learning approaches, in which data remains local during training, also mitigate privacy concerns (Yuan, Ye et al., 2021). A recent example of this approach is the work by Li et al. (2023) which proposed the use of the Federated Learning framework for skin cancer diagnosis. By training models with private patient data on local clients and aggregating models on a central server, this method allows participants to jointly train models without sharing data, thus breaking down data silos and enabling AI collaboration.
- Organizational Measures: Tools like privacy impact assessments, which help identify and reduce privacy risks, are essential (Asgarinia, 2020). They can help identify the potential effects of a project on privacy and work out ways to mitigate potential privacy risks. The concept of privacy-by-design, by which privacy safeguards are integrated into technology design and business practices, is proactive in preventing privacy risks (Cavoukian, 2010). It involves anticipating and preventing privacy-invasive events before they happen rather than waiting for privacy risks to materialize. Privacy-by-design is proactive in nature and aims to prevent harm from occurring rather than offering remedies after the fact.

Algorithm Bias

As we transition from the intricacies of data privacy to the challenges of algorithm bias in AI implementation, it becomes evident that bias manifests as data bias, algorithm bias, and contextual bias, each with distinct implications (O'Neil, 2016). Understanding and addressing these biases is paramount for equitably applying AI technologies.

Data Bias occurs when the training data for an AI system inadequately reflects the target population leading to skewed results and potentially unjust outcomes. An illustrative example is facial recognition systems where in a dataset dominated by light-skinned individuals results in less accurate recognition of individuals with darker skin tones, demonstrating a clear data bias (Buolamwini & Gebru, 2018).

Algorithm Bias arises from the inherent design of the algorithm whereby the assumptions and structure inferred from the training data inadvertently favor certain groups over others. This type of bias can be observed in hiring algorithms that privilege candidates from certain educational backgrounds thus disadvantaging equally qualified candidates from diverse backgrounds (Barocas & Selbst, 2016).

Contextual Bias surfaces when the AI system's operational context is neglected, leading to misinterpretations or inappropriate applications of its outputs. A case in point is an AI system designed for recidivism prediction which might disproportionately affect certain demographic groups if it disregards socioeconomic factors influencing crime rates (Flores, Bechtel, & Lowenkamp, 2016).

Consensus-Driven bias, what is experienced in some of the review panels, illustrates a systemic bias where the tendency to favor traditional or classical research approaches can stifle innovation. Research indicates that most ideators tend to overvalue their ideas, which can be linked to social identity, status and other factors (Sting, F., et al.,2019). This bias towards "classic science" arises not from explicit intention but from the consensus-driven nature of the review process, where diverse panelists find common ground in familiar methodologies, inadvertently disadvantaging innovative research proposals. AI systems, if trained on historical data from these panels, may inherit this bias. They could learn to prioritize proposals aligning with previously successful, traditional research, thereby perpetuating the cycle and potentially overlooking novel, innovative research avenues.

The ramifications of biased AI decision-making are particularly profound in sensitive domains such as hiring, lending, and criminal justice where they can perpetuate or exacerbate existing inequalities (O'Neil, 2016). To mitigate such biases, a multi-pronged strategy is essential.

- Auditing and Testing for Bias: This involves thoroughly examining AI systems to identify discriminatory patterns or unfairness. Techniques like disparate impact analysis and counterfactual testing are instrumental in this process (Friedler et al., 2019).
- Debiasing Data and Algorithms: Adjustments to training data or algorithm modifications are critical in reducing bias. This may include techniques like oversampling underrepresented groups or altering algorithmic feature weights (Mehrabi et al., 2021).
- Fairness in AI Design: Integrating fairness metrics and constraints into AI system design helps to ensures that the operation does not result in unfair outcomes. This involves both the quantification of fairness and the implementation of limitations on unfairness (Mehrabi et al., 2021).

A Multidisciplinary Approach Addressing algorithm bias extends beyond technical remedies. It requires engaging in a broader societal discourse on fairness definitions and their operationalization in AI systems (Barocas, Hardt, & Narayanan, 2019). This highlights the necessity for a holistic approach that blends technical solutions with ethical and societal considerations, ensuring that AI systems align with broader societal values and principles of equity.

Trust and Explainability: Pillars of AI System Adoption

The acceptance and effective deployment of AI systems hinge crucially on two pivotal elements: trust and explainability. Trust in AI systems encompasses users' confidence in their reliability, integrity, and functional efficacy (Ribeiro, Singh, & Guestrin, 2016). Explainability, or interpretability, on the other hand, refers to the AI system's ability to transparently communicate the logic behind its decisions or actions (Adadi & Berrada, 2018). Transparency in AI systems, which is closely linked to their ability to be explainable, refers to how openly and understandably the system reveals its internal mechanisms, including the algorithms it uses and the data it processes. The complexity of AI systems and the sometimes less-than-clear nature of how they arrive at decisions can make achieving this level of openness challenging. However, transparency is essential for fostering trust and acceptance among users and stakeholders, which is vital for the effective integration and use of AI systems (Ribeiro, Singh, & Guestrin, 2016).

Various strategies have been proposed to augment the transparency and explainability of AI systems. One approach involves using inherently interpretable models, such as rule-based learners and logistic regression models, which offer clear rationales for their decisions (Caruana et al., 2015). Alternatively, post-hoc explanations employ simpler models to approximate and elucidate the decision-making process of more complex systems (Lakkaraju et al., 2017). These methods, while beneficial, sometimes fall short of addressing the intricate challenges posed by more advanced AI systems.

Caruana et al. (2015) demonstrated the practical application of such interpretable models by using Generalized Additive Models (GAMs) with pairwise interactions in medical risk prediction. GAMs are a type of statistical model that fit a separate smooth function to each predictor, allowing for the flexibility to capture complex relationships between variables in a more interpretable manner. This approach corrected a false conclusion regarding asthma and pneumonia mortality risk, showcasing the value of interpretable models in real-world scenarios. Nonetheless, the trade-off between model simplicity and predictive accuracy remains a pertinent consideration.

A notable example of the challenges faced by AI/ML-based systems, particularly in the medical device domain, is discussed by Muehlematter, Daniore, and Vokinger (2021). They observed a significant increase in AI/ML-based medical device approvals since 2015, mainly in radiology. However, the regulatory process for these devices in the USA and Europe lacks clarity. The study advocates for greater transparency in device regulation and establishing a comprehensive, publicly accessible database detailing approved medical devices.

This call for transparency aligns with the emerging need for more sophisticated methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations), which will be explored in subsequent chapters of this dissertation (chapter 5). These advanced tools provide deeper insights into complex AI systems, potentially bridging the gaps in trust and explainability highlighted in the current regulatory and operational landscapes.

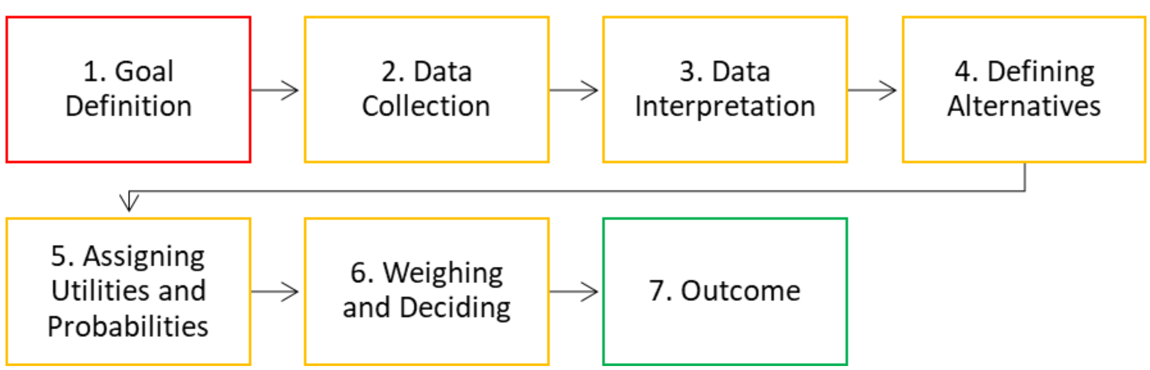
In conclusion, trust and explainability are fundamental to successfully implementing and accepting AI systems. Without these elements, there is a risk of resistance or failure in adopting AI solutions. The forthcoming chapters will delve into how tools like SHAP and LIME can play a transformative role in enhancing the explainability of complex AI models, addressing the challenges outlined in this section, and contributing to building a more trustworthy AI landscape.

Literature-Based Insights into AI's Role in Strategic Decision-Making

In developing a deeper understanding of AI's impact on strategic decision-making in funding agencies, it's pivotal to start by examining established organizational decision-making processes. By analyzing models developed by noted scholars, we can pinpoint a process that mirrors the complexities and demands of funding agency environments. Once a fitting model is identified, we can juxtapose it with the operational models of funding agencies to detect similarities and divergences. Subsequently, the literature offers a trove of potential AI applications that could be matched to each step of the selected decision-making process, thereby identifying where AI could best serve to enhance strategic decisions in the realm of research funding. This approach aims to systematically uncover areas where AI could provide significant advantages in decision-making efficacy and efficiency.

In the pursuit of understanding AI's role within the strategic decision-making of funding agencies, it becomes crucial to consider the basic organizational decision-making process, grounded in seminal works by scholars like Fredrickson (1984) and further developed by Beckmann and Haunschild (2002), El Sawy et al. (2017), Long (2017), and Rousseau (2018). This body of work collectively constructs a framework for navigating complex decisions, offering a systematic pathway that resonates with the operational contexts of funding agencies. Trunk, Birkel, and Hartmann (2020) build on these foundational theories to propose a conceptual model that addresses decision-making in modern, complex organizational contexts. Their model, illustrated in the image provided, delineates a seven-stage process:

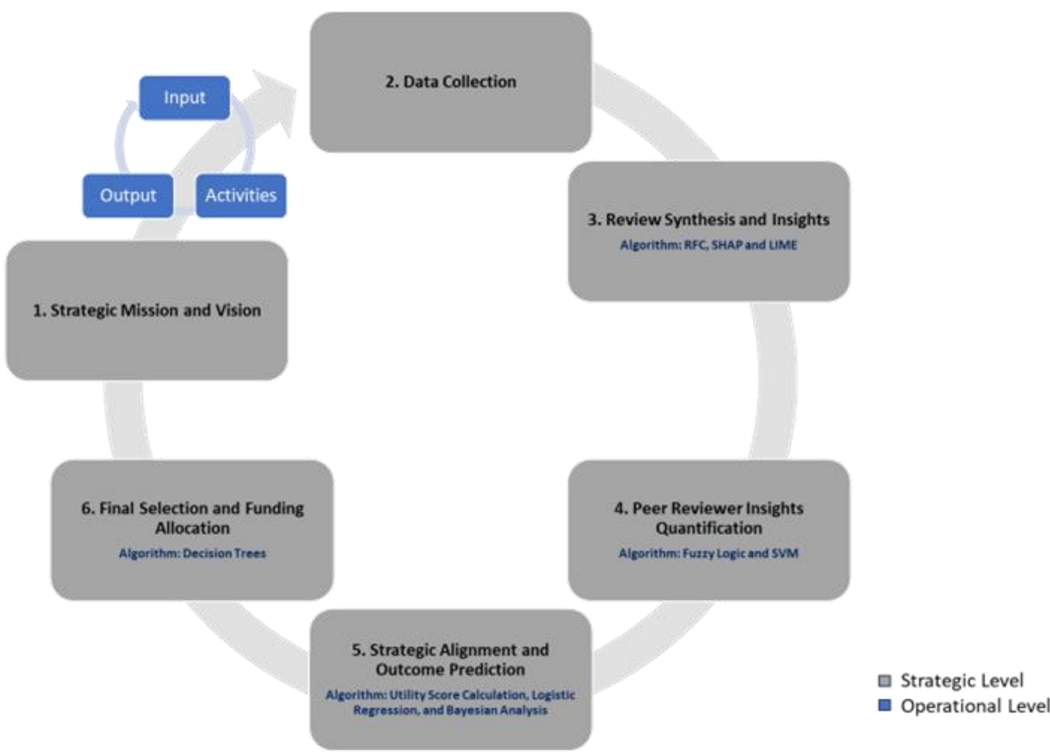
Figure 3.1. Trunk's Decision-Making Framework Heading 7, Figure Title



- Goal Definition: Establishing strategic intentions based on organizational objectives.
- Data Collection: Aggregating relevant information necessary for informed decision-making.
- Data Interpretation: Analyzing data to discern meaningful patterns and insights.
- Defining Alternatives: Identifying different potential courses of action.
- Assigning Utilities and Probabilities: Evaluating each alternative's benefits and likelihood of success.
- Weighing and Deciding: Balancing different alternatives to make a final decision.
- Outcome: Assessing the results of the decision-making process against the set goals.

Trunk's framework emerges as a model tailored for decision-makers, particularly within funding agencies, where uncertainty and complexity often cloud strategic decision-making. It offers a structured approach that delineates each step of the decision process, emphasizing the integration of human intuition with the analytical capabilities of artificial intelligence. This strategic decision-making model is crucial for setting overarching goals and strategic directions.

Figure 3.2. A Visual Guide to AI-Enhanced Strategic Decision-Making Tailored to Funding Agencies



Conversely, the logic chain, rooted in the principles of innovation assessment (Knowlton and Phillips, 2012), serves as a practical tool for executing strategies. It tracks the flow from inputs through to outcomes, providing a tangible measure of the efficiency and impact of implemented activities. This execution-focused model is essential for operationalizing the strategic objectives set forth by decision-makers. Recognizing the distinct yet complementary roles of Trunk's framework and the logic chain, we advocate for an integrated model that bridges the gap between high-level strategic decision-making and on-the-ground execution (Figure 3.2). This proposed model synergistically combines the strategic foresight of Trunk, Birkel, and Hartmann's (2020) framework with the operational clarity of the logic chain. By doing so, it not only guides funding agencies through the intricate process of strategic planning but also ensures that these strategies are effectively translated into actionable plans and measurable outcomes. In this integrated approach, the 'Goal Definition' phase from Trunk's framework lays the initial foundation, articulating the strategic objectives that inform the 'Inputs' within the logic chain. This ensures that every operational activity, output, and outcome is directly aligned with the agency's strategic vision. The model then progresses through Trunk's decision-making steps, enriched by data-driven insights from the operational activities captured within the logic chain, culminating in a 'Weighing and Deciding' phase that is both informed by strategic objectives and grounded in operational realities. This holistic model not only facilitates a more nuanced alternative definition phase but also establishes a continuous feedback loop, ensuring that the strategies of funding agencies evolve in tandem with the outcomes of their funded initiatives.

In the next section, we will embark on a detailed literature review to identify suitable algorithms for each step of the decision-making process within funding agencies. This exploration is grounded in the theoretical use cases in other sectors, aiming to discern how various AI tools and methodologies can augment and streamline funding agencies' decision processes. The goal is to match each stage of the organizational decision framework with AI capabilities that can enhance efficiency, accuracy, and effectiveness, thus facilitating more informed and data-driven decisions in the context of funding and resource allocation.

At the outset, the "Goal Definition" stage is characterized by strategic foresight, where the objective of the decision-making process is unequivocally established. As we transition into the "Data Collection" stage, the utility of AI applications becomes increasingly apparent. Here, Artificial Neural Networks (ANNs), refer to computing systems vaguely inspired by the biological neural networks of human brains, can be used to develop predictive models to help identify and prioritize data collection efforts. For example, Flath and Stein (2018) describe a data science toolbox that uses ANNs to predict the likelihood of customer churn. This information can then be used to target data collection efforts to those customers who are most likely to churn. (Flath and Stein, 2018; Baryannis et al., 2019a, b; Blasch et al., 2019; Calatayud et al., 2019). ANNs can be applied to funding agencies in several ways. For instance, in the context of research funding, "customer churn" could be likened to the likelihood of funded projects not achieving their expected outcomes, researchers not complying with the funding terms, or potential high-value research proposals being overlooked. K-means clustering, a method to find clusters within data, can identify groups of similar data points. This can be useful for segmenting data into different categories, which can be targeted with more specific data collection efforts.

For example, k-means clustering can identify groups of similar research proposals. This could be useful for grouping proposals into different categories, such as by research topic, applicant type, or funding budget. This information could streamline the review process and ensure the most appropriate reviewers review proposals. (Mühlroth and Grottke, 2018; Blasch et al., 2019). Nearest Neighbor algorithms, which identify closely related data points, can identify the data points most similar to a given data point. This can be useful for identifying data that is likely to be relevant to a particular topic or area of interest. For example, a Nearest Neighbor algorithm could be used to identify research proposals similar to previously funded ones. This information could be used to identify promising new research proposals and provide feedback to applicants on improving their proposals. (Pigozzi et al., 2016). All the above tools can be pivotal in optimization, prediction, and facilitating a structured and organized data collection process.

As we progress to the "Data Interpretation" stage, a plethora of AI applications come to the fore, with Bayesian networks, a model that uses probability inference to predict outcomes, (Baryannis et al., 2019a, b; Blasch et al., 2019; Colombo, 2019), decision trees, map out possible outcomes based on decision paths, (Flath and Stein, 2018; Baryannis et al., 2019a), and regression applications, examine the relationship between variables, (Pigozzi et al., 2016; Flath and Stein, 2018) playing crucial roles in aiding a nuanced interpretation of the data through the creation of intricate networks and systematic analysis of the data. Bayesian networks can be used to model the complex relationships between different variables in a dataset. This can help identify hidden patterns and correlations in the data, which can then be used to develop more informed interpretations (Baryannis et al., 2019a, b; Blasch et al., 2019; Colombo, 2019). Bayesian networks can be instrumental in funding agencies for scenario analysis and risk assessment. For example, a Bayesian network could model the probability of research project success based on variables like team expertise, project duration, budget size, and the research field's historical success rates. By inputting current project data, the network could provide the funding agency with a probabilistic assessment of a project's likelihood of success, helping to inform funding decisions. Decision trees work by recursively partitioning the data into smaller and smaller subsets based on the values of different variables. This process can be used to identify the most important variables that influence a particular outcome (Flath and Stein, 2018; Baryannis et al., 2019a). Decision trees could be used to streamline the proposal review process. By training a decision tree model on historical data of funded and unfunded proposals, including features like research area, requested budget, institution type, and researcher's publication record, the model could classify incoming proposals based on their likelihood of meeting the agency's funding criteria. This could help prioritize proposals for detailed review and identify those that may require additional information or clarification. Regression applications can be used to model the relationship between a dependent variable and one or more independent variables. This can help predict the value of the dependent variable given the values of the independent variables (Pigozzi et al., 2016; Flath and Stein, 2018). Regression models could be applied to forecast future funding needs or the potential impact of funded research. For instance, a regression model could analyze factors such as the amount of funding allocated to different research areas, the number of publications produced, and subsequent citations to predict the long-term impact of funding allocations on scientific advancements. This could assist funding agencies in strategic planning and optimizing the allocation of resources for maximum impact on the research community and society at large.

The subsequent "Alternatives Definition" stage leverages the capabilities of fuzzy systems (Pigozzi et al., 2016; Blasch et al., 2019; Baryannis et al., 2019b; Calatayud et al., 2019) and support vector machines (Pigozzi et al., 2016; Flath and Stein, 2018; Mühlroth and Grottke, 2018; Baryannis et al., 2019a; Blasch et al., 2019) to delineate potential pathways and offer a rich set of empirically grounded alternatives. Unlike traditional binary logic that classifies scenarios as either true or false, fuzzy logic introduces degrees of truth. This is analogous to human reasoning, which often operates in shades of gray rather than black and white. In the context of funding agencies, fuzzy systems can evaluate proposals based on a spectrum of criteria that reflect the nuanced, multifaceted nature of research impact. For example, a fuzzy system might assess a proposal's potential for generating high-impact publications, contributing to human capacity building, or leading to successful commercialization, taking into account the inherent uncertainties in predicting these outcomes. This can help funding agencies to identify a wider range of potential funding opportunities to maximize the agency's return on investment. This maximization isn't solely financial; it extends to achieving broader objectives such as advancing knowledge through publications in top-tier journals, fostering innovation through patents, building human capacity in strategic research areas, and promoting economic growth through startups and spinoffs. The goal is to create a portfolio of funded projects that collectively contribute to economic and social advancement. (Pigozzi et al., 2016; Blasch et al., 2019; Baryannis et al., 2019b; Calatayud et al., 2019). Support vector machines (SVMs) are a type of supervised machine learning algorithm that can be used for both classification and regression challenges. They work by identifying the hyperplane that best separates data into different categories. In the context of funding agencies, SVMs can classify research proposals based on their likelihood of achieving the agency's strategic objectives. For instance, SVMs could analyze historical data to classify proposals as high or low potential for yielding patents, or to distinguish between research likely to result in industrial applications versus foundational scientific contributions (Pigozzi et al., 2016; Flath and Stein, 2018; Mühlroth and Grottke, 2018; Baryannis et al., 2019a; Blasch et al., 2019). As we transition to the "Assigning Utilities and Probabilities" phase, Bayesian Networks come into play. Utilities, representing the benefits or satisfaction derived from each funding option, are combined with probabilities that estimate the likelihood of each option's success. Bayesian Networks facilitate this complex assignment by weaving together these utilities and probabilities, thereby refining the decision-making process through a detailed analysis of feasibility and potential impacts. This ensures a more informed and statistically substantiated approach to selecting the most advantageous and probable successful research initiatives.

As the process navigates toward the critical "Weighing and Deciding" phase, decision trees (Flath and Stein, 2018; Baryannis et al., 2019a) and fuzzy systems emerge as vital tools in steering the process toward a decision that aligns most closely with the initial objectives established in the "Goal Definition" stage. Decision Trees provide a visual and structured approach to evaluating each option's potential outcomes, allowing decision-makers to trace paths that closely align with the agency's established goals. Simultaneously, fuzzy systems offer the flexibility to deal with the inherent uncertainties and nuances in research proposals, enabling a more nuanced assessment that considers the degree to which each option aligns with the initial objectives. This combined approach ensures that decisions are made in a manner that is both systematic and sensitive to the complexities of funding research, keeping the process aligned with the agency's foundational goals.

In the final "Outcome" stage, the role of AI applications recedes, giving way to human judgment and strategic insight to assess the resonance of the outcome with the initial goal defined, thereby aiming to achieve the desired objective through a well-charted pathway (Trunk, A., Birkel, H., & Hartmann, E., 2020).

Technological Landscape and AI Applications in Funding Agencies

As we have delineated the pivotal role of AI applications in enhancing the strategic decision-making process, further exploring the real-world implications and applications of these technological advancements is imperative. Particularly, understanding the current technological landscape in funding agencies can offer a pragmatic perspective on how these theoretical frameworks are being translated into actionable insights in the contemporary era. This necessitates a review of the software tools and solutions currently at funding agencies' disposal.

Methodology of the Landscape Analysis

Building upon our methodology delineated in Chapter 2, this segment of our study delves into a specialized landscape analysis, tailored to investigate the technological underpinnings and AI integration within funding agencies. The foundational groundwork, as described in Chapter 2, section 2.2, involved an exhaustive examination of 397 funding agencies, refined through a selection process to a concentrated group of 89 organizations. These agencies were then categorized based on their financial portfolio, allowing for a granular analysis across various scales of operation, from non-profit entities to substantial governmental bodies.

For this focused analysis, we adhered to a similar stratification approach, delineating agencies into financial brackets to ensure a diverse representation across the spectrum of funding capacities. This methodology facilitated the identification of six distinct agencies from each category, culminating in a shortlist of 25 agencies. This selection was designed to encapsulate a wide array of operational dynamics, geographical distributions, and technological orientations, thereby providing a rich tapestry of data for our analysis.

The crux of this landscape analysis lies in its aim to uncover the prevalence and nature of AI tools and software solutions currently employed within these agencies. By scrutinizing the operational dynamics, a term that encapsulates the various processes, workflows, and decision-making frameworks within these organizations we seek to identify gaps, challenges, and opportunities where AI integration could bring about transformative efficiencies and enhancements.

Findings, An Analysis of Software Utilization Across Global Funding Agencies

This analysis aims to identify trends, commonalities, and differences among the technologies used by these agencies, focusing on aspects such as online submission platforms, evaluation mechanisms, and decision-making support systems. In our exploration of the software utilization across funding agencies, we conducted a targeted analysis of a select number of agencies. This sample, though not exhaustive, provides us with a snapshot of various technological practices and the extent of AI integration in decision-making processes across a range of geographical locations. While this does not constitute a comprehensive global overview, it offers valuable insights into the current landscape and highlights potential avenues for technological advancement within the sector. Our findings, derived from this selective approach, aim to contribute to the broader discourse on AI's role in enhancing the operational efficiency of funding agencies.

As part of our investigation into the technological adoption within global funding agencies, we have compiled the data that we collected into a table (table 3.1) that categorizes the software submission platforms utilized by these entities and examines the presence of AI in aiding decision-making. Each column header in the table denotes a specific category of information:

- Country: This header identifies the nation in which the funding agency operates, setting the geographical context for each entry.
- Funding Agency: Under this header, the specific name of the funding organization is listed, providing clarity on the agency being discussed.
- Software for Submission: This category details the specific software tools that agencies use for the submission of proposals and applications, indicating whether they have embraced digital methods or are adhering to traditional practices.
- Decision Making Aided Tech: This column is particularly telling, as it indicates whether the agency has reported using AI or other advanced technologies to assist in the decision-making process, reflecting the penetration of AI in operational practices.

Table 3.1. Overview of Software Tools Employed by Global Funding Agencies

Country	Funding Agency	Software For Submission	Decision-Making Aided Tech
Israel	Israel Science Foundation	Online submission: ISF application	None reported
Israel	Israel Innovation Authority	• Email • Online Submission	None reported
Israel	National Institute for Psychobiology	Email	None reported
Israel	The German Israeli Foundation	Online submission	None reported
Sweden	Vinnova	Online submission	Vinnova tested a method[2] to measure decision quality in funding evaluations, ensuring fairness by identifying and addressing potential assessor bias
Sweden	Swedish Foundation for Strategic Research (SSF)	Online submission	None reported
Sweden	The Swedish Foundation for Strategic Environmental Research (Mistra)	None	None reported
Sweden	Diabetesfonden	Online Submission: SBS manager from digiplant Ab	None reported
Belgium/Wallonia	FNRS (Fund for Scientific Research)	Online submission	None reported
Belgium/Brussels	Innoviris	• Email • Online Submission	None reported
Belgium/Wallonia	Research Wallonia Ministry for Public Service (SPW)	Online Submission: ONTIME	None reported
Belgium	King Baudouin Foundation	Online submission - Microedge Gifts	None reported
Belgium	Belgisch Werk Tegen Kanker – Oeuvre Belge du Cancer	Online submission - CC grant tracker by Digital science and research	None reported

2 https://lnu.se/en/meet-linnaeus-university/current/news/2019/thumbs-up-by-vinnova-for-maria-ulans-method-for-quality-assessment/

Country	Funding Agency	Software For Submission	Decision-Making Aided Tech
China	National Natural Science foundation of China	• Online Submission: created by the agency. • Creating an AI driven mechanism where system will be able to analyze the research projects and publications of potential reviewers and match them with the proposals through semantic comparison. After identification of reviewers with the most appropriate expertise, the system will further check the credit information and select the high-credit reviewers.	Not for decision making but for identification of peer reviewers
China	Tecent Foundation	Online application software: Created by agency. Login by WeChat	None reported
Korea	National Research Foundation of Korea	NA	None reported
Korea	Right Fund	Application submission: Zoomgrants	None reported
USA	Alfred P. Sloan Foundation	Application Submission: Flux (https://www.fluxx.io/)	None reported
USA	American Chemical Society	Online Submission: Salesforce	None reported
USA	Andrew W. Mellon Foundation	Application Submission: Flux (https://www.fluxx.io/)	None reported
USA	Bill and Melinda Gates Foundation	Online submission: Microsoft	None reported
USA	Defense Advanced Research Projects Agency (DARPA)	• online submission: grants.gov • Submission of patents: iedison	None reported

Country	Funding Agency	Software For Submission	Decision-Making Aided Tech
		• Submitting invoices: Wide area workflow	
USA	Little Giraffe Foundation	Submission by email	None reported
USA	National Institutes of Health (NIH)	• Online submission software used is internal: grants.gov. • CSR Assisted Referral Tool (ART)- to identify the CSR study sections that might be appropriate for review of the application. • Report Expenditures and Results tool (RePORTER) (https://reporter.nih.gov/advanced-search). Allows users to search a repository of NIH-funded research projects and access publications, including other valuable information for researchers in the planning process. Has advanced search options than award search tool of NSF. • Matchmaker: Linked with RePorter- Allows a person to submit text of his proposal to find out which are other similar funded projects by NIH	None reported

Country	Funding Agency	Software For Submission	Decision-Making Aided Tech
USA	National Science Foundation (NSF)	• Online submission by grants.gov, research.gov, NSF Fastlane. • Award search https://www.nsf.gov/awardsearch/simpleSearchResult?queryText=desalination&ActiveAwards=true Allows to search for all awarded projects. Simple search features. Doesn't include any clustering.	None reported

By setting out this structured approach, the table allows us to methodically analyze the extent to which funding agencies have integrated technological solutions into their workflows, and specifically, to what degree AI has been adopted to enhance decision-making efficiency and effectiveness. The following list encapsulates the diverse range of software solutions and platforms that were identified across the spectrum of agencies examined in our study:

- Submission Platforms: Many agencies, from the Israel Science Foundation to the National Science Foundation (NSF) in the USA, have adopted online submission platforms. These platforms streamline the application process, whether developed in-house like that of the National Natural Science Foundation of China or third-party solutions like Fluxx used by the Alfred P. Sloan Foundation. However, the integration of AI in these platforms for decision-making support remains largely unreported.
- Decision Support Tools: The National Natural Science Foundation of China is highlighted for its use of AI in identifying suitable peer reviewers, showcasing a potential avenue for AI integration in decision-making.
- Email Submissions: A notable method in Israel and Belgium, with some agencies exclusively relying on this traditional approach.
- Post-Submission Analysis: While tools like the CSR Assisted Referral Tool (ART) and the RePORTER database by NIH provide post-submission insights, they don't directly aid in decision-making. The CSR Assisted Referral Tool (ART) provides insights into potential collaborators, while the RePORTER database offers post-submission insights. However, these insights are not directly used in decision-making. The potential for AI integration in this context is significant, as AI tools can analyze extensive datasets to provide nuanced insights into the funding landscape and potential collaborators, among other factors. This can aid decision-makers in making more informed and comprehensive decisions regarding research funding and collaboration opportunities.
- Unique Approaches: Funding agencies are not only incorporating advanced technologies but also pioneering unique methodologies to enhance their grant management systems. For instance, Vinnova in Sweden is at the forefront of addressing potential biases,

especially concerning gender equality in AI and research funding. They adopt a holistic method to ensure fairness in decision-making, which includes:

– Ensuring balanced gender representation on review committees.
– Providing gender bias training for committee members to appropriately evaluate gender considerations in research subjects.
– Experimenting with AI to manage gender bias in salary decisions, reflecting a forward-thinking use of technology to tackle systemic issues.
– Focusing on the 'who, how, and what' of funding to combat unequal research funding patterns and promote gender equality in every project. This includes mandatory action plans for gender equality in all funded projects.
– Employing continuous evaluation processes that scrutinize the methods used to assess research impact, thus promoting transparency and fairness.
– Offering support functions for program managers to integrate gender aspects into their funding decisions strategically.

Vinnova's methodological innovation underscores a proactive stance in leveraging both technology and policy to address and manage biases, setting a precedent for other funding agencies to follow.

In summary, the utilization of online submission platforms is commonplace among funding agencies, but the integration of AI in decision-making processes is still developing. There is a significant opportunity for AI to enhance the efficiency and effectiveness of grant management, extending from application submission to post-submission analysis. Approaches to AI integration differ widely: for example, the National Natural Science Foundation of China uses AI to identify suitable peer reviewers, demonstrating AI's potential in augmenting decision-making. In contrast, Vinnova in Sweden employs AI to systematically assess and mitigate biases, such as gender bias in decision-making processes. These varied applications of AI signal a move towards more technology-driven operations in the global funding agency landscape, with considerable scope for innovation and improvement.

Potential Commercial Tools for Decision-Making Support

Earlier exploration suggested that global funding agencies are looking toward use of software tools to enhance their decision-making process. What commercial tools are available in the market? These traditional as well as AI-driven tools offer functionalities that can significantly augment the processes within funding agencies. Whether for team profiling, expert search, or text mining, these platforms provide innovative solutions that can streamline operations, enhance decision-making, and foster efficiency. The exploration of these tools is particularly crucial in understanding how AI-driven functionalities, in conjunction with traditional software features, can be harnessed to gain even greater leverage in the decision-making landscape of funding agencies. This discussion aims to shed light on the potential intersections where AI technology can be integrated or enhanced within existing tools to address complex decision-making challenges, thereby offering a more nuanced and efficient approach to funding agency operations. By examining these commercial tools in greater detail, we seek to identify opportunities for AI application that could further refine and optimize decision-making processes, aligning with the overarching goal of leveraging technology to facilitate more informed, effective, and efficient funding decisions.

- Rayyan (Link): Rayyan is an advanced web-based platform designed to facilitate and streamline the systematic literature review process, enabling seamless collaboration among researchers, students, and librarians globally. In the context of funding agencies, Rayyan's AI-driven capabilities could be leveraged to enhance the review of grant applications and research proposals.
- IRISAi (Link): Specializing in text mining, IRISAi extracts data from research articles, patents, and publications. Its AI-driven capabilities can be leveraged to scan proposals for specific information, ensuring comprehensive evaluation.
- Humantic AI (Link): A unique tool that offers personality analysis by reading text. This can be instrumental in analyzing the interpersonal skills of researchers, providing an additional layer of evaluation.
- ideXlab (Link): This platform, with its AI capabilities, aids in expert search. It can be particularly useful for funding agencies to identify potential peer reviewers.
- Grants Search Platforms: Many tools, such as FoundationSearch, GrantStation, GrantSelect, and others, specialize in team profiling. They assist in tracking awards funded to a researcher, providing a comprehensive view of a researcher's grant history. While some of these platforms are AI-driven, others, like Grants.Gov and RePorter, offer these services for free. This indicates the presence of a blend of premium and open-source solutions in the market.
- **Relecura** (Link): This platform focuses on rating individual inventors, although further details weren't specified. It suggests a move towards more specialized tools catering to niche requirements.

Our earlier discussion highlighted the diverse range of software solutions employed by funding agencies across different countries, underscored by the technological landscape presented to these agencies. While some tools are universally applicable, others cater to specific regional or operational needs. The presence of AI in many of these platforms indicates a trend towards more data-driven, automated processes, aligning with our earlier observations on integrating AI in decision-making.

Identifying Gaps and Harnessing AI Capabilities

Building on the analysis of the decision-making process within funding agencies, it becomes possible to identify potential areas of improvement. While the current state showcases a blend of traditional methods and sporadic AI integration, many commercial tools are yet to be harnessed. By juxtaposing the stages of decision-making with the capabilities of these tools, we can pinpoint gaps and envision a roadmap enriched with AI-driven opportunities. The next section delves into each stage, shedding light on the current state, highlighting gaps, and suggesting potential AI tools to bridge these gaps, thereby offering a holistic and enhanced decision-making process.

Stages of the Decision-Making Process, Gaps, and Possible Opportunities

For each stage of the decision-making process, the "Current State" section examines the prevalence and nature of AI applications currently in use. It highlights the extent to which AI technologies have been integrated into various decision-making activities, identifying areas where AI's potential remains untapped or underutilized.

Goal Definition

In the Goal Definition stage, decision-makers establish the objectives and desired outcomes of the decision-making process, relying heavily on their expertise and foresight.

- Current State: At present, this stage is primarily driven by human cognition and strategic foresight, with limited documented evidence of AI-driven tools being employed to initiate goal-setting processes.
- Gap: The literature does not provide substantial evidence of AI-driven tools being used to refine and clarify goals based on historical data, trends, and predictive analytics.
- Opportunity: IRISAi, with its advanced information extraction capabilities, can sift through vast datasets to identify relevant trends, past decisions, and outcomes, providing a rich context for setting more realistic and achievable goals. Similarly, Artificial Neural Networks (ANNs), known for their pattern recognition strength, can analyze historical data to identify underlying patterns and correlations that might not be immediately apparent to human analysts. By leveraging these AI tools, funding agencies can significantly improve the precision and relevance of their goal-setting processes.

Data Collection

In the Data Collection stage, the focus is on gathering relevant information and data that will inform subsequent stages of the decision-making process. Traditionally, this stage has relied on manual methods of data collection, which can be time-consuming and may not capture the full spectrum of relevant information.

- Current State: The advanced capabilities of AI algorithms, such as Artificial Neural Networks (ANNs) for predictive modeling, k-means clustering for efficient data segmentation, and Nearest Neighbor algorithms for pinpointing pertinent data points, demonstrate significant potential for revolutionizing data collection. These algorithms can automate the process, enabling more nuanced and comprehensive information gathering (Flath and Stein, 2018; Baryannis et al., 2019a, b; Blasch et al., 2019).
- Gap: Despite the availability of these AI tools, there's a predominant reliance on traditional methods for data collection.
- Opportunity: Rayyan, with its proficient data extraction capabilities, can automate the sifting through literature and databases to pull relevant information efficiently. When combined with ideXlab, which facilitates access to a broad spectrum of innovation and research, the integration of k-means clustering can further refine this process. K-means

clustering organizes the vast amount of extracted data into meaningful categories, making it easier to identify trends, patterns, and gaps in the collected information (Mühlroth and Grottke, 2018).

Data Interpretation

In the Data Interpretation stage, the collected data is analyzed and contextualized to derive meaningful insights and understandings that will inform decision-making. This stage is crucial for transforming raw data into actionable intelligence.

- Current State: Currently, the use of advanced AI tools such as Bayesian networks, decision trees, and Regression applications is acknowledged in the literature for their capabilities in interpreting complex datasets. These tools enable a systematic analysis of data by modeling relationships, predicting outcomes, and identifying patterns and trends (Baryannis et al., 2019a, b; Blasch et al., 2019; Colombo, 2019).
- Gap: Not all funding agencies fully utilize the sophisticated interpretative power of AI technologies. Many still rely on conventional analysis methods, which may not offer the depth and breadth of insights that AI can provide.
- Opportunity: An opportunity lies in integrating Humantic AI, known for its prowess in analyzing textual data and understanding human personalities from digital footprints, with the modeling capabilities of Bayesian networks. This combination can offer a nuanced understanding of both quantitative and qualitative data. Further enhanced by IRISAi's advanced data extraction techniques, this integrated approach can unlock deeper insights from the data, offering a richer foundation for strategic decision-making. Agencies can significantly improve their data interpretation phase by tapping into these AI tools, leading to more informed and effective decision-making processes (Colombo, 2019).

Alternatives Definition

In this stage, funding agencies explore various strategic options for allocating resources, based on insights gleaned from data interpretation. This crucial phase involves formulating a diverse array of proposals and action plans that could potentially be funded.

- Current State: Tools like Fuzzy systems and support vector machines (SVMs), while established in finance, healthcare, and technology, where they serve critical roles in formulating strategic options and decisions, remain underutilized in funding agencies. Fuzzy systems excel in managing the ambiguity and imprecision often present in real-world scenarios, making them suitable for defining choices of alternatives in uncertain conditions. On the other hand, SVMs are adept at classifying data into distinct categories, which can be instrumental in identifying and categorizing potential alternatives based on predetermined criteria. (Pigozzi et al., 2016; Blasch et al., 2019; Baryannis et al., 2019b; Calatayud et al., 2019).
- Gap: There's a notable gap in leveraging the full capabilities of fuzzy systems and SVMs to proactively create data-driven funding alternatives. This underuse might be due to a lack of familiarity with these tools in the funding domain, concerns about the transparency of AI-driven decisions, or a preference for traditional decision-making processes.

- Opportunity: Incorporating tools like IRISAi, fuzzy systems, and SVMs offers a significant opportunity to transform the Alternatives Definition stage in funding agencies. IRISAi's data extraction and analysis capabilities, combined with the fuzzy systems' ability to manage uncertainty and SVMs' precision in data classification, can uncover new, promising funding opportunities. This integrated approach enables funding agencies to make informed, strategic decisions that align with their goals and maximize the impact of their investments.

Assigning Utilities and Probabilities

In the context of funding agencies, the "Assigning Utilities and Probabilities" stage involves the critical task of determining the potential value (utility) and success likelihood (probability) of various project proposals.

- Current State**:** Bayesian networks are noted for their capacity to model complex probabilistic relationships, providing a structured approach to estimate the likelihood of various outcomes (Baryannis et al., 2019a, b; Blasch et al., 2019).
- Gap: Numerous funding agencies remains predominantly reliant on the nuanced discernment and qualitative evaluations of seasoned experts. This traditional approach underscores the significant gap between potential technological advancements and their practical application in the critical stage of assigning utilities and probabilities within these agencies.
- Opportunity: The integration of Bayesian Networks and Regression applications presents a significant opportunity for enhancing the "Assigning Utilities and Probabilities" stage within funding agencies. Bayesian Networks, known for their ability to model complex probabilistic relationships among various factors, can provide a structured framework for estimating the likelihood of project success (Blasch et al., 2019). For example, the Bayesian network could evaluate the proposal's alignment with emerging trends, the research team's adaptability, and the project's scalability, assigning probabilities to each outcome. When combined with Regression applications, which predict outcomes based on the relationships between multiple variables (Pigozzi et al., 2016; Flath and Stein, 2018), this approach can significantly improve the accuracy and objectivity of utility and probability assessments for project proposals. For example, regression analysis could draw on data from similar past projects, assessing the relationship between proposed methodologies, anticipated timelines, and successful outcomes. Together, these tools could offer a comprehensive, data-driven framework for assigning utilities and probabilities, moving the decision-making process from a realm of subjective expert opinion to one grounded in objective, analytical rigor.

Weighing and Deciding

In the Weighing and Deciding stage of the decision-making process, funding agencies are tasked with evaluating and comparing various funding proposals against a set of criteria to make informed decisions. This stage is crucial as it determines which projects or initiatives receive support based on their alignment with the agency's goals and potential impact.

- Current State: Decision Trees and Fuzzy Systems have been highlighted as instrumental tools in guiding the decision-making process. (Flath and Stein, 2018; Baryannis et al., 2019a). Decision trees aid in simplifying complex decision scenarios into more manageable sub-decisions, illustrating potential outcomes and pathways clearly. Fuzzy systems complement this by effectively managing the inherent uncertainties and vagueness within decision-making processes, thus accommodating the nuanced decision-making that closely resembles human judgment.

- Gap: Despite the utility of these tools, there remains a notable gap in the availability of systems that can effectively weigh alternatives through a multi-criteria decision analysis framework. Many funding agencies continue to rely heavily on expert judgment and qualitative assessments, which may not always capture the full spectrum of data and insights available.
- Opportunity: The integration of Decision Trees, with their ability to map out structured decision pathways (Baryannis et al., 2019a), alongside the robustness of Fuzzy Systems in handling imprecise and ambiguous data (Calatayud et al., 2019), presents a compelling solution. Using these algorithms, funding agencies can adopt a data-focused approach to decision-making. This ensures that resources go to projects that not only meet specific criteria but also have a high potential for making a meaningful difference. Decision trees simplify complex decisions into smaller, more manageable questions, such as whether a project aligns with strategic goals or its potential impact. This method clarifies each proposal's strengths.For uncertainties, fuzzy systems can predict the practical impact of research or gauge a project team's reliability. Adding Humantic AI, which assesses personality from texts, can further help by analyzing team dynamics and soft skills essential for a project's success. It looks at communication, leadership, and teamwork in proposals and publications. By integrating these algorithms, agencies can thoroughly assess proposals, balancing definite criteria against research uncertainties. This leads to more informed decisions and funding projects poised to make significant advancements in their field.

Outcome Evaluation

The "Outcome Evaluation" stage in funding agencies is the process where the results of funded projects are assessed against the initial objectives and expectations. It involves analyzing the deliverables, impacts, and broader contributions of the projects to determine their success and inform future funding decisions.

- Current State: AI's transformative role in evaluating outcomes is evident across various sectors, demonstrating a wide array of applications. In mental health care, AI-powered tools analyze speech patterns and facial expressions to provide timely feedback to professionals, enhancing patient care. In the educational domain, AI systems like Pearson AI assess students' learning patterns, offering personalized instruction and feedback, while in business and marketing analytics, platforms such as Crayon and Google Analytics employ AI to dissect and interpret conversion data, guiding strategic decisions. Furthermore, data analysis tools like PolymerSearch.com utilize AI to facilitate the creation of insightful dashboards and presentations, streamlining the decision-making process. These applications underscore AI's capability to provide comprehensive, data-driven evaluations that significantly influence decision-making across diverse fields.
- Gap: Despite some funding agencies employing software tools like Excel, Salesforce and Microsoft BI to display outcomes, these methods lack an intelligent element in analyzing

the results. The current manual or semi-automated processes may miss critical data patterns and deeper insights that advanced AI analysis could provide. This underutilization of AI's capabilities in outcome evaluation represents a significant missed opportunity. By integrating AI, funding agencies could vastly improve their understanding of project impacts, uncover nuanced insights, and enhance the efficiency and effectiveness of their evaluation processes. This gap suggests the need for a more sophisticated, AI-driven approach to analyze and understand the outcomes of funded projects comprehensively.

- Opportunity: Incorporating IRISAi and Decision Trees into the outcome evaluation process, including the assessment of progress reports, could significantly enhance how funding agencies gauge the success and impact of their supported projects. Progress reports, which applicants submit regularly, are a goldmine of information that, if analyzed effectively, can provide real-time insights into the trajectory and potential outcomes of ongoing projects.

Conclusion

The review of funding agencies' decision-making processes helps clarify the intricate interplay of traditional methods and the burgeoning potential of AI integration. The decision-making landscape is vast and varied, with each stage offering challenges and opportunities. The literature provides a beacon illuminating where the possibility exists for AI tools to be harnessed to enhance, streamline, and revolutionize these processes.

The theoretical and empirical exploration offers invaluable insights, but the real-world implications and practicalities of such integrations remain to be explored. The next chapter delves deeper by bringing to the forefront the voices of those at the heart of these processes: the decision-makers, the beneficiaries of these funds, and the computer scientists who bridge the gap between theory and application.

The chapter reviews their perspectives on the challenges inherent in the current system, their visions for an AI-integrated future, and the potential roadblocks they anticipate. This commentary lends force to our findings from the literature and provides a holistic view, ensuring that our exploration is grounded in the realities of the field.

Chapter 4: Designing an AI Framework for Enhanced Decision-Making in Funding Agencies

This chapter aims to bridge the gap between theoretical concepts and practical applications within the decision-making framework of funding agencies. It seeks to operationalize the insights garnered from previous discussions and introduce a pragmatic approach to integrating Artificial Intelligence (AI) into the funding allocation process. In Chapter 2, we explored the decision-making landscape within funding agencies, pinpointing several challenges that stymie their operations. Alongside this exploration, we conducted targeted interviews to complement the landscape analysis, providing a multifaceted view of the current situation and highlighting the necessity for more sophisticated decision-making tools. Chapter 3 extended this exploration into the realm of artificial intelligence (AI), comparing its applications across various sectors with the technological landscape within funding agencies. This comparison revealed a significant gap: the absence of AI tools tailored to the unique needs of these agencies despite the potential benefits suggested by existing solutions.

This chapter illustrates means to transform these theoretical opportunities into actionable strategies. We propose methods to enhance the decision-making process within funding agencies, illustrated through examples using simulated data owing to issues of real data access and privacy constraints.

The objective is to demonstrate how AI-driven approaches can refine decision-making in funding agencies and to highlight AI features that can mitigate the issues identified in earlier chapters. This provides a blueprint for integrating AI into the funding allocation process and illustrates how these technologies can effectuate tangible improvements in decision-making. Despite the promising potential of these AI-driven methodologies, it's crucial to acknowledge that the real-world applicability and effectiveness of these approaches must be empirically validated through rigorous experimentation with actual data. Moreover, involving domain experts in the validation process is essential to ensure that the AI models align with the nuanced realities of funding decisions and to interpret the findings accurately. This step of conducting real-world experiments and expert validation is beyond the scope of this dissertation.

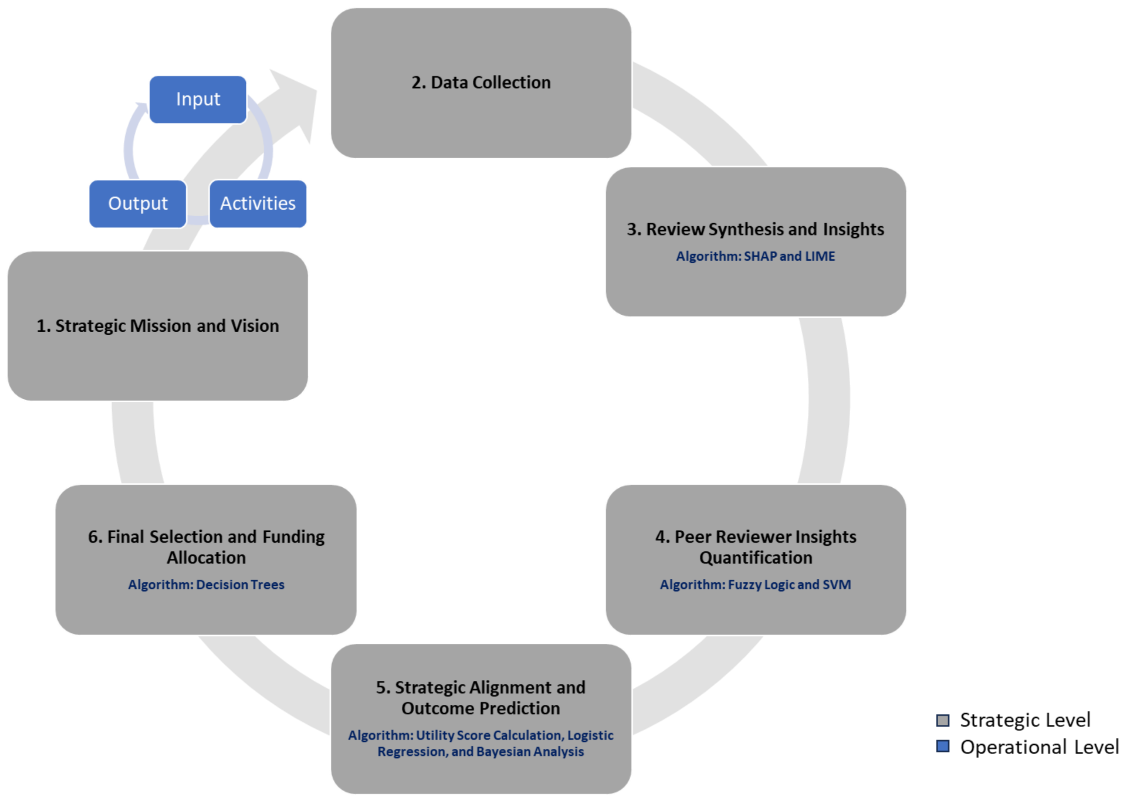
Integrating AI in Funding Agency Decision-Making

In the preceding chapters, we have laid the groundwork for understanding the decision-making processes within funding agencies. In this chapter, we synthesize our findings and present a coherent visual framework for AI-enhanced decision-making within funding agencies, as illustrated in Figure 4.1. This chapter is split into two parts, with the first focusing on integrating decision-making at a strategic level and the second offering operational solutions to address the challenges identified through stakeholder feedback. The visual framework depicted in Figure 4.1 is color-coded to differentiate between strategic and operational components of the decision-making process. The strategic elements are represented in a grey shade, signifying their foundational role in guiding the agency's direction. In contrast, the operational elements are illustrated in a blue shade, indicating their function in the execution of the strategy. Chapter 2 used the framework of Trunk, Birkel, and Hartmann (2020) and their language. It is pertinent now to provide more specific tailoring of language to reflect with greater fidelity the process conducted by research funding agencies. This is a deliberate effort to ensure that the terms used resonate more closely with the activities they represent and the strategic context within which they operate:

- 'Goal Definition' has been changed to 'Strategic Mission and Vision', signaling the foundational objectives of the agency.
- Data Collection will remain the same.
- 'Data Interpretation' has been refined to 'Review Synthesis and Insights', indicating a deeper analytical process.
- 'Alternative Definitions' has been updated to ‘Peer Reviewer Insights Quantification', emphasizing the analytical process of quantifying the decision-making factors that peer reviewers consider significant.
- 'Utilities and Probabilities' has become 'Strategic Alignment and Outcome Prediction', which emphasizes the importance of aligning proposals with strategic aims of the agency and predicting their success.
- Finally, 'Weighing and Deciding' has been rebranded as 'Final Selection and Funding Allocation', highlighting the decision-making outcome of this phase.

Figure 4.1 not only illustrates the workflow of decision-making but also emphasizes the dual nature of the process, combining the high-level strategic mission (in grey) with the detailed operational tasks (in blue). By clearly distinguishing these aspects, the framework ensures that each decision is made with both the broader agency goals and the granular details of each proposal in mind. The strategic layer of the framework delineates the agency's overarching mission, whereas the operational layer reflects the execution of this strategy by the program managers and peer reviewers through the evaluation of proposals. By combining these two layers in our framework, we want to ensure there is a harmonious alignment between strategic intent and operational execution.

Figure 4.1. The Suggested Decision-Making Process



The decision-making landscape within funding agencies is a dynamic interplay between strategic intent and operational execution, a theme vividly captured in Figure 4.1. This visual representation outlines the journey from the foundational "Strategic Mission and Vision" to the tangible outcomes of funding allocations, highlighting the pivotal role of program managers and peer reviewers as intermediaries who translate strategic goals into actionable insights.

The framework begins with the agency's "Strategic Mission and Vision," setting forth the high-level objectives and impacts envisioned for funding initiatives. This strategic foundation shapes the "Inputs" phase, where program managers craft Requests for Proposals (RFPs) that reflect the agency's ambitions. In the "Activities" stage, peer reviewers employ their specialized knowledge to guarantee that proposals demonstrate substantial quality and align with the agency's defined metrics. Their evaluation results in a selection of projects for funding that not only meet scholarly standards but also align with the agency's established guidelines.

Following this, the "Data Collection" phase involves the aggregation of proposals that have been evaluated by peer reviewers and identified as qualified and worthy of funding based on established criteria and guidelines. Balancing the detail-oriented analysis of peer reviewers with the agency's broad strategic aims can be complex. While reviewers may concentrate on the quality of proposals, wider objectives might be overshadowed. In this chapter’s first demonstration of how AI might help to bridge this gap at the "Review Synthesis and Insights" phase, we employ a Random Forest Classifier to create a predictive model reflective of the peer review process. The utilization of the Random Forest Classifier (RFC) serves as a strategic endeavor to gain a deeper understanding of the evaluative patterns inherent in peer reviewers' decisions. The necessity of this understanding stems from the ambition to seamlessly integrate AI into the evaluation process. By grasping the subtleties of how reviewers discern and decide upon the merits of each proposal, we can align AI systems to mirror these human expert judgments.

RFC is adept at uncovering the multifaceted criteria employed by reviewers because it aggregates multiple decision-making pathways, offering a holistic perspective on the decision-making criteria. This attribute makes it an ideal tool for approximating the complex assessment process of human experts. By simulating this process, the RFC provides an analytical framework that can predict outcomes based on historical data, giving us a replicable and scalable model of human evaluative behavior.

In pursuit of transparency within this AI-augmented decision-making framework, we employ SHAP and LIME, both powerful interpretability tools. SHAP clarifies which features carry the most weight in the model's predictions, thus indicating what peer reviewers might deem important in their assessments. On the other hand, LIME zooms in on individual predictions to unravel the model's reasoning in specific cases. Together, these tools offer a dual lens of interpretability, providing both a broad and detailed understanding of the decision-making process.

The integration of SHAP and LIME with the predictive model derived from RFC is a crucial step towards demystifying the peer reviewers' decision-making process. It enables us to identify and quantify the importance of different proposal features from the reviewers' perspectives. Such insights are invaluable as they guide us in refining the AI system to ensure that it not only replicates but also enhances the decision-making prowess of human experts, facilitating an AI-assisted review process that is coherent with the strategic mission and operational excellence of funding agencies.

In the "Peer Reviewer Insights Quantification" phase, we refine our analysis by transforming the qualitative assessments of peer reviewers, traditionally cast in binary terms of funding or not, into a structured and measurable format. Utilizing Fuzzy Logic, a mathematical approach that accommodates the complexity and ambiguity inherent in human judgment, we transform these nuanced assessments into numerical scores. Fuzzy Logic excels in representing the gray areas of decision-making, mirroring the way humans think about and rate various aspects of proposals, such as innovation or team expertise, on a spectrum rather than in binary terms. For instance, a proposal with a high innovation score is classified not merely as innovative but is placed within a spectrum, ranging from low to high innovation. Similarly, the expertise of a team is evaluated on a scale from novice to expert, acknowledging the varying levels of knowledge and experience. This method enables a more detailed and accurate representation of each proposal's strengths, facilitating a decision-making process that appreciates the complexity and depth of research endeavors.

The process begins by applying feature importance scores derived from our earlier analysis. These scores illuminate what aspects of proposals are deemed most critical by reviewers. We then employ these scores as the foundation for creating fuzzy rules. These rules articulate how each feature's importance translates into specific numerical values, effectively scoring each proposal on the attributes that matter most to the evaluation process.

Following the quantification through Fuzzy Logic, we introduce Support Vector Machines (SVM) into our methodology. SVM is a type of machine learning algorithm that classifies data by finding the optimal boundary between different outcomes. In this context, SVM uses the numerical scores generated by our fuzzy rules to categorize proposals into likely success or failure outcomes based on historical decision patterns.

This integration of Fuzzy Logic and SVM moves us beyond mere binary classifications to a model that quantifies the nuanced, multifaceted aspects of peer reviewer decisions. It leverages the subtle evaluations of peer reviewers, converting complex judgments on innovation, risk, and alignment into numerical scores through Fuzzy Logic. This method enriches the evaluation process, allowing us to mirror the complexity of human judgment within an AI framework. It aims to augment, not replace, the human evaluative process, ensuring that our AI-driven assessments accurately embody the priorities and discernment of peer reviewers.

Advancing to "Strategic Alignment and Outcome Prediction," this stage is where the agency's leadership evaluates the equilibrium between its strategic vision and mission against the outcomes of the operational cycle. It involves scrutinizing whether the proposals selected for funding accurately embody the agency's priorities. A utility function here plays a critical role, as it assigns weights to proposal attributes, reflecting their importance from the agency's perspective. This mechanism ensures the AI system not only prioritizes projects based on their inherent quality but also aligns them with the agency's strategic goals.

To quantify this alignment and predict the potential success of each proposal, logistic regression and Bayesian analysis are employed. These methods assess proposals for both their likelihood of achieving desired outcomes and their fit with strategic priorities, thus bridging the gap between the agency's long-term objectives and the immediate outputs of the operational cycle. Through this process, the leadership could verify if the projects recommended for funding align with and represent the agency's strategic interests, ensuring that decision-making is both forward-looking and rooted in the agency's foundational aims.

Our exploration has elucidated a sophisticated framework that intertwines the strategic vision with operational execution within funding agencies. This dual-layered approach illustrates how the agency's leadership and operational teams, comprising program managers and peer reviewers, meticulously translate strategic objectives into actionable evaluation criteria for research proposals. By embedding AI solutions into this process, we ensure a seamless alignment that not only adheres to the agency's overarching goals but also enhances the granularity and fairness of operational assessments.

This integration of AI, through tools like Random Forest Classifiers, SHAP, LIME, and utility functions, equips the agency with the means to distill complex, qualitative judgments into quantifiable insights. This process bolsters the operational layer's ability to reflect the strategic layer's intentions accurately, ensuring that funding decisions are both rooted in expert academic evaluations and aligned with the agency's metrics of success. Such a harmonized approach promises to usher in an era of heightened strategic foresight and operational efficiency in public funding, setting a new benchmark for the judicious allocation of resources in fostering impactful research.

In the forthcoming section, we will delve into the specifics of the algorithms recommended for each step of this integrated process and outline our strategy for their deployment. While we utilize simulated data to illustrate our points, our aim is to showcase the vast potential and capabilities of these AI-enhanced solutions, paving the way for future real-world applications and experiments within the realm of public funding agencies.

Operationalizing AI: Unveiling Peer Review Decisions and Enhancing Decision-Making Processes

As we embark on a detailed exploration of AI's role in enhancing the decision-making processes of funding agencies, it is crucial to emphasize the exploratory and illustrative nature of this exercise. Our inquiry begins with a focus on the evaluative methods employed by peer reviewers, a critical component in the funding cycle. Drawing upon insights from literature and the application of algorithms across various sectors, we aim to shed light on how reviewers assess proposals and identify key decision-making factors. Building on our understanding of peer reviewer evaluation methods, the subsequent phase of our exploration turns to the strategic priorities of funding agencies. This step is critical in determining whether there is a synergy between what peer reviewers value in proposals and the overarching objectives set by the agency's leadership. Our goal is to propose tools that could help ascertain whether the selections made by reviewers not only merit the proposals on their own but also align with the strategic objectives at the heart of the agency's mission.

However, it is important to acknowledge that the forthcoming analysis is built on simulated data and does not involve the direct input of peer reviewers, experts, or stakeholders. The absence of these essential perspectives and the use of dummy data mean our findings are suggestive rather than definitive. A full-scale, real-world experiment, harnessing actual review data and involving the active participation of the research community, would be necessary to confirm the validity and effectiveness of the AI methods proposed.

Despite these constraints, this initial exploration serves as a foundational step towards constructing a comprehensive framework for the potential integration and testing of AI in the decision-making process. The objectives are multifaceted: to probe the reproducibility of peer evaluations, an issue of considerable debate in scholarly circles; to attempt to replicate their scoring models; and to demystify the 'black box' of review by understanding how various features are weighted in their assessments.

In this implementation section, we will delineate our approach in the following order:

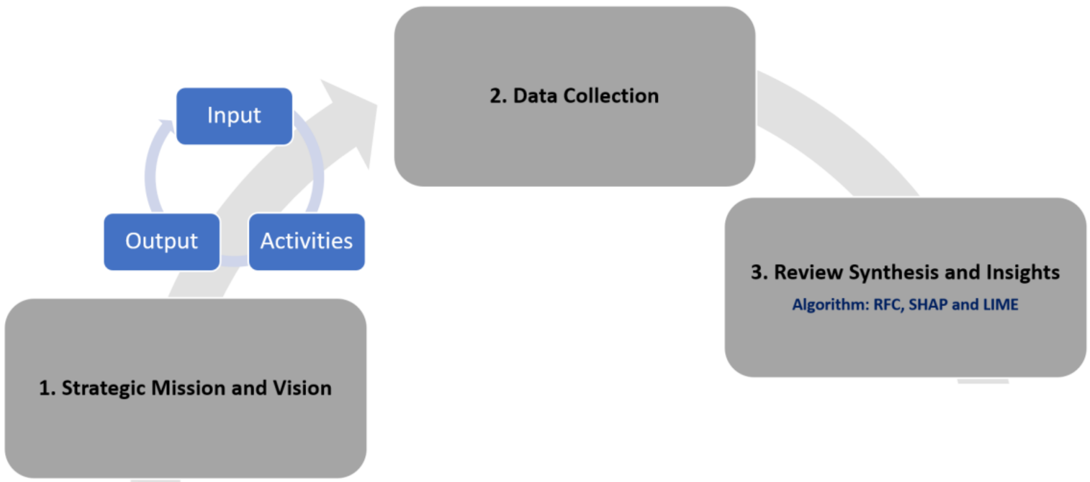
- Defining each stage of the process and situating it within our broader framework.
- Elucidating the methodologies selected for each phase, explaining why these algorithms are suited to our aims.
- Providing coding examples that demonstrate the capabilities of the suggested algorithms, offering a glimpse into their practical applications. These will be included in the appendix (Code Sample).
- Discussing the potential outcomes and implications of these methods, with a keen eye on how they could be adopted by funding agencies to refine and possibly automate elements of the peer review process.

Through this structured examination, we not only aim to gain a deeper understanding of the decision-making criteria of peer reviewers but also explore how AI might contribute to a more transparent, reproducible, and efficient allocation of funding.

Data Analysis and Review Synthesis and Insights stages

Embarking on a detailed exploration of the 'Data Analysis and Review Synthesis and Insights within the decision-making ecosystem of funding agencies, this section delves into the multifaceted process of project selection. As we commence the practical exploration of AI's role within the funding agency's decision-making structure, our starting point assumes the receipt of a shortlist of proposals that have been diligently vetted by program managers and peer reviewers. This vetted list, already filtered through the operational cycle of initial assessments, serves as the foundation for our subsequent AI analysis. Our current discussion is centered on leveraging AI to deepen the analysis post the peer reviewers' detailed selection of proposals, rather than detailing operational aspects such as the assignment of proposals to reviewers. This delineation ensures we concentrate on the strategic decision-making flow, highlighting how AI can amplify the insights drawn from the selection process. Later in this chapter, we will circle back to the integration of AI in the operational activities, discussing how AI could be woven into earlier stages of the proposal vetting process. In this segment of our exploration, we focus on harnessing AI to enhance the insight extraction phase following the meticulous selection of proposals by peer reviewers. We are poised to dissect and understand the data that embodies the reviewers' discernment, wherein lies the alignment or at times, the divergence with the agency's aspirations outlined in their Request for Proposals (RFPs).

Figure 4.2. Data Collection &Review Synthesis



In the 'Review Synthesis and Insights' phase, we endeavor to transform the traditionally opaque review process into a system that is both understandable and transparent. Acknowledging the complexity and depth of peer reviewers' decision-making processes, we propose the Random Forest Classifier (RFC) as an initial model to tackle this challenge. This approach is supported by literature, as explored in Chapter 3, which highlights the RFC's effectiveness in the data interpretation phase of the decision-making process. Despite the intricate nature of these decisions, the RFC stands out for its proficiency in analyzing the multi-dimensional data, making it an ideal starting point.

The RFC acts as a surrogate for the collective insight of peer reviewers, leveraging historical review data to forecast outcomes with a binary decision, fund or not fund, akin to the conclusions drawn by human reviewers. This model's choice is underpinned by several key strengths:

- Pattern Recognition: It adeptly identifies patterns within the data that resonate with the complex, nuanced decision-making process of peer reviewers, providing a binary output that aligns with the initial review outcomes.
- Ensemble Approach: The RFC employs an ensemble method, combining insights from numerous decision trees. This approach effectively mitigates overfitting and boosts the model's applicability, closely mirroring the multifaceted evaluations performed by human reviewers.
- Versatility in Data Handling: It excels in processing both categorical and continuous variables, ensuring a thorough analysis of the diverse datasets found in proposal submissions. This versatility is crucial in accommodating the wide range of data types encountered in research proposals.

- Generalizability: The aggregation of decisions from various trees enhances the model's generalizability, making it superior to other algorithms in navigating the complex datasets associated with proposal evaluations.

To understand which features most significantly influence our model's predictions and to better mimic the decision-making process of peer reviewers, we incorporate SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) into our analytical framework. These tools provide insights into the importance and impact of various proposal features within the model, offering a clearer view of how closely our model's considerations align with those of human reviewers. These tools are instrumental in illuminating the essence of peer review evaluations, offering insights into the critical features that influence these decisions. SHAP, leveraging game theory, breaks down the model's predictions to assess the impact of each feature in various combinations, providing a macro-level view of feature importance and revealing the priorities underlying peer reviewers' decisions. Conversely, LIME simplifies the RFC's complex decision-making by observing how minor alterations in input affect predictions. By constructing a simpler, interpretable model around specific predictions, LIME enables a focused examination of the factors crucial for individual cases, offering micro-level insights into each prediction made by the RFC.

This comprehensive approach aims not just to understand the evaluative acumen of human experts but also to investigate any potential misalignment with the strategic goals of the organization, a topic that will be delved into further in the Strategic Alignment and Outcome Prediction stage. By integrating the Random Forest Classifier with interpretability tools such as SHAP and LIME, our goal is to make the peer review process more transparent. We seek to comprehensively understand the factors that influence funding decisions, thereby enhancing the objectivity and transparency of these decisions. This endeavor will allow us to assess the alignment of peer reviewer decisions with the agency's broader mission and objectives, paving the way for a more informed and strategic application of AI in the funding decision-making process.

Methodological Approach

Advancing to the Practical Implementation: This segment transitions our theoretical exploration into a tangible demonstration, illustrating the deployment of the algorithms discussed. Detailed within the appendix (Code Sample), the provided code exemplifies how machine learning, particularly through designated steps, can simulate the evaluative mechanisms of funding agencies.

- Generate Simulated Data: In this phase, we construct a synthetic dataset representing the scores of the various features by the peer reviewers of 500 project proposals. This number was chosen as a middle ground to accommodate the range of project volumes handled by both large and small funding agencies. The dataset includes attributes such as Return on Investment (ROI), risk level, and others, mirroring the evaluative criteria prevalent across numerous funding agencies. These attributes are intended to simulate the scores typically assigned by peer reviewers, focusing on the abstract qualities prioritized in funding decisions and capturing the variability and complexity of real-world scenarios. The distribution of 'Not Fund' decisions in our simulation reflects the commonality of such outcomes in actual funding processes, ensuring an accurate representation of the decision-making landscape. The attributes are randomly assigned to ensure a broad representation, which aids in a comprehensive analysis of potential reviewer preferences. The flexibility in attribute selection allows for updates to align with specific metrics of different agencies, ensuring the simulated data remains relevant and aligned with agency priorities. The 'Binary_Decision' column in our data frame results from a rule-based logic simulating the scoring by operational teams (program managers and peer reviewers). Proposals are labeled as 'Fund' if they show strong innovation and ROI (scores above 0.5), with manageable risk levels (score below 0.5). All other proposals are tagged as 'Not Fund'. This simplification in the decision-making model is deliberate, aimed at facilitating subsequent application to various predictive models without complicating the analysis. In this initial study phase, a sensitivity test was not conducted to maintain focus on creating a foundational dataset that realistically reflects the nuanced decision-making process in funding evaluations, within the simulated environment we have constructed.

- Model Training and Prediction: The Random Forest Classifier is trained on this dataset. Its task is to identify the patterns and factors that traditionally influence the success or rejection of proposals. The RFC operates on the principle encapsulated by the equation:

$$RF(x) = \frac{1}{N}\sum_{i=1}^{N} T_i(x)\ ,$$

where x represents the features of a proposal, N is the number of trees in the forest, and Ti (x) is the prediction of the i-th decision tree. This ensemble method aggregates the decisions from multiple decision trees, each trained on a random subset of the data, to make a final decision on whether a proposal should be funded. Specifically, for the binary decision of fund or not fund, the RFC uses a majority voting system to determine the outcome, described by the equation:

$$\text{Class}(x) = \text{mode}\{T_1(x), T_2(x), \ldots, T_N(x)\}$$

, where mode signifies the most common prediction across all trees. The binary decision output of the RFC aligns with the operational need of the funding agency to categorize proposals into 'Fund' or 'Not Fund' categories. This methodological approach ensures that the model's predictions reflect the nuanced and multi-faceted evaluation process of human reviewers, aiming to support the executive team in making informed and strategic funding decisions.
- Model Evaluation: The model's performance is assessed using a separate dataset to gauge its predictive accuracy. This evaluation is critical for gauging the potential real-world applicability of our AI model. It is essential to note that the output of the model is intended to simulate the peer reviewers' decisions, serving as a proxy for their evaluative processes. Recognizing the importance of this alignment, further efforts are necessary to

refine and enhance the model's accuracy, ensuring it effectively mirrors the nuanced decision-making of peer reviewers.

- Interpreting the Model's Decisions: To decode the model's decision-making process, we turn to SHAP and LIME. SHAP quantifies the contribution of each feature to the prediction, following the equation:

$$\mathrm{SHAP}(x) = \phi_0 + \sum_{i=1}^{n} \phi_i(x_i)$$

  , where ϕ_0 is the base value or average prediction of the model, x_i represents the value of feature i, and $\phi_i(x_i)$ is the SHAP value for feature i, indicating its impact on the model's output. This formula helps in understanding the overarching importance of features across all proposals.

  On the other hand, LIME provides local explanations, approximating the model behavior around a specific instance. The LIME explanation for a prediction is given by:

$$\mathrm{LIME}(x) = \xi + \sum_{i=1}^{n} \beta_i z_i$$

  , where ξ represents the local intercept, β_i are the weights for the locally linear model, and z_i are the perturbed sample features. LIME's approach clarifies the reasoning behind the model's prediction for each proposal by fitting a simple model locally around the prediction.
- Visualization of Interpretations: To facilitate a clearer understanding, we graphically represent the insights provided by SHAP and LIME, making it straightforward to identify which features wield the most influence on the decision-making process.

Understanding the Model's output

Implementing the Random Forest classifier, we anticipate the initial low accuracy due to the randomness of our data, a common challenge in the preliminary stages of model development. To enhance the model's performance in a real-life setting, an approach involving iterative training with real, structured data and fine-tuning of the model parameters would be essential.

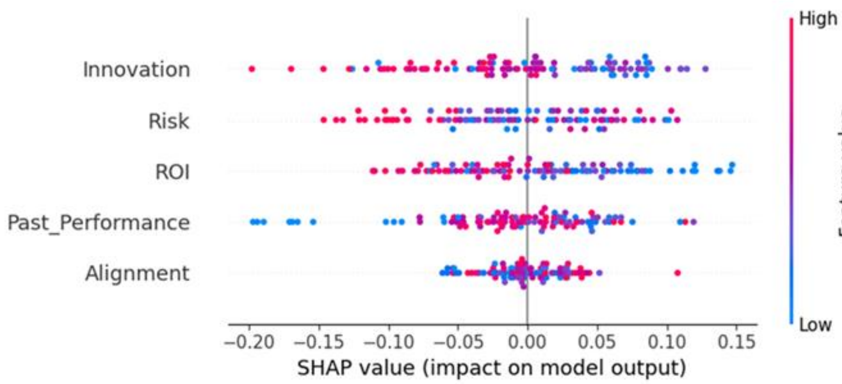
In our analysis, the SHAP summary plot, figure 4.3, serves as a critical tool, providing a visual representation of how different features like Innovation, Risk, ROI, Past Performance, and Alignment influence our Random Forest model predictions. Before delving into the influence of each feature, let's clarify what we're seeing in the plot:

The SHAP summary plot has two axes:

- The x-axis represents the SHAP value, which indicates the impact of each feature on the model's output. A SHAP value can be positive or negative; a positive value increases the likelihood of a proposal being successful according to the model's prediction, while a negative value decreases it.
- The y-axis lists the features being analyzed. Each dot on the plot represents the SHAP value for a feature for an individual prediction. This means each proposal in our dataset contributes one dot per feature to the plot.

- The color scale represents the value of the feature, from low to high, across the dataset. For example, blue dots represent lower feature values, while red dots represent higher feature values.

Figure 4.3. SHAP Value Impact Analysis on Predictive Model Features



   – Innovation: The plot shows a mix of positive and negative SHAP values for Innovation, implying that in some cases, innovation greatly increases the chances of a proposal being successful, while in others, it may not be as critical.
   – Risk: The Risk feature predominantly shows negative SHAP values, suggesting that higher perceived risks within a proposal tend to decrease its chance of success.
   – ROI (Return on Investment): This feature has a spread of SHAP values but is generally positive, indicating that proposals with a higher ROI are often seen as more likely to succeed.
   – Past Performance: The SHAP values for Past Performance are generally positive but less pronounced, which means it's a factor in success but possibly one among many the model considers.
   – Alignment: The SHAP values for Alignment are clustered around zero, indicating that this feature does not have a strong impact on the model's prediction of success, which could suggest that the model does not perceive it as a significant factor or that it may not have been well-represented in the training data.

Through these insights, funding agencies can strategically adjust their evaluation criteria to prioritize features that correlate with successful outcomes. For instance, if strategic alignment is crucial, it could be emphasized in the utility function used later in this chapter in the evaluation process, ensuring that proposals which align with the agency's strategic goals are given precedence.

The findings from this exercise, although based on simulated data, demonstrate the capacity of SHAP visualizations to guide funding agencies in making more informed, data-driven decisions. To refine these insights for real-world application, validation with actual data and ongoing model improvement will be necessary. These steps will bolster the model's predictive power, making it a more reliable tool for decision support.

This deep dive into feature impact sets the stage for the subsequent phase of defining proposal alternatives and refining the evaluation process. Upcoming steps will incorporate the nuanced insights from SHAP and LIME into a more sophisticated, AI-powered evaluation framework, using fuzzy logic to transform qualitative assessments into quantitative data and SVM for predictive classification.

Why Should Policymakers Care?

The "Data Analysis and Review Synthesis and Insights" stage is pivotal in understanding how AI can significantly impact the decision-making processes within funding agencies. By integrating AI tools like the Random Forest Classifier (RFC), along with interpretability mechanisms such as SHAP and LIME, the traditionally opaque review process can be transformed into one that is transparent and understandable.

- Enhanced Decision-Making Transparency: This phase's importance lies in its ability to unravel peer reviewers' often complex and subjective decision-making process. By employing AI, agencies can achieve a level of transparency and consistency in funding decisions that is hard to attain through human review alone. This transparency is crucial for policymakers as it provides a foundation for trust and accountability in allocating public or organizational funds.
- Data-Driven Insights: Advanced analytical tools like RFC allow for a deeper dive into the multidimensional data of project proposals, offering a more nuanced understanding of patterns and trends that may not be immediately apparent to human reviewers. For policymakers, this means decisions can be based on a comprehensive analysis of data, leading to more informed and strategic choices.
- Objective Evaluation of Proposals: By mirroring the decision-making process of peer reviewers and using AI to predict funding outcomes, the process becomes less subjective. The AI model's ability to process and analyze vast amounts of data objectively can help identify the most promising proposals that align with the strategic goals of the funding agency.
- Alignment with Strategic Goals: The application of interpretability tools like SHAP and LIME aids in scrutinizing the decision-making process at both macro and micro levels. This scrutiny ensures that the funding decisions are not only based on the merits of the proposals but are also in sync with the broader strategic objectives of the agency. For policymakers, this alignment is critical as it ensures that the funding process contributes to the overarching goals and missions of the organization.

Mitigating Risks: The Crucial Role of Human Oversight in AI-Driven Funding Decisions

During the "Data Analysis and Review Synthesis and Insights" phase of integrating algorithms into the funding agencies' decision-making process, the potential for AI systems to produce misleading outcomes cannot be overlooked. These pitfalls stem from various inherent limitations and challenges associated with AI methodologies.

Bias in data is a critical concern, and algorithms may perpetuate and amplify biases present in the training dataset. If this data reflects past prejudices or non-inclusive practices, AI systems might unfairly favor certain types of projects or applicants, leading to decisions that reinforce inequality and misguide decision-makers. Similarly, AI's tendency to prioritize quantitative metrics can result in the underrepresentation of qualitative aspects like innovation potential or social impact, which, although harder to quantify, are vital for comprehensive decision-making.

The complexity of AI models, such as the Random Forest Classifier, poses risks of misinterpretation. Without a deep understanding of the model's logic, policymakers and reviewers might place unwarranted trust in its recommendations. Furthermore, the risk of overfitting, where the model is too finely tuned to historical data, can result in poor performance on new, unseen proposals, potentially excluding innovative projects that diverge from past trends.

Transparency and explainability issues also loom large; while interpretability tools like SHAP and LIME endeavor to demystify AI decisions, they may not fully elucidate the rationale behind every decision. This opacity can breed skepticism, especially when AI conclusions are counterintuitive or conflict with expert assessments. Moreover, AI models may fail to adapt to the evolving priorities and contexts of funding agencies, offering recommendations that are out of sync with current strategic objectives.

Technical dependencies compound these challenges, as deploying AI solutions necessitates reliable infrastructure. Technical malfunctions, data breaches, or other systemic failures can distort the analytical process, leading to flawed decision-making.

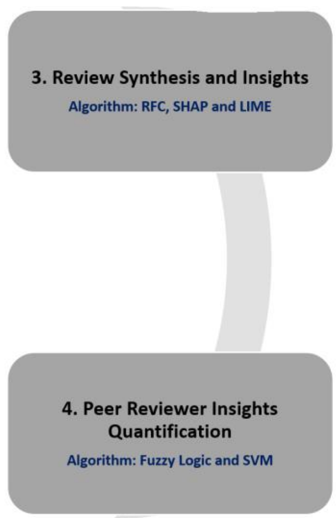
Given these challenges, it is imperative to maintain human oversight throughout the AI integration process. Humans must remain in the loop to evaluate and refine AI outputs and ensure that these technologies learn from and adapt to the nuanced domain of funding decisions. Human expertise can guide AI to better align with the strategic imperatives and ethical standards expected in public funding environments.

The discussion will advance AI's analytical capacity in the subsequent section by integrating a fuzzy score system. This system aims to decipher the nuanced decisions of peer reviewers, broadening the spectrum of analysis to capture a more refined understanding of the factors driving funding decisions. This approach underscores the ongoing interaction between human intelligence and AI, fostering a dynamic learning environment where both entities evolve to improve the efficacy and integrity of funding agency decision-making processes.

Peer Reviewer Insights Quantification

Building on the foundational insights from the SHAP and LIME analysis, which decode the importance of various proposal features from a reviewer's perspective, we now progress to a more nuanced interpretation of these features through the lens of Fuzzy Logic. The question we aim to answer in this stage can be summarized as follows: How can we transcend the binary 'yes' or 'no' decisions of peer reviewers and adopt a nuanced numerical system that more accurately reflects the subtleties of their evaluations?

Figure 4.4. Peer Reviewer Insights Quantification



Fuzzy Logic offers a sophisticated approach to interpret the nuanced judgments of peer reviewers, who often provide binary recommendations like 'fund' or 'not fund,' accompanied by scores across various features. Instead of merely accepting these binary outcomes, Fuzzy Logic provides a way to understand the degree of certainty or hesitancy behind each decision.

For example, when a reviewer recommends funding a proposal, Fuzzy Logic allows us to ascertain whether this decision was made with high confidence or if it was a borderline case. This is achieved by examining the underlying scores for features like innovation, risk, and alignment with strategic goals. Fuzzy Logic takes these scores and applies a set of rules that reflect the ambiguity and complexity of human judgment. In the context of Fuzzy Logic, the SHAP values from the previous stage can guide us in constructing the rules that determine how each feature influences the final decision. For example, if the mean absolute SHAP value for innovation is high, it suggests that the innovation score of a proposal is a strong influencer in the peer reviewers' funding decisions. We could then create a Fuzzy Logic rule that assigns a higher membership value for funding when the innovation score is high.

In simpler terms, if innovation often makes a big difference in whether proposals get funded or not (according to SHAP), we use this information to tell our Fuzzy Logic system, "Pay more attention to innovation scores." This helps our system to mimic the complexity of human decisions by incorporating the varying degrees of importance that reviewers place on different aspects of a proposal.

The output of a Fuzzy Logic system is a fuzzy score that indicates the degree to which a proposal meets the criteria for being funded, which is more informative than a simple 'yes' or 'no.' Fuzzy Logic interprets the subtleties in peer review scores by utilizing membership functions to articulate the extent to which a proposal embodies characteristics like innovation or risk. These functions offer a more granular look at the proposal qualities, assigning a continuous spectrum of values that range from complete non-membership to full membership in a given category. For instance, a proposal could be considered 'moderately innovative' by the reviewer with a membership value suggesting it's not entirely outside the realm of innovation, yet not the pinnacle of it, either. This allows for a refined understanding of a peer reviewer's confidence level in their recommendation, adding depth to the decision-making process in funding agencies.

This gradation is valuable in scenarios where there are more proposals worth funding than there are available resources. It enables funding agencies to prioritize proposals that are not only recommended for funding but also rank higher in terms of the reviewers' confidence levels, as interpreted by the fuzzy scores.

Leveraging the capabilities of the Support Vector Machine (SVM) model, we aim to add depth to our analysis of funding proposals. By applying SVM to scores derived from Fuzzy Logic, we categorize each proposal more precisely based on its likelihood of being funded. This approach enhances our ability to interpret the complex evaluations of peer reviewers, transitioning from simple binary decisions to a nuanced understanding that reflects the full spectrum of their assessments.

The SVM model serves as a critical tool in this phase, enabling us to sift through the fuzzy scores and classify proposals into categories that more accurately depict their funding potential. This classification not only identifies which proposals are likely to succeed but also provides insights into the varying levels of confidence behind each funding recommendation.

This strategic application of SVM, rooted in the nuanced evaluations provided by Fuzzy Logic, allows us to mimic the intricate decision-making process of peer reviewers with greater fidelity. It bridges the gap between the qualitative judgments of reviewers and a structured, quantifiable framework for proposal evaluation.

Through this process, we are not just replicating the peer reviewers' evaluations but enhancing them with a layer of precision and depth that was previously unattainable.

Methodological Approach

- Rule-Based Scoring from Insights: The journey begins with transforming the analytical insights from SHAP and LIME into actionable criteria within a fuzzy logic framework. Instead of merely observing feature impacts, we embed this knowledge into fuzzy rules that mimic the complexity of peer reviewer evaluations. For instance, the SHAP analysis's revelations about features like innovation or risk inform how we structure our fuzzy logic rules, allowing for a nuanced assessment of proposals.
- Creation and Role of Membership Functions: In our fuzzy logic system, the membership functions are pivotal in converting quantitative data into qualitative evaluations. We

utilize the automf(3) function, which automatically generates three membership levels (low, medium, high) for each input feature. A triangular membership function, one of the most common types, is defined mathematically for a feature x, as follows:

$$\mu_A(x) = \begin{cases} 0, & \text{if } x \leq a \text{ or } x \geq c \\ \dfrac{x-a}{b-a}, & \text{if } a < x \leq b \\ \dfrac{c-x}{c-b}, & \text{if } b < x < c \\ 0, & \text{if } x \geq c \end{cases}$$

where a, b and c are the parameters defining the 'feet' and 'peak' of the triangle, thus shaping the fuzzy set. In the context of our application, these functions provide a flexible and nuanced way to categorize proposal features into qualitative assessments, essential for the subsequent rule-based evaluation.

- Quantification of Peer Reviewer Judgments: Leveraging fuzzy logic, we transition from binary (fund or not fund) to nuanced scoring, capturing the subtleties in peer reviewer judgments. The membership function equations play a critical role here; they quantitatively define how each proposal's features align with different evaluative criteria, such as 'low', 'medium', or 'high' levels of innovation or risk. This alignment is then processed through the fuzzy rules to compute the fuzzy score, effectively quantifying the complex decision-making criteria of funding agencies into a single, interpretable score. Thus, the fuzzy score emerges as a synthesized representation, encapsulating the multifaceted appeal of each proposal and enabling a more nuanced and scalable evaluation system that reflects the varying degrees of recommendation strength inherent in peer reviewer judgments. This is represented by the fuzzy logic equation:

$$\text{Score} = \text{Fuzzy System}(I, R, O, P)$$

, where I, R, O, P are the inputs for Innovation, Risk, ROI, and Past Performance, respectively. The output, Score provides a gradated valuation of proposals, enriching the decision-making process with degrees of recommendation strength.

- Dataset Enrichment with Fuzzy Scores: The integration of fuzzy scores into our dataset can be visualized as adding a new column S, where each row i in the dataset gets a score S_i based on our fuzzy logic system. This enriches the dataset by providing a comprehensive view of each proposal's value, represented as:

$$S_i = \text{Fuzzy System}(I_i, R_i, O_i, P_i)$$

- SVM for Nuanced Classification: Armed with a dataset enriched by fuzzy logic-derived scores, we employ the Support Vector Machine (SVM) model. This step is not just about filtering proposals but about applying a sophisticated classification layer that respects the fuzzy scores' granularity, enabling us to discern and prioritize proposals with higher precision. The SVM function is denoted as:

$$f(x) = \text{SVM}(X, S)$$

where X represents the features, and S the fuzzy scores.

- Validation and Testing: The SVM model is then tested against a fresh set of proposals, constituting 20% of the dataset, to verify its predictive prowess. This evaluation phase, with a test size of 0.2, is vital for ensuring the model's effectiveness in real-world scenarios. It gauges the model's ability to accurately forecast the potential success of new proposals, providing a robust measure of its predictive accuracy and reliability.
- Assessment of Model Accuracy: Finally, we measure the success of our SVM model through its accuracy in prediction. An elevated accuracy rate would underscore the robustness of our integrated AI approach, affirming its value as a reliable enhancement to traditional proposal review processes. We assess the SVM model's success via accuracy, recall, and precision:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

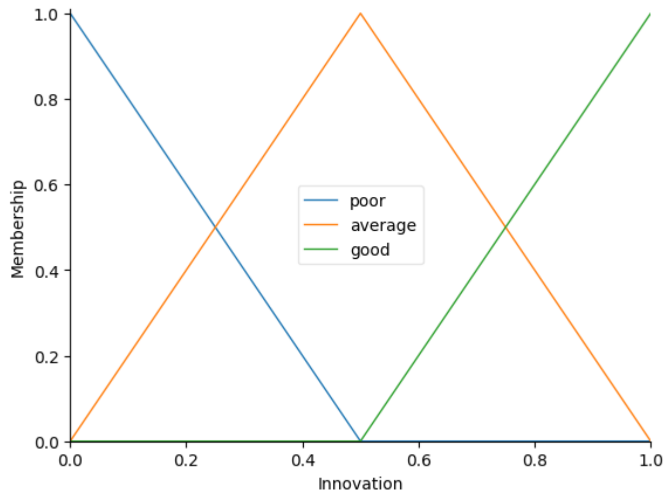
where *TP* (True Positives) are the cases correctly identified as positive, *TN* (True Negatives) are the cases correctly identified as negative, *FP* (False Positives) are the cases incorrectly identified as positive, and *FN* (False Negatives) are the cases incorrectly identified as negative. These metrics illuminate the model's performance, with accuracy indicating overall correctness, recall showing the ability to identify positive cases, and precision reflecting the accuracy of positive predictions. High precision with lower recall might indicate a bias towards being too conservative in predicting positives, while higher recall with lower precision might suggest a bias towards over-predicting positives.

Understanding the Model's Output

Building upon the nuanced insights SHAP and LIME analyses provide, we enter the "Peer Reviewer Insights Quantification" phase. Here, we transition from the binary decisions of peer reviewers embodied in straightforward 'fund' or 'not fund' determinations to a richer, more detailed evaluation framework powered by Fuzzy Logic and Support Vector Machines (SVM) discriminating capabilities.

The analysis framework we have implemented sheds light on the multifaceted nature of the peer review process, combining the precision of Fuzzy Logic with the predictive power of SVM to provide a more nuanced view of proposal evaluations. Our visual and quantitative analyses, ranging from histograms of Fuzzy Scores to detailed correlations with SVM predictions, aim to demystify the complex decision-making landscape. The subsequent visualizations and tables are not merely outputs but narratives that unfold the layered dimensions of evaluation, informed by advanced analytics.

Figure 4.5. Membership Function Visualization for Categorizing Levels of Innovation in Fuzzy Logic



Membership Function for Innovation

Figure 4.5 illustrates the fuzzy logic membership functions for evaluating innovation within proposals. Here's an expanded description emphasizing the added value over binary evaluation:

X-Axis (Innovation Score): This represents a continuous scale from 0 to 1, where 0 indicates no innovation and 1 signifies the highest level of innovation. Unlike a binary system that would classify proposals as innovative or not, this scale acknowledges varying degrees of innovation.

Y-Axis (Degree of Membership): Shows how strongly a proposal is considered to belong to each innovation category. A score closer to 1 on this axis indicates stronger membership in a given category.

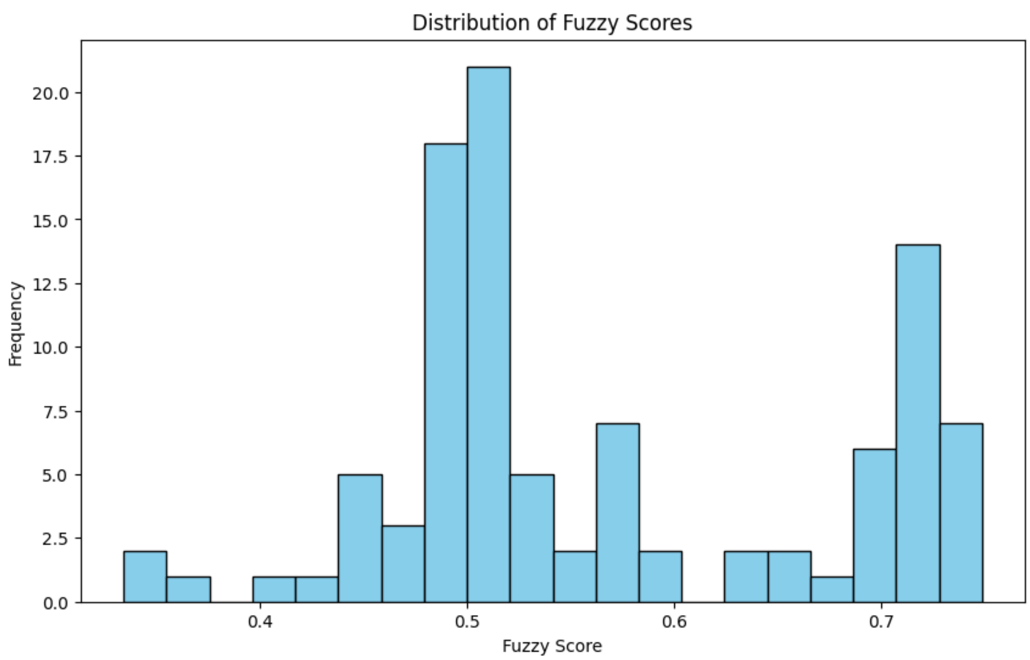
Lines (Membership Functions): The blue line marks the boundary for "poor" innovation. Proposals scoring near 0 on innovation would have a high membership value here. The orange line indicates "average" innovation. Proposals that score around the middle range on the innovation scale would be most strongly associated with this category. The green line represents "good" innovation. Higher innovation scores, approaching 1, would result in a high membership value for this category.

Each proposal's innovation score can be partially mapped onto more than one category, showcasing the flexibility and richness of fuzzy logic compared to a binary system. For example, a proposal with an innovation score of 0.5 could be considered somewhat innovative but not fully, which a binary system would fail to capture. This nuanced analysis enriches the decision-making process by acknowledging the spectrum of innovation inherent in proposals, allowing funding decisions to be more reflective of each proposal's actual characteristics rather than a simplistic yes or no. It opens up a more detailed dialogue about the proposal's merits, potentially identifying promising research that may not be classified as innovative in a binary sense but still holds considerable value.

Distribution of Fuzzy Scores

The histogram displays the frequency of different fuzzy scores across all proposals. It provides a visual understanding of where most proposals stand according to the fuzzy logic system, showing the spread of potential for funding based on the nuanced analysis. The graph highlights that many proposals may not fit neatly into 'Fund' or 'Not Fund' categories but fall somewhere in between. This aligns with the nuanced decision-making of peer reviewers, who may consider multiple factors and degrees of quality when evaluating proposals. The fuzzy scores represent this complexity by assigning a continuous score rather than a simple yes or no.

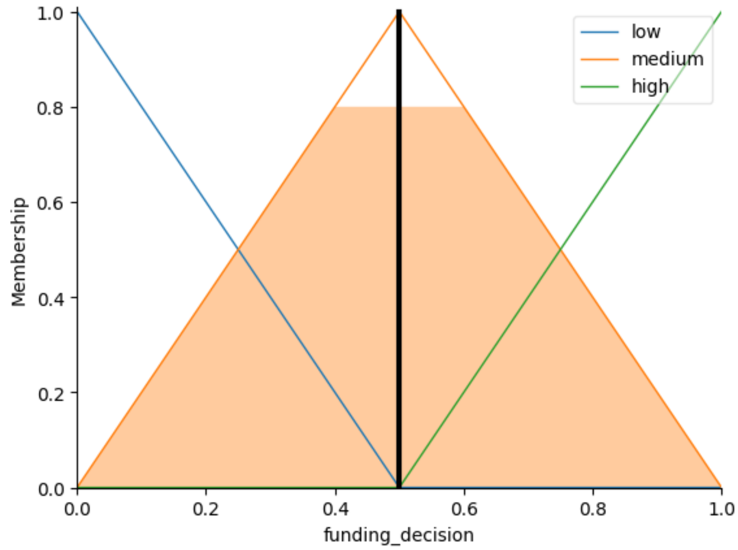
Figure 4.6. Analyzing the Spread of Proposal Evaluations: A Histogram of Fuzzy Logic Scores



Fuzzy Score for a Single Proposal

Figure 4.7, with a triangle in the middle illustrates the membership functions for a single proposal's fuzzy score, indicating how the model categorizes it within the low, medium, and high funding likelihood ranges. This specific proposal falls squarely in the 'medium' range, suggesting an average likelihood of receiving funding, based on the fuzzy logic assessment.

Figure 4.7. Using Fuzzy Logic and Member Function for Funding Decision



In the process of decision-making for funding proposals, certain thresholds and conditions are set to guide the allocation of resources effectively. These parameters, which play a crucial role in determining funding recommendations, are established in consultation with stakeholders to ensure they align with the organization's strategic objectives and the collective expertise of peer reviewers. For demonstration purposes, we have assigned the following provisional values to the fuzzy logic-based scoring system:

- Proposals with a fuzzy score of 0.7 or higher are flagged for strong funding recommendation, indicating a high level of confidence in their potential.
- Proposals that achieve fuzzy scores between 0.5 and 0.7 are recommended for funding, suggesting they meet several key criteria for success.
- Proposals with fuzzy scores ranging from 0.4 to just under 0.5 are considered for funding, marking them as having potential but perhaps requiring further scrutiny or additional information.
- Proposals scoring below 0.4 are not recommended for funding, as they are deemed to fall short of the necessary threshold for potential success.

Table 4.1 explores the nuanced decisions derived from fuzzy logic, juxtaposed against the binary decisions of peer reviewers. The data reveals an intricate pattern of recommendation levels that go beyond a simple 'fund' or 'not fund' directive. For proposals originally designated for funding, we see a distribution across nuanced categories:

- Consider for Funding: A total of 143 proposals that were not funded in the binary decision fall into this nuanced category, suggesting these proposals might have unrecognized potential.

- Do Not Fund: 8 proposals are consistently recognized as not suitable for funding across both binary and nuanced assessments.
- Recommend Funding: 215 proposals, not funded in the binary decision, are seen as potentially fundable in the nuanced view, indicating a possible underestimation in the initial binary assessment.
- Strongly Recommend Funding: 57 proposals not funded by the binary decision are viewed as strong candidates for funding by the fuzzy logic system, highlighting its capability to identify funding-worthy aspects that the binary decision might miss. Interestingly, all 77 proposals that were funded in the binary decision are strongly recommended for funding in the nuanced assessment, reaffirming their perceived value.

The distribution across these nuanced categories for proposals, particularly those not initially recommended for funding, indicates that the fuzzy logic system can uncover valuable qualities in proposals that a binary decision-making process might overlook.

Table 4.1. Analyzing Fuzzy Logic Insights: A Detailed Breakdown of Nuanced Funding Recommendations vs. Peer Reviewers' Binary Decisions

Nuanced Decision	Consider for Funding	Recommend Funding	Strongly Recommend Funding	Do Not Fund	Total
Binary Decision					
Fund	0	0	77	0	77
Don't Fund	143	215	57	8	423
Total	143	215	134	8	500

Table 4.1 underscores the value of fuzzy logic in capturing the gradations and complexities of the peer review process. By assigning proposals to categories like 'Consider for Funding' or 'Strongly Recommend Funding,' the model reflects a more detailed and differentiated understanding of each proposal's merits, revealing the subtleties that a binary decision might overlook. The inclusion of a 'Do Not Fund' category even for some proposals initially marked for funding illustrates the model's capacity to critically reassess and offer a more conservative stance based on the comprehensive analysis of proposal features.

Table 4.2 shifts our focus to the SVM predictions, which are derived from a binary perspective informed by the nuanced evaluations of the fuzzy logic system. We utilized a test split of 0.2, meaning that 20% of our data was reserved for testing the model's predictions, ensuring that we could objectively evaluate its performance on unseen data. The SVM model demonstrated a high accuracy of 0.90, indicating a strong alignment with the binary outcomes, correctly predicting the majority of cases as either Funded or Not Funded.

However, with a precision of 0.62, the model shows a tendency to overestimate a proposal's likelihood of being funded. This overestimation could be attributed to the learned characteristics from the disproportionately larger number of Not Funded cases (423 Not Funded vs. 77 Funded in the entire dataset) in the training data. The recall of 1.00 suggests that the model successfully identified all the Funded proposals in the test set, highlighting its effectiveness in capturing potential success stories.

The use of fuzzy logic in the SVM's input could be providing a more nuanced view of each proposal's potential, allowing the model to identify qualities that suggest success beyond the binary decision framework. This nuanced approach might be capturing aspects of proposals that are not immediately apparent in the binary 'Funded/Not Funded' labels, suggesting that these proposals, despite initial reservations, possess qualities that align with the criteria for success.

While the SVM model's alignment with the initial impressions is strong, its notable deviations, especially in predicting success for proposals not initially recommended for funding, underline the model's ability to challenge and expand upon these initial assessments. However, this also implies that there are instances where it overestimates a proposal's likelihood of being funded, which could be due to the characteristics learned from the training data or the additional insights gained through the fuzzy logic system's nuanced evaluations.

Table 4.2. Comparison of SVM Model Funding Predictions with Peer Reviewers' Decisions: Evaluating the Alignment in Funding Outcomes

SVM Prediction	0	1	All
Binary Decision			
0	74	10	84
1	0	16	16
All	74	26	100

Comparing Tables 4.1 and 4.2 highlights the complementary nature of nuanced evaluations and predictive modeling in enhancing our understanding of peer review decisions. Table 4.1, with its graduated categorization, provides a detailed landscape of proposal evaluations, offering depth to the binary decisions of peer reviewers. Table 4.2, through SVM predictions, validates and challenges these initial decisions, showcasing the model's capability to identify potential overlooked by human evaluators. These tables exemplify the transition from traditional, binary evaluation methods to a more sophisticated, data-informed decision-making process that better captures the complexity of proposal evaluation and funding decisions.

In summary, our journey through the integration of SHAP and LIME analyses, alongside the implementation of fuzzy logic and SVM predictions, has afforded us a comprehensive understanding of peer reviewers' decision-making processes. The initial exploration with SHAP and LIME shed light on the importance and influence of various proposal features, revealing a complex web of factors that guide reviewers' binary decisions. This initial step highlighted the multifaceted nature of the review process, demonstrating that decisions are not merely binary but are influenced by a nuanced interplay of proposal characteristics.

By transitioning to a fuzzy logic model, we introduced a system capable of capturing these nuances, translating qualitative assessments into a spectrum of quantifiable scores. This method allowed us to mimic the complexity and ambiguity inherent in human judgment, moving beyond the binary 'fund' or 'not fund' decisions to a more graduated understanding of proposal merit. The membership functions, influenced by the insights gained from SHAP and LIME, provided a visual and quantitative framework for categorizing proposals based on their perceived innovation, risk, and alignment with strategic objectives.

The subsequent application of SVM predictions built upon the nuanced categorization provided by fuzzy scores, offering a binary glimpse into the potential future of each proposal. However, unlike the original binary decisions of peer reviewers, SVM predictions were informed by a rich tapestry of data, including the nuanced evaluations from the fuzzy logic system. This approach enabled a more refined classification of proposals, identifying those with the highest likelihood of success even when traditional peer review might have overlooked them.

By comparing the findings from the SHAP and LIME analyses and the original binary decisions to the outcomes of the fuzzy logic model and SVM predictions, we observed a significant enhancement in our ability to understand and predict the complex decision-making process of peer reviewers. The fuzzy logic system revealed the subtleties and gradations in reviewer evaluations, while SVM predictions provided a predictive model that considers these nuances in forecasting proposal success.

In answering the question, "How can we transcend the binary 'yes' or 'no' decisions of peer reviewers and adopt a nuanced numerical system that more accurately reflects the subtleties of their evaluations?" we have demonstrated that it is indeed possible to move beyond simple binary outcomes. Through the integration of SHAP and LIME for initial analysis, fuzzy logic for nuanced evaluation, and SVM for predictive modeling, we have created a multi-layered approach that captures the depth and complexity of peer reviewer decisions. This comprehensive framework enhances our understanding of the peer review process and enables funding agencies to make more informed, strategic decisions that align with their objectives, ensuring that proposals are evaluated on a spectrum of merit rather than a binary scale.

Why Should Policymakers Care?

Policymakers should deeply care about transitioning from the binary decision-making framework to a nuanced interpretation using Fuzzy Logic in the funding evaluation process. This evolution is vital for several reasons:

- Reflecting the Complexity of Decisions: Real-world decision-making, especially in the context of funding, is rarely black and white. Fuzzy Logic provides a more accurate reflection of the subtleties involved in these decisions, capturing the degrees of confidence or hesitation that reviewers feel towards each proposal. This complexity is crucial for policymakers to understand, as it aligns the decision-making process more closely with the intricate realities of policy and funding environments.
- Enhanced Decision Quality: By adopting a nuanced numerical system through Fuzzy Logic, policymakers can ensure that funding decisions are not just binary but reflect a spectrum of evaluations. This leads to a more refined and quality-focused selection process, where proposals are evaluated more thoroughly based on their merits and alignment with strategic goals.
- Resource Optimization: In scenarios where the demand for funding exceeds available resources, Fuzzy Logic allows for a more discriminative approach to allocating funds. Policymakers can prioritize proposals that not only meet the funding criteria but also exhibit higher confidence levels from reviewers, ensuring that resources are utilized efficiently and effectively.
- Improved Transparency and Accountability: Moving towards a more granular evaluation system enhances transparency in the decision-making process. Policymakers can offer more detailed justifications for funding decisions, which, in turn, improves accountability and trust in the funding process.

Mitigating Risks: Balancing Precision and Risk

Integrating Fuzzy Logic and Support Vector Machine (SVM) models into the funding decision process could potentially lead to complications if not managed carefully. One risk is the misapplication of Fuzzy Logic principles, which could result in overly complex or ambiguous decision rules. This complexity might obscure, rather than clarify, the underlying reasoning of funding decisions, leading to confusion among decision-makers and applicants alike. For example, consider a scenario where Fuzzy Logic is used to assess the risk and innovation levels of research proposals. If the decision rules are too complex, a proposal with moderate risk and high innovation might receive the same funding priority as one with high risk and moderate innovation, simply because the decision criteria are not distinct or well-defined enough. This lack of clarity could perplex decision-makers, who might struggle to understand why two seemingly different proposals are evaluated similarly, and complicate the applicants' understanding of how to align their proposals with funding priorities.

Moreover, the integration of these advanced tools requires a deep understanding of their mechanisms to ensure they are applied appropriately. Without this expertise, there is a risk of misinterpreting the nuanced outputs these models provide.

Another potential issue is the reliance on historical data to inform the SVM and Fuzzy Logic systems. If this data is biased or unrepresentative of the current funding landscape, the AI models may produce skewed or outdated recommendations. This could lead to a cycle of reinforcing past biases or failing to adapt to evolving strategic goals and priorities within the funding agency.

Technical challenges also pose significant risks. The integration of sophisticated AI tools like SVM and Fuzzy Logic into the funding decision process requires robust computational infrastructure and data management practices. Failures in these systems could lead to disruptions in the decision-making process, data loss, or breaches, undermining the integrity and reliability of funding decisions.

To mitigate these risks and harness the benefits of integrating Fuzzy Logic and SVM into the funding evaluation process, a multifaceted approach is needed. Firstly, ensuring that the staff responsible for implementing and managing these tools are thoroughly trained in their use and the interpretation of their outputs is crucial. Continuous education and training will help prevent misapplication and misinterpretation of the models.

Secondly, it's important to establish a feedback loop where the outcomes of AI-assisted decisions are regularly reviewed and compared against the agency's strategic goals and real-world outcomes. This iterative process allows for the refinement of AI models, ensuring they remain aligned with the agency’s objectives and adapt to changes in the funding environment.

Thirdly, maintaining transparency throughout the decision-making process is essential. Detailed documentation of how Fuzzy Logic and SVM models influence decisions can help in understanding their impact and in refining their algorithms over time.

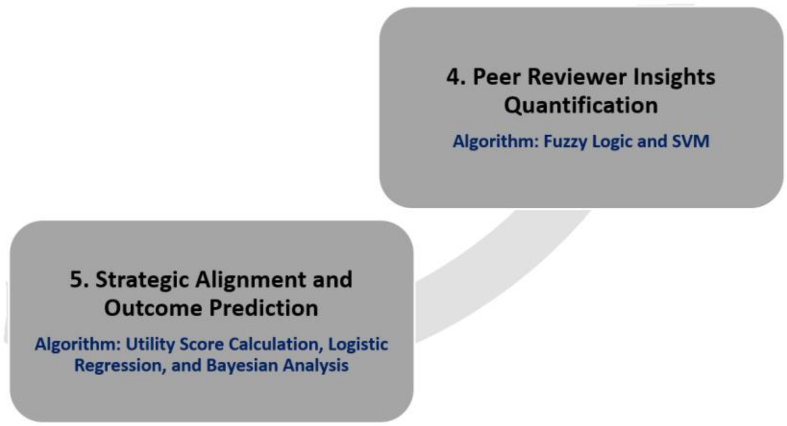
Lastly, investing in robust technical infrastructure and cybersecurity measures will safeguard the AI systems against technical failures and security breaches, ensuring the reliability and integrity of the funding decision process.

By addressing these potential pitfalls proactively, the integration of Fuzzy Logic and SVM into the funding decision process can be a transformative move, enhancing the sophistication, fairness, and strategic alignment of funding decisions in alignment with policy goals.

Strategic Alignment and Outcome Prediction

Building on the insights from the previous stages, our exploration now shifts towards understanding what is fundamentally important to the funding agencies themselves. This section, Strategic Alignment, and Outcome Prediction, marks a pivotal transition from simply deciphering peer reviewers' evaluations to strategically tailoring the funding process in harmony with the agency's objectives.

Figure 4.8. Strategic Alignment and Outcome Prediction



In the earlier phase, Peer Reviewer Insights Quantification, we adeptly transformed peer reviewers' intricate evaluations into quantifiable fuzzy scores. This translation was not just about conversion but about capturing the essence of peer reviewers' nuanced judgments in a manner that facilitates a direct comparison across proposals, ensuring a deep understanding of what drives their decisions.

As we venture into the Strategic Alignment and Outcome Prediction phase, our narrative takes on a new dimension. The aim here is not merely to understand or predict outcomes based on historical data but to actively shape these outcomes to resonate with the agency's strategic imperatives. We introduce utility scores as a means to embody the agency's specific valuation of a proposal's merits and its alignment with overarching strategic goals. These utility scores, distinct from the fuzzy scores derived from peer reviews, encapsulate the agency's perspective on a proposal's potential impact, innovation, and strategic fit.

The distinction between fuzzy scores and utility scores is fundamental. While fuzzy scores offer a structured reflection of peer reviewers' insights, utility scores embody the agency's calculated judgment on the potential success and strategic value of proposals. It is this nuanced interplay between the expert evaluations of peer reviewers and the strategic considerations of the funding agency that enriches our decision-making framework. By integrating these perspectives, we ensure that funding decisions are informed not only by expert opinion but are also strategically aligned with the agency's long-term goals and priorities.

This harmonization between peer reviewer expertise and strategic objectives lays the groundwork for a more informed, objective, and strategic funding allocation process. Through the application of utility scores and success probability estimations, we fine-tune the selection process, ensuring that funded projects are those that offer the most significant alignment with the agency's mission and strategic vision. Thus, this stage represents a sophisticated evolution in our methodology, transitioning from an understanding of individual evaluations to a holistic strategic alignment, ensuring the most impactful and meaningful investment in research and development endeavors.

In sum, this phase amplifies the dialogue between peer reviewer insights and the strategic goals of the funding agency, embodying a dual approach that respects the intricate judgments of expert reviewers while steering these evaluations towards the agency's strategic objectives. It is a testament to the power of integrating nuanced peer review insights with strategic considerations to foster a more impactful and aligned funding mechanism.

Methodological Approach

In our approach, we have crafted a sequence of steps to enhance the decision-making framework with AI insights:

- Integration of Peer Reviewer Insights and SVM Analysis: We commence by harnessing the insights encapsulated in fuzzy scores alongside the predictive outcomes provided by SVM analysis. These components translate the nuanced judgments of peer reviewers into quantifiable metrics, laying the groundwork for a nuanced understanding of each project's merits.
- Strategic Prioritization and Utility Score Formulation: Central to this phase is articulating the agency's strategic priorities, assessed through various project attributes like ROI, Risk, Innovation, and Past Performance. By applying preference functions and assigning strategic weights to these attributes, we calculate a utility score for each proposal, reflecting its alignment with the agency's goals and perceived value. In our model, the preference functions are defined as follows, where each function is tailored to reflect the strategic importance of the corresponding attribute:
  For ROI, we recognize the exponential value of returns, modeled with a logarithmic preference function:

  $$p_{\text{ROI}}(x) = \log(1 + x)$$

  Risk is considered inversely, acknowledging that higher risks are generally less desirable, represented by a negative square root function:

  $$p_{\text{Risk}}(x) = -\sqrt{x}$$

  Alignment with the agency's mission is directly proportional, doubling the attribute's value to emphasize its importance:

  $$p_{\text{Alignment}}(x) = 2 \cdot x$$

  Innovation, being crucial, is evaluated with a quadratic function to emphasize the increasing value of highly innovative projects:

  $$p_{\text{Innovation}}(x) = \left(\frac{x}{10}\right)^2$$

Past Performance is considered linearly, indicating its direct correlation with the utility score:

$$p_{\text{Past Performance}}(x) = x$$

These preference functions, coupled with strategic weights, form the backbone of our utility score computation, mathematically represented as:

$$U = \sum_{j \in \{\text{attributes}\}} w_j \cdot p_j(x_j)$$

where w_j is the weight and $p_j(x_j)$ is the preference function applied to attribute x_j.

- Probabilistic Success Estimation: Building on the utility scores, we employ two algorithms, logistic regression and Bayesian analysis to derive probabilities of success for each proposal. This approach provides a comprehensive understanding of the likelihood of each proposal's success, grounded in statistical analysis and enriched by the agency's strategic lens. It ensures that our evaluation transcends simplistic metrics, embracing a broader perspective that aligns with the agency's strategic objectives. Logistic regression provides a direct probabilistic prediction based on utility scores and other features, showcasing how well proposals align with predefined success criteria. The logistic model typically calculates probabilities using the sigmoid function:

$$P(\text{Success}) = \frac{1}{1 + e^{-(b_0 + b_1 x_1 + \cdots + b_n x_n)}}$$

where:
$P(\text{Success})$ is the probability of the proposal being successful.
$b_0 + b_1 x_1 + \cdots + b_n x_n$ are the coefficients determined by the logistic regression model.
$x1, \ldots, xn$ are the features, including the utility score and other proposal attributes.

Conversely, Bayesian analysis leverages the interdependencies among proposal attributes, offering a nuanced view of success probabilities that reflects both the complexity of proposals and the strategic nuances valued by stakeholders. In Bayesian terms, we calculate the posterior probability of success given the evidence from the proposal attributes and utility scores:

$$P(\text{ Success} \mid \text{Evidence }) = \frac{P(\text{ Evidence} \mid \text{ Success}) \times P(\text{Success})}{P(\text{Evidence})}$$

where:
$P(\text{ Success} \mid \text{Evidence})$ is the posterior probability of success.
$P(\text{ Evidence} \mid \text{Success})$ is the likelihood of observing the given evidence if the proposal is successful.
$P(\text{Success})$ is the prior probability of success.
$P(\text{Evidence})$ is the probability of the evidence under all conditions.

Understanding the Model's Output

Table 4.3 delineates the interplay between utility scores and success probabilities, as forecasted through Bayesian analysis and logistic regression. These elements collectively illuminate the pathway toward informed decision-making in funding allocation. Here's a distilled interpretation of the findings:

Table 4.3. Strategic Alignment and Outcome Prediction Output

Utility Score	Success Probability Bayesian	Success Probability Logistic
0.29	1	0.38
0.65	0	0.31
0.46	0	0.38
0.71	0	0.32
0.45	0	0.43
0.42	0	0.47
0.28	1	0.46
0.5	0	0.34
0.51	1	0.40
0.28	1	0.41
0.32	0	0.44
0.71	0	0.24

Utility Score Assessment: Reflects the integration of the agency's strategic priorities into the evaluation of each proposal. Higher utility scores signify a proposal's strong alignment with the agency's goals, suggesting a higher likelihood of contributing to the agency's strategic objectives effectively. This metric serves as a foundation for discerning which proposals embody the most substantial potential benefits.

Bayesian Success Probability: The Bayesian Success Probability is derived through a Bayesian Network model that encapsulates the interdependencies among discrete features of proposals, such as ROI, Risk, Alignment, Innovation, and Past Performance, and their collective impact on the Utility Score and success. The network structure, informed by domain knowledge and statistical relationships, allows for the computation of success probabilities by evaluating the combined influence of these factors. By applying the estimate_success_probability function (in the appendix, Code Sample) to each proposal, we leverage Bayesian inference to calculate the likelihood of success, with a value close to 1 indicating strong confidence in a proposal's foundation for success. This method effectively captures the nuanced dynamics and uncertainties inherent in the evaluation process, providing a probabilistic assessment grounded in the complex interactions of proposal attributes.

Logistic Regression Success Probability: The Logistic Regression Success Probability is calculated using a logistic regression model that assesses the impact of both individual features like ROI, Risk, Alignment, Innovation, and Past Performance, as well as the aggregated Utility Score, on the likelihood of proposal success. The predict_proba method (in the appendix, Code Sample) of the logistic model offers a straightforward mechanism to estimate these probabilities, yielding values that reflect the model's confidence in the proposal's success potential. A success probability nearing 1 signifies a strong predictive validation of the proposal's viability, underscoring its alignment with the factors deemed critical for success. This approach harnesses the predictive strength of logistic regression to offer clear, quantitative insights into the proposal's likelihood of success, based on an integrative analysis of key characteristics and their strategic value.

A high utility score paired with low success probabilities could occur due to several reasons:

- Model Sensitivity: The Bayesian and logistic regression models might be sensitive to specific features or patterns in the data that are not fully captured by the utility score calculation. For instance, even if a proposal aligns with strategic priorities (high utility score), historical data might show similar proposals have a lower success rate.
- Risk Consideration: Proposals with high strategic alignment (high utility) might also carry higher risks or uncertainties that are not fully accounted for in the utility score but are captured in the success probability models.
- Data Discrepancies: There might be discrepancies or anomalies in the historical data used to train the success probability models, leading to counterintuitive predictions.
- Strategic Misalignment: The strategic priorities encapsulated in the utility scores may not fully align with the patterns of success indicated by historical proposal outcomes. This misalignment could suggest a need to revisit the strategic weights and preference functions used to calculate utility scores.

Funding agencies could benefit from these insights by

- Identifying High-Potential Proposals: The juxtaposition of success probabilities from Bayesian and logistic analyses with utility scores allows agencies to identify proposals with universally high success potential. This identification aids in the strategic allocation of resources to initiatives most likely to succeed and fulfill the agency's objectives.
- Balancing Innovation and Risk: Discrepancies between the success probabilities provided by Bayesian and logistic models, especially for proposals with high utility scores, warrant a careful evaluation of innovation against potential risks. Such analysis enables agencies

to make informed decisions, considering both the groundbreaking nature of a proposal and its feasibility.

- Refining Evaluation Criteria: The collective insights from utility scores and success probabilities enable agencies to refine their evaluation criteria for future funding cycles. Proposals that consistently align with strategic goals and exhibit high probabilities of success can guide the recalibration of evaluation metrics to better capture the qualities of successful initiatives.
- Enhancing Decision-Making Transparency: The quantitative nature of utility scores and success probabilities contributes to a transparent and justifiable decision-making process. Agencies can leverage this data to communicate funding decisions to stakeholders, demonstrating a rigorous, data-informed approach to selecting projects that align with strategic priorities.

Why should policy makers care?

Policymakers should be deeply invested in the "Strategic Alignment and Outcome Prediction" phase of the funding process due to its pivotal role in ensuring that funding decisions are not only based on past performance or expert evaluations but are also strategically aligned with the agency's long-term goals and mission. This stage transitions from merely interpreting peer reviewers' assessments to actively shaping funding outcomes to resonate with the agency’s strategic imperatives, embodying a more proactive and purpose-driven approach to funding. Drawing from the author’s experience, the reliance solely on peer review evaluations without considering national priorities can lead to a misalignment in funding allocation. For instance, in one scenario, our agency ended up funding a disproportionate number of cancer research proposals over diabetes-related projects. This discrepancy occurred not due to a strategic decision but because the pool of cancer research proposals was inundated with high-quality submissions, overshadowing the equally critical field of diabetes research. The absence of a mechanism like a utility function to guide the funding emphasis meant that high academic merit became the sole criterion, inadvertently neglecting national health priorities which demanded urgent attention to diabetes research.

This example underscores the necessity of integrating a utility function in the funding decision process. Such a function could systematically account for national priorities and strategic goals, offering incentives or allocating a specific quota for underrepresented but crucial research areas like diabetes. Through this strategic alignment mechanism, funding agencies can ensure that their resource allocation not only rewards academic excellence but also addresses the broader spectrum of national and societal needs.

Utilizing utility scores as a novel metric allows for a direct representation of the agency’s valuation of proposals, integrating both the intrinsic merits of the projects and their alignment with strategic objectives. This dual assessment ensures that funding allocations are not just reflections of past preferences but are forward-looking, considering the potential impact and strategic fit of each proposal. The ability to predict outcomes based on these utility scores and success probability estimations enables a more nuanced and dynamic funding strategy that can adapt to changing priorities and societal needs.

Mitigating Risks: Navigating Complexities in AI-Powered Funding Outcomes

In the "Strategic Alignment and Outcome Prediction" phase, integrating Bayesian analysis and logistic regression to forecast success probabilities presents several complexities that could potentially mislead the funding decision process. Here's how things might go awry:

- Model Overfitting or Underfitting: If these models are overly tuned to the historical data, they might fail to accurately predict the future success of proposals, leading to funding potentially unsuccessful projects or overlooking promising ones. Overfitting could make the models too specific to past data, while underfitting could result in them being too generalized, ignoring subtle yet critical nuances.
- Data Quality and Representation Issues: The reliability of Bayesian and logistic regression analyses hinges on the quality and representativeness of the data. If the historical data contains biases or inaccuracies, or if it doesn't capture the full spectrum of factors influencing success, the resulting predictions could be skewed, misguiding the funding allocation process.
- Misalignment of Strategic Priorities: The utility scores, while designed to reflect the agency's strategic priorities, might not always be in sync with the actual determinants of project success as captured by the models. This misalignment could lead to funding decisions that are strategically sound on paper but do not translate to success in practice, indicating a potential misdirection of resources.
- Complexity in Model Interpretation: The intricate nature of Bayesian networks and logistic regression models might pose challenges for stakeholders in understanding and interpreting the results. This complexity could lead to miscommunication or misinterpretation of the data, undermining the decision-making process.

To mitigate the risks associated with integrating Bayesian analysis, logistic regression, and the utility score in the funding decision process, a dynamic interaction between human expertise and AI models is essential. This synergy is vital for maintaining the relevance and strategic alignment of the predictive tools with the evolving objectives of the funding agency. Human evaluators play a critical role in this ecosystem, continuously engaging with the AI outputs to validate, interpret, and refine the predictions, ensuring that they remain contextually informed and adaptable.

Regularly updating and validating these models against new data and changing strategic goals is necessary to keep them attuned to the agency's needs. This iterative process of calibration involves not just the technical adjustment of the models' parameters but also aligning them with the utility score, which represents the strategic intent of the agency. Such continuous recalibration ensures that the predictive models and the utility score collectively provide a robust framework for funding decisions, one that is both quantitatively accurate and qualitatively aligned with strategic priorities.

Additionally, incorporating a fuzzy score in the evaluation process enhances the spectrum of analysis, adding a qualitative layer that complements the quantitative insights from Bayesian and logistic regression models. This integrated approach promotes a transparent, adaptable, and strategically coherent decision-making environment, where the nuanced decisions of peer reviewers are better understood and aligned with the agency's long-term goals. Ultimately, this harmonized interaction between human evaluative expertise and sophisticated AI tools cultivates a funding ecosystem that is not only data-driven but also strategically responsive and aligned with the broader objectives of advancing research and innovation. Consider a scenario in the funding agency's decision-making process where two research proposals, one in renewable energy and the other in medical research, are evaluated for potential funding. Both proposals have received similar scores in terms of innovation and scientific merit from peer reviewers. However, the agency's strategic focus for the current year emphasizes renewable energy due to national priorities and global trends.

By incorporating a fuzzy score, the evaluation process can add nuanced, qualitative analysis to these proposals. For instance, the renewable energy proposal might score highly on strategic alignment with the agency's objectives, reflecting not just the proposal's inherent qualities but also its fit with broader societal and environmental goals. This score is then integrated with the quantitative insights from Bayesian and logistic regression models, which have assessed the proposals based on historical data and predictive success criteria.

In this example, while both proposals are quantitatively similar in their scientific merit and potential for success, the fuzzy score's qualitative analysis reveals a higher strategic value in the renewable energy proposal. This nuanced understanding allows the funding agency to make a more informed, strategic decision that aligns with its long-term goals, ensuring that the chosen research not only advances scientific knowledge but also contributes to the agency’s strategic priorities and national interests.

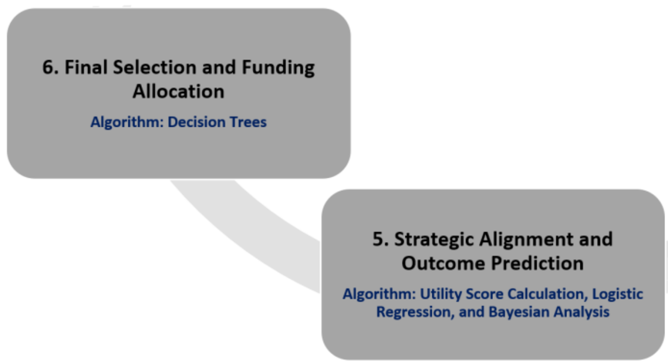
Through this harmonized approach, the funding agency leverages the depth of qualitative assessment provided by the fuzzy score, alongside the breadth of quantitative analysis from Bayesian and logistic regression models, creating a comprehensive, transparent, and strategically coherent funding decision-making process. This integrated evaluation framework ensures that funding decisions are not only based on data but are also aligned with the strategic objectives and broader goals of advancing impactful research and innovation.

Final Selection and Funding Allocation

In the final phase of enhancing funding agency decision-making with AI, we reach the "Final Selection and Funding Allocation" stage. Here, we leverage a Decision Tree Classifier, as supported by literature recommendations explored in Chapter 3, to transform our comprehensive dataset, now enriched with utility scores, success probabilities from logistic regression and

Bayesian analysis, and the nuanced insights from fuzzy scores, into actionable funding recommendations.

Figure 4.9. Final Selection and Funding Allocation



The Decision Tree Classifier acts as the cornerstone of our decision-making process. By methodically evaluating our dataset, it assigns proposals to categories ranging from 'Low Priority for Funding' to 'High Priority for Funding'. This assessment not only considers utility scores in light of the agency's strategic goals but also integrates success probabilities to ensure alignment with the agency's risk appetite. Such an approach guarantees that funding decisions are transparent, justifiable, and strategically aligned.

Employing the Decision Tree Classifier, we distill complex insights, from peer reviews to predictive success probabilities, into definitive, strategic funding decisions. This enhances the transparency and alignment of decisions with the agency's strategic objectives. The classifier's accuracy in discerning suitable funding categories further validates our AI-powered framework's efficacy.

This comprehensive, AI-driven process, from initial peer reviewer insights through to strategic project evaluation and final funding recommendation, illustrates a data-informed, strategic approach to funding allocation. It marks a pivotal move towards a methodology that supports impactful research and innovation in alignment with the funding agency's overarching goals.

Methodological Approach

- Preparation of the Analytical Dataset: we begin with the assembly of a comprehensive Data Frame that integrates all prior analyses, including utility scores and success probabilities derived from logistic regression and Bayesian analysis.

- Categorization Based on Strategic Alignment: We introduce a new 'Funding_Category' column to categorize proposals into three tiers: 'Low Priority for Funding', 'Consider for Funding', and 'High Priority for Funding'. Unlike the nuanced decisions derived from fuzzy logic, these categories are directly influenced by utility scores and success probabilities, mirroring the agency's strategic objectives and the proposals' projected outcomes. This differentiation underscores the agency's focus on aligning funding decisions with its broader strategic imperatives. The categorization can be mathematically represented as:

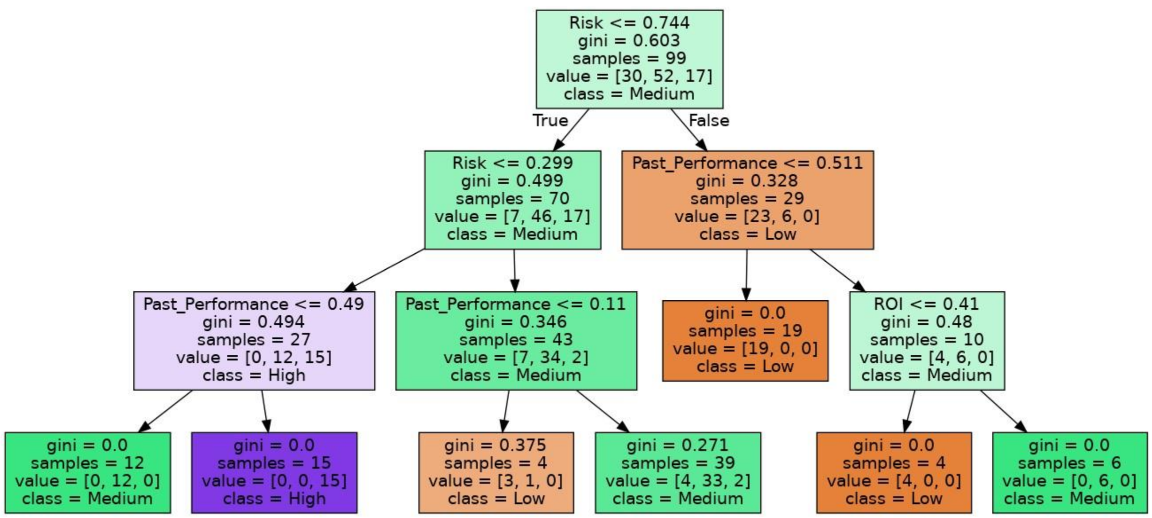
$$Funding\_Category = \begin{cases} \text{'Low Priority for Funding'}, & if\ Utility\_Score \leq 0.33 \\ \text{'Consider for Funding'}, & if\ 0.33 < Utility\_Score \leq 0.66 \\ \text{'High Priority for Funding'}, & if\ Utility\_Score > 0.66 \end{cases}$$

- Feature Selection for Decision-Making: The selection of 'Utility_Score', 'Success_Probability_Logistic', and 'Success_Probability_Bayesian' as the primary features for the Decision Tree Classifier is a strategic choice, aiming to streamline the decision-making process by focusing on the most informative and impactful indicators of a proposal's alignment with the funding agency's strategic goals and its likelihood of success. This focus on specific features aims to ensure that the classifier's predictions are both relevant and reflective of the agency's strategic priorities, leveraging comprehensive metrics that encapsulate the essence of each proposal's potential value and likelihood of success. It is important to recognize that the choice of features for the Decision Tree Classifier will involve a process of trial and error to determine the optimal combination that yields the most accurate and meaningful predictions. This iterative process allows for the refinement of the model based on empirical results, ensuring that the selected features effectively contribute to the decision-making framework. Additionally, engaging with decision-makers to gather feedback on the chosen features is crucial. Their insights and preferences play a vital role in aligning the model's focus with the strategic objectives and priorities of the funding agency. By incorporating feedback from those who have a deep understanding of the agency's goals and the challenges in project selection, we can ensure that the model remains relevant and effective in its task.
- Training the Decision Tree Classifier: With our dataset prepared and features selected, we proceed to train the Decision Tree Classifier. This step involves splitting our dataset into training and testing sets to ensure that our model can learn from a subset of the data before being tested on unseen data. The classifier is trained to recognize patterns within the training set that correlate with the funding categories, enabling it to make informed decisions about which projects to fund.
- Evaluating Model Performance: Upon training, the classifier's performance is assessed by predicting funding categories for the test set and comparing these predictions against the actual categories. The accuracy of these predictions serves as a measure of the model's effectiveness in aligning funding decisions with the strategic goals of the agency.
- Visualization for Transparency: To enhance the interpretability and transparency of our decision-making process, we export the trained Decision Tree Classifier into a visual format. This visualization delineates the decision paths taken by the classifier, illustrating how different criteria lead to specific funding decisions. It demystifies the decision-making process, making it accessible and justifiable to stakeholders.

Understanding the Model's Output

The decision tree is a visual representation of a series of binary choices that lead to a final decision on the priority level for funding proposals. At each decision point or "node," the tree considers a particular attribute of a proposal, such as its risk level, past performance, or return on investment (ROI), and guides the decision based on whether the proposal meets specific criteria associated with that attribute.

Figure 4.10. Decision Tree Analysis: Visualizing Strategic Funding Categories Based on Proposal Metrics



For example, the tree might first evaluate a proposal's risk: if the risk is below a certain threshold, the tree will follow one branch; if not, it will follow another. This process continues through the tree, considering different attributes at each node until it reaches a "leaf," which assigns a priority level for funding to the proposal. Here is how we could interpret the graph:

- Root Node: The topmost node (Risk <= 0.744) uses the 'Risk' feature to make the first decision. If the 'Risk' score is less than or equal to 0.744, it follows the branch to the left; otherwise, it follows the branch to the right.
- Gini Index: The 'gini' value is a measure of impurity or diversity used to determine the node's quality of split. A Gini index of 0 indicates that the node is perfectly pure, meaning all records it contains fall into a single category. Values closer to 1 indicate a higher level of disorder or mixture of categories.
- Samples: This indicates the number of samples from the training dataset that fall into that node.
- Value: The 'value' array gives the distribution of the samples across different categories at that node. For example, [30, 52, 17] means there are 30 samples of the 'Low Priority for

Funding', 52 samples of 'Consider for Funding', and 17 samples of 'High Priority for Funding' at the root node.

- Class: This suggests the dominant class at that node based on the sample distribution. In the case of the root node, 'Medium' (or 'Consider for Funding') is the dominant class because it has the highest number of samples (52).
- Leaf Nodes: The terminal nodes (leaves) give the final decision of the classifier. If a sample reaches a leaf, it is classified into the category indicated by the 'class' attribute of that leaf.

Why Should Policy Makers Care?

- Strategic Decision-Making: By observing which attributes and thresholds the tree uses to determine funding priority, agencies can ensure that their funding decisions align with their strategic objectives. For instance, if a low-risk profile is deemed crucial for a proposal to be considered high priority, the agency can focus on proposals that meet this criterion.
- Transparency and Communication: The decision tree can be a valuable tool for communicating the rationale behind funding decisions to stakeholders. It clearly shows the criteria used to evaluate each proposal, providing a transparent account of the decision-making process.
- Policy and Criteria Refinement: The decision tree can help agencies identify which criteria have the most significant impact on funding decisions. Suppose an attribute like alignment with strategic goals seems to have less impact on the final decision than desired. In that case, agencies can adjust their evaluation criteria or the model to correct this.
- Benchmarking and Continuous Improvement: Agencies can use the decision tree as a baseline for evaluating the effectiveness of their decision-making process over time. By analyzing how modifications in strategic focus or external factors influence the decision tree's outcomes, they can make data-driven improvements to their funding strategies.

Mitigating Risks: Optimizing Funding Outcomes

Implementing the "Final Selection and Funding Allocation" methodology with a Decision Tree Classifier could face several challenges that might disrupt the intended strategic alignment and outcome prediction:

- Overfitting of the Decision Tree: There's a risk that the Decision Tree Classifier might become too complex, fitting the training data too closely and failing to generalize to unseen data. This overfitting could lead to inaccuracies in categorizing proposals, potentially favoring or penalizing projects based on idiosyncrasies of the training set rather than their actual merits or strategic fit.
- Bias in Feature Selection: Selecting features like 'Utility_Score', 'Success_Probability_Logistic', and 'Success_Probability_Bayesian' is critical. If these features don't adequately capture the agency's strategic goals or if they are biased

towards certain types of projects, the resulting funding decisions could be skewed, misaligning with the agency's objectives.

- Misinterpretation of Model Outputs: Decision trees can be complex and their decisions, while seemingly straightforward, can be based on subtle interactions between features. If stakeholders misinterpret these outputs, it could lead to funding decisions that are not fully aligned with the strategic intent, undermining the model’s utility.
- Data Quality and Representation Issues: The model's effectiveness is contingent on the quality and representativeness of the data used for training. Poor quality, outdated, or unrepresentative data can lead to inaccurate predictions, hindering the decision-making process and potentially leading to suboptimal funding allocations.
- Change in Strategic Priorities: The strategic objectives of the agency may evolve over time, but the Decision Tree Classifier, once trained, might not automatically adapt to these changes. This lag can result in a misalignment between the funding decisions and the current strategic goals of the agency.

To mitigate these risks, several steps can be taken:

- Regular Model Reevaluation and Updating: Continuously monitor and update the Decision Tree Classifier to ensure it remains aligned with the latest strategic goals and data trends. Regular retraining with updated data can help prevent overfitting and bias.
- Comprehensive Feature Analysis: Conduct thorough analyses to ensure that the selected features for the Decision Tree accurately represent the strategic priorities and success factors of the agency. Involving domain experts in this process can enhance the relevance and accuracy of the feature selection.
- Transparent Communication and Training: Ensure that all stakeholders understand how the Decision Tree Classifier works and how to interpret its outputs. Providing training sessions and detailed documentation can help prevent misinterpretation of the model's decisions.
- Quality Data Management: Invest in robust data management practices to ensure the data used for training the model is of high quality, representative, and up-to-date, reflecting the latest trends and outcomes in the funding landscape.
- Agility in Strategic Planning: Establish mechanisms to regularly review and quickly integrate changes in strategic priorities into the decision-making model, ensuring the Decision Tree Classifier remains a relevant and effective tool for funding allocation.

By proactively addressing these potential issues, the integration of a Decision Tree Classifier into the funding decision process can be optimized, enhancing the strategic allocation of resources and ensuring that funding decisions are data-informed, transparent, and aligned with the agency's evolving strategic goals.

Our narrative journey through AI integration in funding decision processes unveils not only the transformative potential of this technology but also the inherent challenges and risks. As we ventured into the realm of AI to enhance reproducibility, transparency, efficiency, and objectivity in funding decisions, we also encountered the complexities of translating peer reviewer judgments into a standardized, quantifiable format. The creation of a utility score represented an attempt to encapsulate the leadership perspective, merging it with the granular insights of peer evaluations.

While AI's integration promises a paradigm shift towards more data-driven and strategic funding decisions, it is not without its pitfalls. The challenges of AI integration include the risk of perpetuating biases present in historical data, the potential for overfitting models to past outcomes, and the complexity of ensuring that AI-generated recommendations align with the ever-evolving strategic objectives of funding agencies. Moreover, the reliance on AI could lead to a diminished role for human intuition and expertise, which are crucial in navigating the subtleties and variances inherent in scientific evaluation.

The consequences of unmitigated risks in AI integration could be far-reaching. Without careful calibration and continuous human oversight, AI systems might make funding recommendations that are misaligned with current scientific and societal priorities, potentially stifling innovation and equity in research funding. The lack of transparency and explainability in AI processes could also erode trust among stakeholders, undermining the legitimacy of funding decisions.

To mitigate these risks, a balanced approach is essential, where AI's analytical strengths are harmoniously integrated with the nuanced understanding and strategic oversight provided by human experts. This approach entails continuous monitoring, evaluation, and adaptation of AI systems to ensure they remain aligned with the dynamic landscape of research funding and the principles of ethical and responsible decision-making.

In wrapping up, our exploration in thissection highlights the dual narrative of AI in research funding: the immense potential to revolutionize the decision-making process and the critical need for vigilance and collaboration to navigate the associated challenges. As we advance, the journey will delve into tailoring AI solutions to specific use cases and bottlenecks identified in our research, further refining the decision-making framework in funding agencies. This ongoing story is a testament to the journey towards a future where funding decisions are not only more informed and strategic but also more equitable, accountable, and aligned with the broader mission of advancing scientific inquiry and innovation.

Targeted AI Solutions for Funding Agencies

As we transition from exploring a holistic, AI-enhanced decision-making system to investigating specific applications, we now turn our focus to addressing the challenges highlighted during stakeholder interviews. Our goal is to present a spectrum of algorithmic options, each with distinct capabilities and considerations, to address the nuanced demands of matching peer reviewers to research proposals.

Automated Peer Reviewer Assignment

The pivotal role of peer reviewer assignment in research proposal evaluations calls for more than a mere administrative pairing. It is a critical exercise that influences the integrity and trajectory of research funding, as emphasized in our earlier discussions. To elevate the precision and fairness of this process, we propose a machine learning-driven system designed to refine the alignment between a reviewer's expertise and a proposal's subject matter, transcending the limitations of traditional selection methods.

The move towards algorithmic peer reviewer matching is envisioned not as a replacement of the human element but as its augmentation. This advancement aims to ameliorate the inherent subjectivity and bias of manual evaluations. Our proposed system employs a suite of algorithmic strategies, each contributing its unique strengths to the task:

Keyword Matching involves scanning proposals and reviewer profiles for pertinent keywords that reflect research interests or expertise. Its straightforward implementation and rapid processing capabilities make it a popular initial choice for automated text analysis. The transparency of its criteria is a notable advantage, providing clarity in the decision-making process. However, keyword matching faces challenges, including the risk of oversimplification and inaccurate matches due to the context-dependent nature of language. Furthermore, the requirement for manual curation of keyword lists may be labor-intensive, potentially undermining the efficiency of the process.

TF-IDF (Term Frequency-Inverse Document Frequency) Analysis extends beyond simple keyword matching by quantifying the significance of a word within a document relative to a corpus, thus offering a more nuanced, context-aware approach. This method effectively reduces common noise by assigning lower weights to frequent but irrelevant words. Despite these improvements, TF-IDF is still limited to term matching and produces high-dimensional, sparse vectors that may require additional dimensionality reduction techniques. A "sparse vector" refers to a vector in which most elements are zero. Each dimension in the vector corresponds to a unique word in the overall corpus of documents. If a document only contains a small subset of these words, then most of the vector's elements will be zero, indicating the absence of the rest of the words.

Semantic Embeddings represent an advanced method, providing rich vector representations of words and phrases that encapsulate deeper meanings and relationships. Semantic embeddings involve the use of algorithms to create vector representations of words and phrases, capturing not just the presence of terms but also their meanings and the relationships between them. These embeddings allow for a more profound understanding of text and offer versatility across various Natural Language Processing tasks. The trade-offs include their resource-intensive nature, which can be challenging for organizations with limited computational capabilities, and their inherent complexity, which may obscure the rationale behind specific matches.

Finally, Large Language Models (LLMs) like GPT-3, trained on extensive datasets, emulate human-like text comprehension and generate advanced semantic text analysis. LLMs offer dynamic learning capabilities and an advanced level of contextual comprehension. However, they are computationally intensive and can perpetuate biases present in their training data, raising concerns about fairness and transparency in the matching process. Moreover, using LLMs frequently involves interfacing with external APIs, which raises significant data privacy concerns. When sensitive or proprietary information is involved, the reliance on external API services can pose risks related to data security and sovereignty, requiring stringent measures to safeguard the confidentiality and integrity of the data being processed.

Each method's implementation will depend on the agency's needs, balancing simplicity, accuracy, and resource constraints. It's a delicate interplay of advancing technology and maintaining the human touch that characterizes effective peer review processes.

In light of the simulated nature of our data, we recognize that the demonstrated accuracies and effectiveness of these models may differ in real-world applications. Therefore, we present these AI strategies as a conceptual framework, with the understanding that empirical validation with actual data is essential for future research beyond this dissertation.

Methodological Approach

In this section, we delve into the practical implementation of an algorithmic system designed to streamline matching research proposals with the most suitable academic reviewers. We developed a simulated dataset to model the matching of research proposals with the most apt academic reviewers. Due to the absence of actual proposals and the constraints imposed by intellectual property considerations, a simulation involving 10 proposals and 4 reviewers was constructed using Large Language Models (LLMs), specifically text-davinci-003. The prompt directed the LLM to generate proposals and reviewer profiles with some disciplinary overlap, ensuring a realistic and challenging matching scenario. The disciplines' overlap between proposals and reviewers was intentional, providing a nuanced setup to test the effectiveness and precision of the matching algorithms. Such a setup mimics the real-world scenario where reviewers often have expertise spanning multiple, related fields, thus adding layers of complexity to the matching process. This approach not only facilitates the development of sophisticated matching algorithms but also offers a sandbox for experimenting with various computational strategies to achieve the best alignment between reviewers' expertise and the thematic content of the proposals. To facilitate the matching, we employ a three-pronged computational approach:

- TF-IDF Vectorization: We generate a matrix of TF-IDF (Term Frequency-Inverse Document Frequency) scores that reflect the importance of words within the proposals and reviewers' interests relative to a collection of texts. This matrix serves as the foundation for calculating cosine similarity scores, providing a baseline measurement of textual relevance. The TF-IDF score for a term in a document is calculated as:

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \text{IDF}(t)$$

where:

$\text{TF}(t, d)$ is the term frequency of term t in document d.

$\text{IDF}(t, d)$ is the inverse document frequency of term t , calculated as $\text{IDF}(t) = \log\left(\frac{N}{\text{df}(t)}\right)$, with N being the total number of documents and $df(t)$ the number of documents containing term t.

- Sentence Embeddings: We convert proposal and reviewer texts into high-dimensional vectors using the 'all-MiniLM-L6-v2' model from sentence transformers. These embeddings capture semantic nuances at the sentence level, enabling a more refined comparison of the proposals and reviewers' interests.
- LLM Embeddings: To capture deeper linguistic patterns and subtleties, we leverage embeddings from a Large Language Model (LLM), specifically GPT-3's text-embedding-3-small. These embeddings offer a sophisticated analysis of the text, revealing intricate alignments between proposals and reviewer expertise that may not be apparent through traditional methods.

We analyze the dataset to discern the most appropriate reviewer for each proposal. The analysis proceeds through the following steps:

- We compute the cosine similarity scores using the TF-IDF matrix to identify initial matches based on textual relevance.
- We further analyze the semantic similarity between proposals and reviewers by comparing their sentence embeddings.
- For a more nuanced understanding, we examine the LLM embeddings, which consider the broader context and deeper language patterns.

The matching of proposals and reviewers is quantified by computing the cosine similarity between their respective vectors (TF-IDF, sentence embeddings, and LLM embeddings):

$$\text{CosineSimilarity}(V_1, V_2) = \frac{V_1 \cdot V_2}{|V_1||V_2|}$$

Where V_1 *and* V_2 are the vector representations of the proposal and reviewer's profile, respectively.

Each of these methods illuminates different facets of the matching process, allowing us to triangulate the best reviewer for each proposal. For instance, while TF-IDF may highlight reviewers with interests in specific terms present in the proposals, the sentence embeddings may suggest matches based on the overall thematic content. LLM embeddings, with their advanced understanding of language, may unveil subtler connections that the other methods miss. It is important to note that the predictive accuracy of our models is contingent upon the scope and quality of the data we use. Since we're currently operating with simulated datasets, further experimentation with real-world data is necessary to validate and enhance the reliability of our approach. For a more robust application, incorporating a broader dataset and iterative model refinement will be essential steps in achieving a system that not only automates but augments the peer reviewer selection process with precision.

Methodological Output

The computational analysis yielded quantitative similarity scores across three distinct methods: TF-IDF Cosine Similarity, Embeddings Cosine Scores, and LLM Similarity Scores. These scores represent the degree of textual and semantic alignment between each research proposal and the expertise of potential peer reviewers. Tables 4.5, 4.6, and 4.7 present these results, offering a comparative view of the different measures.

This table provides the cosine similarity scores based on TF-IDF vectorization. The scores range from 0 to 1, where higher values indicate greater textual relevance between proposals and reviewers' research interests.

Table 4.5. TF-IDF Cosine Score Matrix Between Proposals and Reviewer Expertise

Proposal	Reviewer 1	Reviewer 2	Reviewer 3	Reviewer 4
Proposal 1	**0.22669204**	0.05991927	0.06734914	0.16958444
Proposal 2	0.00928996	**0.4347961**	0.02345147	0.05236621
Proposal 3	0.10504094	0.07034281	**0.27588192**	0.0899709
Proposal 4	0.1235251	0.04942682	0.06794146	**0.48415037**
Proposal 5	0.00800135	0.04497545	0.03299447	**0.11266205**
Proposal 6	0.00780118	0.02996051	0.01969321	**0.04397416**
Proposal 7	0.05259771	0.0869149	0.06259185	**0.09443298**
Proposal 8	0.11723393	0.04702453	**0.23209542**	0.07393683
Proposal 9	0.01652217	0.03403628	0.01528573	**0.07438471**
Proposal 10	0.00899238	0.01852464	0.00831943	**0.01857697**

The TF-IDF scores in table 4.5 reflect direct word correlations between proposals and reviewers' interests, with lower scores often expected due to its focus on specific terms over general meaning. For example, a notable score between Proposal 2 and Reviewer 2 indicates there are words commonly used by both, hinting at a possible good match.

Table 4.6. Embeddings Cosine Similarity Scores Matrix Between Proposals and Reviewer Expertise

Proposal	Reviewer 1	Reviewer 2	Reviewer 3	Reviewer 4
Proposal 1	**0.66688347**	0.11799975	0.00913928	0.21374485
Proposal 2	0.18082309	**0.7830719**	0.11291002	0.09007866
Proposal 3	-0.08634101	0.05194986	**0.72061366**	0.03496295
Proposal 4	0.23185849	0.07448343	0.07964548	**0.6115011**
Proposal 5	0.04515564	0.05736925	**0.23112231**	0.10094491
Proposal 6	0.03381684	0.07053979	**0.10454457**	0.09324034
Proposal 7	0.00895264	**0.21436653**	0.03871019	-0.00774641
Proposal 8	-0.08648443	-0.01102615	**0.10281372**	0.00410353
Proposal 9	0.11871822	**0.12764686**	0.07185243	0.04992406
Proposal 10	**0.35336617**	0.17707303	0.10220738	0.1464178

In contrast, the scores derived from sentence embeddings in table 4.6 offer a more substantial measure of semantic coherence. This method, by interpreting the surrounding context of words, provides a richer analysis of the proposals' thematic essence. The notably high score connecting Proposal 2 with Reviewer 2 signals a significant semantic correspondence, hinting at a potentially fruitful review pairing. The same applies to Proposal 3 with Reviewer 3.

Table 4.7. LLM Similarity Scores Matrix Between Proposals and Reviewer Expertise

Proposal	Reviewer 1	Reviewer 2	Reviewer 3	Review 4
Proposal 1	**0.70466987**	0.26417198	0.23881241	0.31036715
Proposal 2	0.2899655	**0.66203703**	0.19571782	0.19571782
Proposal 3	0.12901175	0.15296323	**0.71023615**	0.14602454
Proposal 4	0.39897209	0.21005064	0.20653234	**0.67179618**
Proposal 5	0.20101445	0.18377613	**0.26217213**	0.17563109

Proposal	Reviewer 1	Reviewer 2	Reviewer 3	Review 4
Proposal 6	0.15260795	0.20143713	**0.29358053**	0.10438141
Proposal 7	0.17958702	**0.31880236**	0.14152623	0.16108887
Proposal 8	0.20474994	0.13802257	**0.24819202**	0.20432528
Proposal 9	**0.29136385**	0.15942507	0.19404498	0.14979571
Proposal 10	**0.38839356**	0.33092103	0.18985086	0.24207876

The LLM-based scores in table 4.7 present the most pronounced and consistent correlations across the dataset. This suggests that, when full linguistic context and complex patterns are taken into account, proposals and reviewers' interests align more closely than what previous methods indicated. For instance, the alignment between Proposal 1 and Reviewer 1 emerges as particularly strong, suggesting that the depth of understanding afforded by LLMs could be highly beneficial in identifying suitable reviewer-proposal pairings.

The divergence in results between methods stems from their varying approaches to text analysis. TF-IDF skews towards quantifying term frequency, often glossing over the subtleties of language. Sentence embeddings enhance the analysis by accounting for context and semantics but might still miss the nuanced linguistic intricacies that LLMs capture. The LLMs, with their sophisticated grasp of language, tend to provide a more holistic and uniform view of textual similarity. This is evident in the way LLMs uniformly recognized the alignment across a broader range of topics, such as matching a proposal on "Climate Change Impacts on Coral Reef Ecosystems" with a reviewer focused on marine life and environmental changes, even if specific terms don't directly overlap. This nuanced understanding reinforces LLMs' capability to bridge linguistic gaps between proposals and reviewers' expertise, showcasing their potential for more nuanced and accurate matchmaking in peer review processes.

Moving forward, it's paramount that these computational assessments undergo validation against human expertise to confirm that high similarity scores truly equate to appropriate reviewer-proposal matches. Depending on this validation, we may need to fine-tune our models—for instance, adjusting the LLM approach to better distinguish between varying degrees of match suitability.

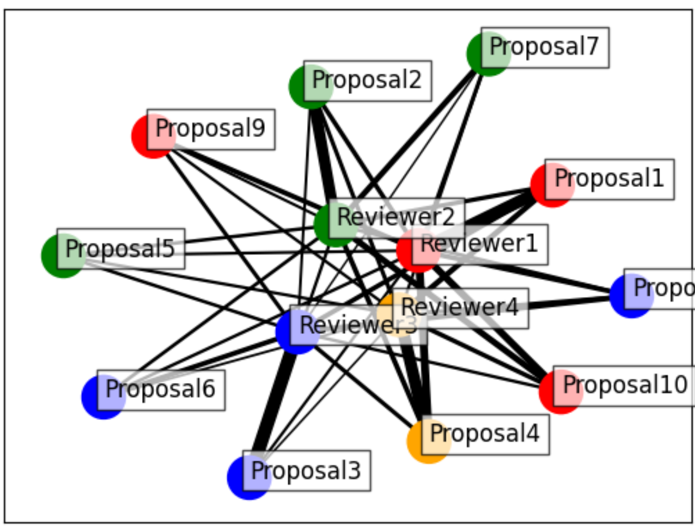
The goal is to seamlessly integrate these computational strategies into a comprehensive reviewer matching system, potentially automating the initial phase of the matching process. However, it's vital to ensure that this automation is complemented with human oversight, allowing for consideration of dynamic research trends, interdisciplinary value, and the strategic aims of the funding organization.

As we continue to refine our matching system, we introduce graph-based techniques to offer a more intricate analysis. These techniques allow us to visualize and measure the strength of connections between research proposals and reviewers in a nuanced way.

Our methodology for this enhanced analysis involves combining numerical scores from TF-IDF and sentence embeddings to assign weights to the 'edges' in the network graph. These edges represent the connections between proposals and reviewers, and the weighting reflects the potential match strength based on textual and semantic similarities.

In our analysis, we apply the Louvain method, a popular community detection algorithm, to identify 'communities' within the network graph that signify shared research interests or thematic connections between proposals and reviewers. This approach partitions the network into color-coded clusters, each representing a group of nodes, either proposals or reviewers, that are more densely connected to each other than to the rest of the network. By visualizing these communities, we gain a macroscopic view of the network's structure, which not only suggests potential individual matches but also reveals overarching patterns of similarity, thematic clustering, and collaborative potential within the research landscape. Such insights are invaluable for funding agencies as they enable a deeper understanding of how different proposals and reviewers fit into the larger context of research themes and trends, thus supporting more strategic and informed decision-making in the funding process.

Figure 4.11. Network Analysis of Proposal-Reviewer Matches Using LLM Similarity Weights



Our network graph reveals several key insights:

- Proposals with a red hue, such as 'Proposal 1' and 'Proposal 10', indicate a strong association with 'Reviewer1', suggesting that these proposals align well with the reviewer's expertise in the healthcare domain, particularly in areas utilizing advanced machine learning.

- Proposals colored in green, including 'Proposal 2', 'Proposal 5', and 'Proposal 7', reflect a significant match with 'Reviewer 2', denoting a shared focus on quantum computing and the development of algorithms for next-generation computational models. The pronounced thickness of the edge between 'Proposal 2' and 'Reviewer 2' surpasses that of other connections, signifying a stronger similarity or potential match. This implies that the research topic of 'Proposal 2' aligns exceptionally well with 'Reviewer 2's expertise, suggesting a highly relevant and strong potential for an informed evaluation.
- The blue nodes for 'Proposal 3', 'Proposal 6', and 'Proposal 8' suggest these proposals resonate with 'Reviewer3's research interests in environmental changes and marine life, signaling a thematic alignment with studies on climate change and coral reef ecosystems.
- Lastly, proposals matched with 'Reviewer4' in orange, such as 'Proposal4', denote a congruence with research themes related to linguistics and machine learning for natural language processing, indicating that these proposals might benefit from the reviewer's expertise in cognitive science and automated translation systems.

Designing an AI Prototype for Enhanced Transparency and Trust in Funding Agencies

In the pursuit of integrating artificial intelligence into the funding decision-making process, the issue of explainability arises as a crucial concern. Stakeholders have voiced apprehensions about AI systems acting as "black boxes" opaque entities whose workings and decisions are not readily apparent. This opacity can hinder acceptance and trust within the scientific community. Earlier in this chapter, we discussed tools such as SHAP and LIME under "Review Synthesis and Insights" stage which aimed to uncover the significance of features according to peer reviewers. These tools not only provide clarity on how AI models arrive at decisions but also help in aligning AI systems with the values and goals of funding agencies.

In the realm of funding agencies, where the impact of decisions is significant, AI systems must offer clear and justifiable results. While simple algorithms like decision trees and linear regression models provide a transparent view into the AI's decision-making process, their limited complexity can sometimes fall short in capturing the nuances of the data (Candelon, Evgeniou, & Martens, 2023; Schmidt, Biessmann, & Teubner, 2020). Conversely, as we deal with more complicated decision-making scenarios, interpretability tools such as SHAP (Shapley Additive exPlanations) become essential. These tools can dissect complex models to show how different factors influence AI predictions, striking a balance between interpretability and predictive power.

Methodological Approach

In our progression toward a more interpretable AI-assisted decision-making process for funding agencies, we employ SHAP as one of the tools that brings transparency to complex models. Here's how we put this into action:

We start by creating a fictional historical dataset, simulating the diverse considerations in funding decisions, such as innovation scores, team expertise, budget requests, project duration, and more. Although we lack real data, this fabricated dataset allows us to demonstrate our methodology, which must be further validated in real-world applications.

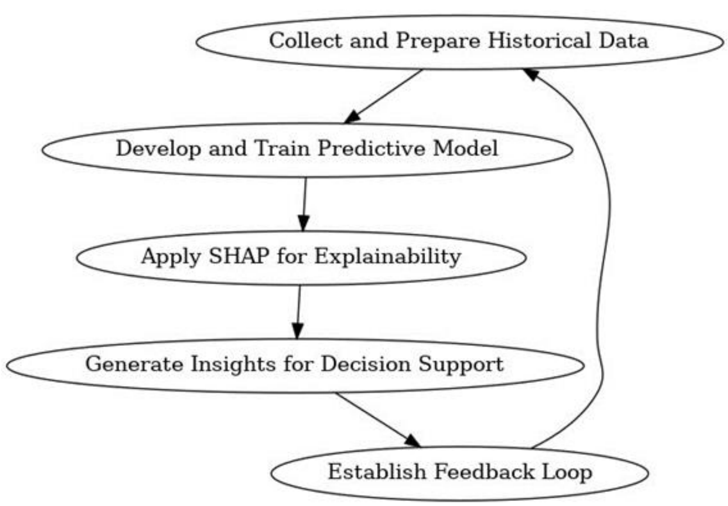
Using a Random Forest Classifier, a machine learning algorithm praised for its ability to handle a mix of data types and complex interactions, we develop a predictive model. This model aims to predict funding outcomes, trained on our synthesized dataset.

After training, we introduce SHAP analysis into the mix. SHAP (SHapley Additive exPlanations) breaks down the predictions of our model, clarifying the role each feature plays in the decision. It answers questions like "How much does innovation score influence the likelihood of receiving funding?" by assigning a value to each feature for every prediction. These values are not just numbers; they represent the weight of each feature in the model's decisions, illuminating the 'why' behind the model's output.

This approach transcends the capabilities we discussed earlier in the chapter, where we used SHAP and LIME to understand peer reviewers' preferences. Here, we're digging deeper into SHAP's utility, aiming to demystify the model's functioning for those who rely on its decisions.

The entire process, from preparing the simulated data to generating insights for decision support, is structured into a clear workflow in Figure 4.12. We collect and prepare the data, develop and train the predictive model, apply SHAP for explainability, and then generate insights to support funding decisions. This workflow is designed to be cyclical, with a feedback loop that allows continuous improvement based on new data and outcomes.

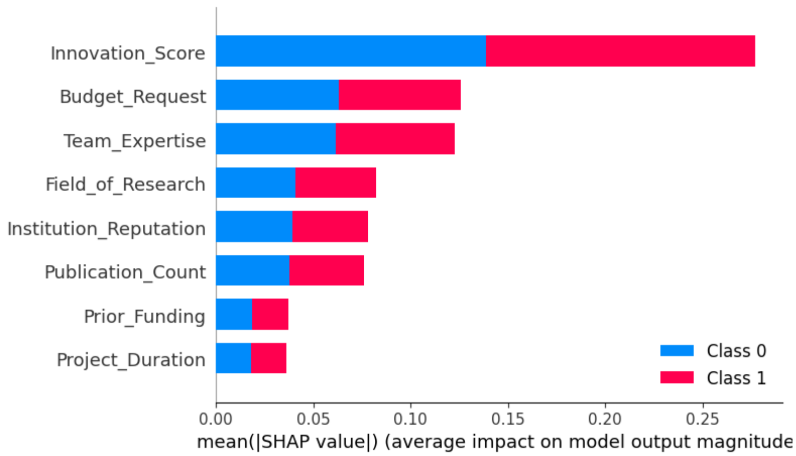
Figure 4.12. The Data-Driven Decision-Making Cycle Enhanced by SHAP for Model Transparency and Insight Generation



Methodological Output

The SHAP summary plot displayed in Figure 4.13 serves as a key to understanding the decision-making criteria of our predictive model regarding funding outcomes. The color-coding in the plot, with blue representing Class 0 and red representing Class 1, allows us to discern the features' influence on different predicted outcomes. For instance, a feature that has longer red bars suggests it has a stronger impact when the model predicts Class 1.

Figure 4.13. Feature Impact Analysis: SHAP Values Indicating Importance in Funding Decision Model



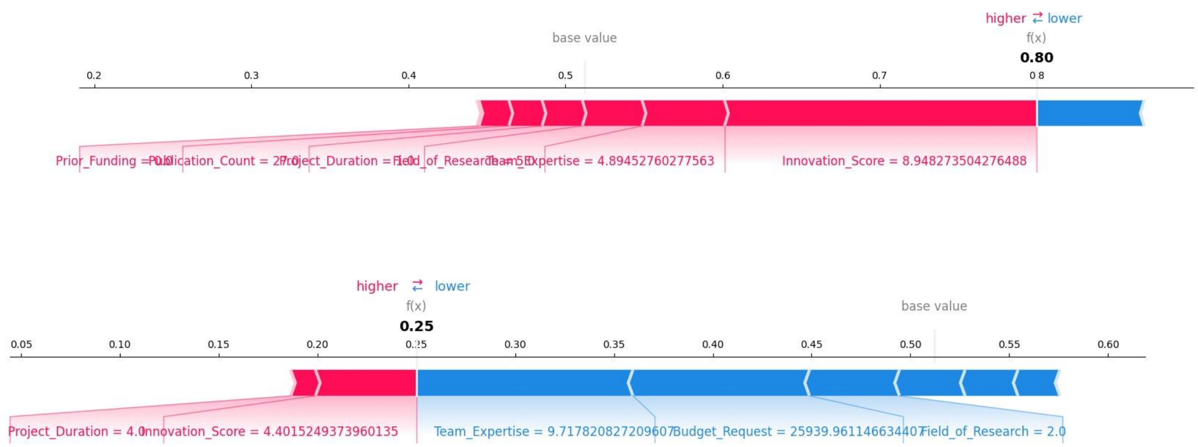
- Innovation Score: The prominence of the innovation score, indicated by the substantial length of the bars, underscores its critical role. This tells us that the model places a high value on the novelty and creative potential of research proposals.
- Budget Request: Following closely is the budget request, with its significant but slightly lesser impact compared to innovation. It appears that while the cost of the research is important, it is the inventive qualities that take precedence.
- Team Expertise: Equally impactful as the budget is the expertise of the research team. This reflects the model's emphasis on the capability and experience of the individuals behind the proposals.
- Field of Research and Institution Reputation: These factors, while influential, rank below innovation, budget, and team expertise. Their moderate impact suggests they are secondary but still relevant considerations in the predictive assessment.
- Publication Count: The model gives some weight to the historical academic output, indicative of a moderate effect on the decision. This may reflect an acknowledgment of past scholarly contributions without overshadowing the potential of new research.
- Prior Funding and Project Duration: These have the smallest impact on the model's predictions, which could imply that the model is more forward-looking, focusing on the proposal's current merits rather than past funding or the duration of the project.

Local Insights: Interpreting Feature Influence in Funding Decisions

In our pursuit of a deeper understanding of how AI models make funding decisions, we take a closer look at individual proposals using SHAP force plots. These plots offer a window into the model's logic for each specific case, revealing how various factors weigh in on the decision to accept or reject a funding proposal.

In the first example, illustrated in the SHAP force plot, we observe that the Innovation Score exerts a strong positive influence, suggesting that groundbreaking ideas are highly valued. Conversely, in the second example, despite a favorable Innovation Score, a combination of other factors, including Team Expertise and Budget Request, tip the scale toward rejection. This nuanced evaluation highlights the model's complex decision-making process, where multiple attributes are balanced to determine the likelihood of funding success.

Figure 4.14. Illustrating Feature Contributions to Predictive Decisions with SHAP



Additionally, we apply LIME to further simplify and explain individual predictions. While SHAP provides a global perspective, LIME narrows down to specific predictions, constructing a simpler model around the prediction to clarify the rationale. For instance, one LIME analysis indicates that a high budget request may detract from the chances of acceptance, even if the proposal is innovative. The graphical representation in LIME clearly marks the positive and negative contributions of each feature, making it easier to understand why a proposal was likely to be rejected.

Figure 4.15. LIME Application to Explain a Funding Decision

These detailed insights from both SHAP and LIME are invaluable for funding agencies. They demystify the AI decision-making process, ensuring that the allocation of resources is transparent and justifiable. By incorporating these tools, agencies not only support clear and accountable decision-making but also pave the way for continuous improvement of their evaluation processes. This approach aligns with the ethical commitment to fairness and transparency, bolstering trust among applicants and stakeholders in the integrity of the funding process.

Streamlining Proposal Management with AI: Tackling Volume and Complexity

As we venture further into optimizing the management of research proposals, we confront the need to efficiently handle the increasing number and complexity of submissions. Traditional review processes are being stretched to their limits, calling for a modernized approach that leverages artificial intelligence to maintain accuracy while accelerating the workflow.

Harnessing Zero-Shot Classification: A Novel AI Approach for Streamlined Proposal Categorization

Zero-shot classification represents a leap forward in machine learning, enabling models to recognize and categorize text into themes or topics that were not part of their initial training data (Xian et al., 2018). This approach is built upon the idea of semantic representations, it teaches models to generate and utilize rich contextual embeddings that map both familiar and novel concepts into a shared semantic space. By doing so, the model can make educated guesses about the most fitting categories for new submissions based on their contextual similarities to known data.

At the heart of this system is BERT (Bidirectional Encoder Representations from Transformers), an advanced natural language processing model that has been trained on a vast array of text. BERT's deep training allows it to understand the subtleties of language, which makes it exceptionally well-suited for the task of zero-shot classification. For funding agencies, this means being able to swiftly and effectively organize grant proposals, even those that venture into new and undefined research territories.

Employing BERT for zero-shot classification offers a significant advantage: it assigns confidence scores for each category it suggests, ensuring that proposals are not just sorted rapidly but also with a high level of precision. This is especially beneficial for sorting proposals in nascent research fields, where there may be a lack of established benchmarks or sufficient historical data to guide classification.

Methodological Approach and Output

In our code, we are harnessing the power of artificial intelligence to categorize research proposals by topic swiftly and accurately using a technique known as zero-shot classification. This advanced AI method, enabled by a pre-trained model available through the Hugging Face transformers library (Wolf et al., 2020), doesn't require prior knowledge of the specific topics; it can intelligently assign categories to texts based on its understanding of language semantics.

Here's what the code is designed to do:

- It loads a zero-shot classification model, setting it up to evaluate text against a series of possible topics.
- It defines a function, **classify_topic**, which takes a piece of text and a list of candidate labels or topics and uses the model to classify the text.
- We input example abstracts representing a research proposal into the model.
- The model assesses each abstract and assigns it to the most fitting topic from a predefined list that includes areas like "Environmental Science" and "Space Exploration".
- Along with the topic, the model provides a confidence score, reflecting how certain it is about the classification.

When we run this code, a sample of our results are as follows:

- The first abstract, concerning marine biodiversity and climate change, is classified under "Environmental Science" with a moderate confidence score of approximately 0.56, suggesting a reasonable match but indicating that there might be room for ambiguity or overlap with other topics.
- The second abstract, focused on public health strategies for infectious diseases, is confidently categorized as "Public Health" with a higher confidence score of about 0.68, signaling a strong match between the content and the category.
- Subsequent abstracts are classified with increasing confidence scores, with the last abstract being linked to "Space Exploration" with a very high confidence of over 0.91, implying a very clear and specific match between the proposal content and the topic.

These outcomes demonstrate the model's ability to interpret the essence of various research proposals and align them with the most relevant topics. The confidence scores provide additional insight into the clarity of the match, which can be particularly useful for program managers in funding agencies as they prioritize and route proposals for further evaluation.

By implementing this AI-driven classification system, we can streamline the initial stages of proposal management, ensuring that each piece of research is recognized for its thematic significance and directed appropriately within the funding process. This not only maximizes efficiency but also helps maintain a high standard of relevance and precision in the evaluation of burgeoning research initiatives.

Navigating the Uncharted: Unsupervised Learning for Dynamic Proposal Categorization in Funding Agencies

As we progress in our exploration of AI's applications within the funding agency's framework, we delve into the potential of unsupervised learning, a method that excels in categorizing content without relying on predefined labels or examples (Xu & Wunsch, 2005). This approach is particularly suited for the dynamic and ever-expanding landscape of research where novel themes emerge, and standard classifications may not yet exist.

Zero-shot classification, while a supervised learning technique, is adept at categorizing texts into both seen and unseen topics by leveraging a model's existing knowledge base. It predicts the relevance of content to various categories, even if those categories weren't part of its initial training set, making it a flexible tool for classifying proposals against a backdrop of known research domains.

In contrast, unsupervised learning methods, like K-means clustering (Jain, 2010), Hierarchical Clustering, and Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003), don't require labeled data to find structure within a dataset. These methods autonomously identify clusters and patterns, making sense of the data by revealing natural groupings and topics. For funding agencies, this means the ability to detect and adapt to emerging research trends and domains without the need for manual categorization or prior examples, a significant advantage when mapping the frontiers of scientific inquiry.

Methodological Approach and Output

We start our demo by applying some of the unsupervised learning techniques to analyze a diverse collection of 20 research abstracts. This approach mirrors the wide-ranging subjects encountered in real-world proposal submissions, embracing the variety that characterizes the current research landscape.

We commenced our analysis with TF-IDF vectorization, transforming the textual data into numerical values that highlight the importance of each word across the collective body of abstracts. Following this transformation, we engaged K-Means clustering, a technique that sorts these abstracts into five naturally emerging groups, determined by the similarity of their textual features. The K-Means algorithm partitions the documents into k clusters by minimizing the within-cluster variance, defined as:

$$\sum_{i=1}^{k} \sum_{x \in C_i} |x - \mu_i|^2$$

Where C_i is the set of points in cluster i and μ_i is the centroid of C_i.

This process eschews pre-set categories, allowing for the spontaneous emergence of clusters guided by the inherent relationships within the text.

Simultaneously, we applied Latent Dirichlet Allocation (LDA) for topic modeling, a process that discerns the predominant themes within the corpus of abstracts. LDA assigns topics to documents and words to topics, based on the posterior distribution:

$$P(\text{topic} \mid \text{document}) \propto P(\text{document} \mid \text{topic}) \cdot P(\text{topic})$$

LDA reveals the overarching topics present in each abstract, facilitating the discovery of thematic trends and patterns within the pool of submissions.

The fruits of this computational labor were then systematically organized into a data frame, a tabular representation that aligns each abstract with its corresponding cluster and LDA-identified topic. This juxtaposition forms a clear and interpretable outline, which provides invaluable insights into the thematic diversity of the proposals. It forms a solid basis for more nuanced, data-informed review strategies that can adapt to the dynamic nature of research fields.

Table 4.8. Unsupervised Topic Classification

Abstract	Cluster	LDA Score
The impact of climate change on global agricultural practices is profound, necessitating the study of adaptive strategies to ensure food security.	1	3
Analyzing the correlation between urbanization and the mental health of adolescents in metropolitan areas	3	1
Exploring the potential of quantum computing in solving complex computational problems that are intractable for classical computers.	4	2
Investigating the role of social media in shaping public opinion during election cycles.	3	2
A comprehensive study on the use of CRISPR technology for targeted gene editing and its ethical implications.	0	4
Developing a new framework for cybersecurity in the age of Internet of Things devices.	0	0
Examining the effects of microplastics on marine ecosystems and the food chain.	2	4
Assessing the effectiveness of virtual reality as a tool for enhancing learning experiences in K-12 education.	1	3
The use of machine learning algorithms in predicting stock market trends based on historical data.	1	4
Understanding the role of gut microbiota in human health and disease.	3	1

Abstract	Cluster	LDA Score
The development and testing of self-driving car technology in urban environments.	0	2

In summary, the data frame encapsulating our unsupervised classification's outcomes offers a detailed map of the proposals' thematic terrain. It's a critical tool that not only simplifies the initial categorization of submissions but also equips program managers with actionable insights for the strategic handling of the review process. The analytical results, carefully compiled, present a clear pathway for funding agencies to navigate the complexities of proposal management with confidence and precision.

Conclusion

As we conclude this chapter, we reflect on the journey that began in Chapter 3, where we set out to integrate AI methodologies into the decision-making processes of funding agencies. From the initial stages, where alternatives were defined and utilities assessed, to the complex task of proposal categorization, the chapter has systematically explored the application of AI to streamline and enhance various facets of the funding decision pipeline.

Through the deployment of both supervised and unsupervised machine learning techniques, we have illustrated how AI can provide scalable solutions to the challenges posed by large volumes of diverse research proposals. We demonstrated the practicality of zero-shot classification in swiftly categorizing proposals into predefined themes, enabling program managers to efficiently handle submissions across numerous evolving research fields. Furthermore, we delved into the capabilities of unsupervised classification methods, showcasing their potential to discover organic groupings and latent topics within proposals, thus facilitating a data-driven understanding of the research landscape.

The chapter highlighted the critical role of explainability tools such as SHAP and LIME in providing transparency and insight into AI-driven evaluations. These tools act as bridges between complex algorithmic decisions and the stakeholders who rely on them, offering clarity and actionable understanding necessary for ethical and equitable decision-making.

In summary, this chapter has not only presented a suite of AI approaches for enhancing the operational efficiency of funding agencies but also underscored the importance of explainability and fairness in AI applications. As we transition to the next chapter, we carry forward these insights, aiming to address specific use cases and bottlenecks identified during our interviews with stakeholders. We will continue to propose innovative AI solutions, keeping in mind the evolving needs of the funding agencies and the research community at large.

Chapter 5: Final Remarks

As we conclude this dissertation, we reflect on a journey that has woven the threads of Artificial Intelligence (AI) with the intricate operations of funding agencies, aiming to unveil AI's potential in enhancing decision-making processes marked by improved efficiency, transparency, and equity.

Drawing from my experiences and insights gained through this exploration, it became apparent that the utilization of AI in the realm of funding agencies is not just a matter of technological upgrade but a strategic necessity. Surprisingly, most funding entities remain detached from the AI revolution, with notable exceptions like the NNSFC, whose AI adoption details remain elusive, revealing a gap in transparency and understanding. This stark underutilization underscores a broader issue: the reluctance to evolve and embrace new methodologies that could significantly enhance the scientific and administrative aspects of funding.

The concept of the science of science (SciSci) resonates deeply with this narrative (National Science and Technology Council, 2008), advocating for an empirical and theoretical approach to understanding and improving the scientific enterprise, including R&D management decisions. As science progresses across various fields, so should the tools we employ to guide, evaluate, and measure this advancement. Our traditional reliance on peer review, despite its merits, often falls short in meeting the evolving demands of scientific inquiry and national priorities, as evidenced by the disproportionate funding allocation to certain research areas in my professional experience.

The integration of AI offers a promising avenue to address these challenges. It brings to the table an array of capabilities, from data processing and analysis to predictive modeling and strategic alignment that can significantly refine how funding agencies operate. However, this integration is not without its challenges. The apprehension within the scientific community towards AI, often perceived as a 'black box', highlights the necessity of demystifying AI processes and fostering a collaborative environment where AI and human expertise coalesce to produce more objective, transparent, and strategic funding decisions.

This dissertation, therefore, is not just an academic exercise but a venture into reimagining how funding agencies can leverage AI to align more closely with national priorities and the evolving landscape of scientific research. By integrating AI, we do not seek to replace the nuanced human judgment intrinsic to peer review but to augment it, ensuring that decisions are both scientifically robust and strategically focused.

In essence, this research serves as a precursor to a broader, more systematic integration of AI in the funding process, advocating for an approach that is open, exploratory, and cognizant of the delicate balance between technological innovation and ethical considerations. It is a call to action for funding agencies to not only embrace AI but to do so with a vision that transcends operational efficiency, aiming instead to fundamentally enhance the scientific, strategic, and ethical fabric of their decision-making processes.

Restating Research Problem and Objectives

This inquiry was prompted by the challenge of discerning AI's role in refining funding agencies' decision-making frameworks. The objectives were twofold: to dissect the current mechanisms and to propose AI-driven solutions that could mitigate existing challenges.

Summary of Key Findings

In this dissertation, we have charted a course through the multifaceted landscape of Artificial Intelligence (AI) within public funding agencies, assessing its potential to transform their decision-making processes. We delved into a comprehensive landscape analysis in Chapter 2, uncovering the complex operational challenges that these agencies confront and pinpointing opportunities where AI could serve as a pivotal tool for innovation and improvement. Valuable perspectives were gleaned as well from stakeholder interviews. These conversations shed light on the present and anticipated influence of AI, resonating with recurring themes of efficiency enhancement and the necessity to navigate ethical considerations thoughtfully. The insights gained from these dialogues underscored the need for AI systems that not only optimize decision-making but also uphold ethical standards. Subsequently, Chapter 3 laid the historical and theoretical groundwork, exploring the evolution of AI and its intersection with decision theory, which provided a critical context for the subsequent examination of AI's practical applications. This foundation was crucial for understanding the capacity and limitations of AI within the intricate web of funding decisions. In response to these collected insights, Chapter 4 presented a strategic AI framework, illustrating proposed models and methodologies designed to achieve a harmonious fusion of AI's computational prowess with the indispensable nuances of human expertise. This framework advocates for AI's adoption in a manner that maintains a delicate equilibrium between the precision of algorithms and the discernment of human judgment.

Taken together, these chapters form a narrative arc that begins with the identification of challenges and leads to the proposition of strategic, AI-infused solutions, setting the stage for a future where public funding agencies can leverage technology to serve the public good with greater efficacy, transparency, and fairness.

Discussion on AI Integration

Our comprehensive examination not only addressed isolated challenges but also offered a holistic view of the funding landscape. Through landscape analysis, stakeholder interviews, and literature review, we crafted a two-tiered framework encapsulating both strategic and operational dimensions. This framework serves as a blueprint for integrating various AI models to address identified gaps at each stage and enhance existing processes, ensuring a seamless and efficient funding mechanism.

Policymakers should have a vested interest in AI integration at each step of the funding process for several reasons. At the strategic level, AI can provide a macro-level analysis of funding trends, aligning decision-making with national and global research priorities. Operationally, AI can streamline tasks such as peer reviewer matching and proposal management, thereby increasing efficiency and reducing the time and resources spent on administrative processes.

However, integrating AI into the funding process can introduce risks such as potential biases in algorithmic decisions, loss of transparency, and over-reliance on automated systems. To mitigate these risks, it's imperative to implement safeguards like algorithm auditing, transparency tools like SHAP and LIME, and maintaining human oversight. These measures can ensure that AI acts as an aid rather than a replacement to human judgment, preserving the integrity of the funding process while leveraging AI's capabilities to enhance decision-making.

Reflection on Methodology

Combining qualitative interviews and quantitative AI model analysis, the mixed-method approach provided a comprehensive understanding of the complexities involved in AI integration within public funding agencies. The addition of data simulation into this methodology offered valuable insights, particularly in environments where real data was scarce or sensitive. Through the creation of simulated datasets, we could model and test the behavior of AI systems in controlled, yet realistic, scenarios, providing a preliminary assessment of how these systems might perform in actual operations.

For instance, in the process of automating peer reviewer assignments, data simulation allowed us to experiment with various matching algorithms and evaluate their effectiveness in aligning reviewer expertise with proposal content. This approach helped in identifying potential strengths and weaknesses of different AI models before their real-world application.

However, the use of data simulation also introduces specific challenges and limitations that need to be carefully considered. One primary concern is the accuracy and realism of the simulated data. If the simulated datasets do not adequately reflect the complexity and variability of real-world data, the findings from these simulations might lead to misleading conclusions about the effectiveness of AI integration. Additionally, there's a risk of overfitting AI models to simulated data, which may not translate well to real-world scenarios, resulting in poor performance when applied to actual data.

Moreover, while data simulation can provide valuable insights into the potential capabilities of AI systems, it cannot fully capture the dynamic and often unpredictable nature of human decision-making processes within funding agencies. Thus, while simulations are a useful tool in the early stages of AI integration planning and testing, they should be complemented with pilot studies and real-world trials to validate AI models thoroughly.

Practical Implications

The practical implications of this dissertation extend beyond offering a strategic guide for AI adoption; they also invoke a broader discourse on the ethical, strategic, and operational facets of integrating AI into funding agency workflows. For policymakers and funding leaders, the insights presented herein illuminate the path toward adopting AI not just as a tool for operational efficiency, but as a catalyst for fostering a more transparent, accountable, and strategic funding ecosystem. This shift necessitates not only a technological transformation but also a cultural and procedural evolution within organizations, embracing AI as a partner in decision-making rather than merely an analytical tool.

Furthermore, for AI developers, this research highlights the imperative of designing AI systems that are not only technically proficient but also ethically responsible and socially sensitive. The development of AI solutions for funding agencies must prioritize transparency, explicability, and alignment with the public interest, ensuring that the integration of AI into public sector decision-making enhances, rather than undermines, public trust and societal welfare.

Additionally, the discussions around data simulation and the integration of AI tools like fuzzy scoring and SVM in the decision-making process reveal the nuanced challenges of balancing advanced AI capabilities with the inherent uncertainties and complexities of funding decisions. This balance underscores the need for continuous learning, adaptation, and ethical vigilance in the deployment of AI systems, ensuring that they effectively serve the strategic objectives and ethical standards of funding agencies.

Theoretical Contributions

The theoretical contributions of this dissertation indeed offer a substantial addition to the discourse on AI within public administration. To further enrich this discussion, it's pertinent to consider the interdisciplinary nature of AI's application in public funding. This work not only contributes to public administration theory but also intersects with the science of science (SciSci), which seeks to understand and improve the scientific enterprise through data-driven methods.

By integrating concepts from AI, decision science, and public administration, this dissertation offers a unique perspective on how AI can be strategically leveraged to enhance the efficiency, transparency, and effectiveness of funding agencies. It also raises important considerations about the ethical implications of AI in public decision-making, contributing to the broader debate on the governance and regulation of AI technologies.

Furthermore, this research provides a conceptual bridge between theoretical insights and practical applications, suggesting a methodological pathway for future empirical studies to test and refine the proposed AI-integrated frameworks. This dual contribution of theory and practice enriches the academic field and offers a valuable guide for practitioners in the public sector looking to navigate the complexities of AI integration.

Limitations and Future Research

The limitations of this study, primarily its reliance on simulated data, highlight critical areas for future research. While the foundational understanding established here is robust, the exploration of AI's potential in funding agencies needs to be expanded to include real-world data. This expansion is crucial for validating the theoretical models and frameworks proposed in this dissertation.

Future research should aim to conduct longitudinal studies to assess the long-term impacts of AI integration in funding agencies, focusing on outcomes such as decision-making efficiency, the accuracy of funding allocations, and the overall effectiveness of the funding process. These studies could provide valuable insights into the sustainability and evolution of AI systems in real operational environments.

Additionally, investigating AI's applicability across different public sector domains would offer a comparative analysis of the challenges and benefits of AI integration. This could include sectors such as healthcare, education, and infrastructure development, where funding decisions are critical to strategic national priorities.

Another important area for future research is the development and testing of AI systems that can dynamically adapt to changing strategic goals and priorities of funding agencies. This would address one of the critical challenges identified in this study, the need for AI systems that are not only accurate and efficient but also flexible and adaptable to evolving policy landscapes.

Lastly, it is imperative to explore the ethical dimensions of AI integration in greater depth. Future research should delve into the development of ethical frameworks and guidelines for AI use in public administration, ensuring that AI integration aligns with principles of fairness, transparency, and public accountability.

Final Thoughts

This dissertation has shed light on AI's transformative capabilities within funding agencies, advocating for a judicious yet forward-looking adoption strategy. The journey of weaving AI into the fabric of public administration is nascent but promising, with the potential to revolutionize the sector's operational ethos and impact.

Reflecting on the discourse and findings presented, it becomes evident that the integration of AI in funding agencies is not merely a technical upgrade but a strategic shift towards more data-driven, transparent, and equitable decision-making processes. This shift, however, must be navigated with a deep understanding of AI's capabilities and limitations, ensuring that its deployment enhances rather than compromises the decision-making quality.

The cautious yet optimistic approach advocated here underscores the need for AI solutions that transcend technical excellence to embody ethical integrity and transparency. These solutions should not only align with the strategic objectives and operational needs of funding agencies but also resonate with the broader societal values and ethical standards.

As we stand on the brink of this transformative journey, this dissertation acts as a crucial beacon, guiding the path towards an era where AI not only powers but also empowers the public funding landscape. It heralds a future where AI, coupled with human insight and ethical governance, can create a more efficient, transparent, and fair funding ecosystem, ultimately contributing to the advancement of scientific and societal progress.

In sum, the narrative we've traversed encapsulates both the promise and the challenges of AI integration in funding agencies, marking the commencement of an exploratory path towards understanding and harnessing AI's full potential in public administration. This dissertation, therefore, is not just a scholarly exploration but a clarion call to policymakers, practitioners, and researchers to collaboratively forge a future where AI serves as a pivotal ally in the quest for a more informed, just, and impactful public funding paradigm.

Appendix . Implementing AI Models for Enhanced Funding Decision Analysis

Code Sample

```
import numpy as np
import pandas as pd
import shap
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier

# Simulated Data Generation for Funding Decisions
‘’’This section of the code is dedicated to generating a simulated dataset that mimics the characteristics of project
proposals evaluated by funding agencies. The dataset includes several attributes typically assessed in research
proposals, such as Innovation, Risk, ROI (Return on Investment), and Past Performance. These attributes are
randomly assigned numerical values between 0 and 1 to represent a diverse range of proposals.’’’

np.random.seed(42)
data = {
    'Proposal_ID': range(1, 501),  # 500 proposals
    'Innovation': np.random.uniform(0, 1, 500),
    'Risk':  np.random.uniform(0, 1, 500),
    'ROI':  np.random.uniform(0, 1, 500),
    'Past_Performance': np.random.uniform(0, 1, 500)
}

df = pd.DataFrame(data)

# Rule-Based Funding Decision
‘’’A rule-based function is defined to simulate the binary decision-making process of funding agencies. This
function classifies proposals as 'Fund' if they exhibit high Innovation and ROI scores, coupled with a low Risk
score. All other proposals are classified as 'Not Fund'. This binary decision is mapped to numeric values where
'Fund' is 1 and 'Not Fund' is 0, facilitating further analysis.’’’

def funding_decision(row):
    if row['Innovation'] > 0.5 and row['ROI'] > 0.5 and row['Risk'] < 0.5:
        return 'Fund'
    else:
        return 'Not Fund'

# Apply the function to each row in the DataFrame
df['Binary_Decision'] = df.apply(funding_decision, axis=1)

# Map 'Fund' to 1 and 'Not Fund' to 0
df['Binary_Decision'] = df['Binary_Decision'].map({'Fund': 1, 'Not Fund': 0})

# Dropping 'Proposal_ID' as it is not a feature for prediction
X = df.drop(['Binary_Decision', 'Proposal_ID'], axis=1)
y = df['Binary_Decision']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Model Training and SHAP Value Calculation
'''The RandomForestClassifier model is trained on the dataset excluding the Proposal_ID, which is not a predictive
feature. After training, SHAP values are computed to interpret the model. SHAP values provide insight into how
each feature influences the model's prediction, which is crucial for understanding the decision-making process.'''

model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

# Initialize SHAP explainer
explainer = shap.Explainer(model, X_train)

# Compute SHAP values
shap_values = explainer(X_test)

# SHAP Summary Plot
'''The summary plot visualizes the distribution and impact of SHAP values for each feature across all test samples.
This plot is key for identifying which features are most influential in the funding decision, reflecting the simulated
rule-based logic applied earlier. '''

# This should include all features for binary classification
shap.summary_plot(shap_values[..., 1].values, X_test, feature_names=X_test.columns)

# Model Evaluation Metrics
'''After training the RandomForestClassifier model, it is essential to evaluate its performance to understand how
well it can generalize to new, unseen data. This section calculates three common evaluation metrics: accuracy,
precision, and recall.'''

from sklearn.metrics import accuracy_score, precision_score, recall_score

# After fitting the model, make predictions
y_pred = model.predict(X_test)

# Calculate metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")

# Initializing Fuzzy Logic System
'''Here we set up the fuzzy logic system, defining inputs, outputs, and membership functions for evaluating the the
proposals.'''
# Antecedents (Inputs)
innovation = ctrl.Antecedent(np.arange(0, 1.1, 0.1), 'Innovation')
risk = ctrl.Antecedent(np.arange(0, 1.1, 0.1), 'Risk')
roi = ctrl.Antecedent(np.arange(0, 1.1, 0.1), 'ROI')
past_performance = ctrl.Antecedent(np.arange(0, 1.1, 0.1), 'Past_Performance')

# Defining Fuzzy Membership Functions
'''This part of the code defines how the inputs are classified into different levels of membership for each attribute,
such as 'low', 'medium', and 'high'.'''
innovation.automf(3)
risk.automf(3)
roi.automf(3)
past_performance.automf(3)

# Consequent (Output)
funding_score = ctrl.Consequent(np.arange(0, 1.1, 0.1), 'Funding_Score')
```

```
funding_score['low'] = fuzz.trimf(funding_score.universe, [0, 0.3, 0.6])
funding_score['medium'] = fuzz.trimf(funding_score.universe, [0.4, 0.7, 1.0])
funding_score['high'] = fuzz.trimf(funding_score.universe, [0.7, 1.0, 1.0])

# Establishing Fuzzy Rules
'''This section creates rules that determine how the input values influence the final funding score based on fuzzy
logic.'''
rule1 = ctrl.Rule(innovation['poor'] | risk['good'], funding_score['low'])
rule2 = ctrl.Rule(roi['average'] | past_performance['average'], funding_score['medium'])
rule3 = ctrl.Rule(innovation['good'] & risk['poor'], funding_score['high'])



# Fuzzy Logic Control System
'''We compile the fuzzy rules into a control system to process inputs and compute fuzzy scores.'''
funding_ctrl = ctrl.ControlSystem([rule1, rule2, rule3])
funding = ctrl.ControlSystemSimulation(funding_ctrl)

# Computing Fuzzy Scores
'''In this block, we calculate the fuzzy scores for each proposal using the control system we established.'''
fuzzy_scores = []
for i in range(len(df)):
    funding.input['Innovation'] = df.loc[i, 'Innovation']
    funding.input['Risk'] = df.loc[i, 'Risk']
    funding.input['ROI'] = df.loc[i, 'ROI']
    funding.input['Past_Performance'] = df.loc[i, 'Past_Performance']
    funding.compute()
    fuzzy_scores.append(funding.output['Funding_Score'])
df['Fuzzy_Score'] = fuzzy_scores

# Visualize Membership Functions for Innovation
innovation.view()

# Plotting Fuzzy Score Distribution
'''This script produces a histogram to display the distribution of fuzzy scores across all proposals.'''
plt.figure(figsize=(10, 6))
plt.hist(df['Fuzzy_Score'], bins=20, color='skyblue', edgecolor='black')
plt.title('Distribution of Fuzzy Scores')
plt.xlabel('Fuzzy Score')
plt.ylabel('Frequency')
plt.show()

# Nuanced Categorization Logic
'''The code here applies a nuanced categorization to each proposal based on its fuzzy score, enhancing the
decision-making beyond a binary 'fund' or 'not fund'.'''
conditions = [
    df['Fuzzy_Score'] >= 0.7,  # Strongly recommend funding
    (df['Fuzzy_Score'] < 0.7) & (df['Fuzzy_Score'] >= 0.5),  # Recommend funding
    (df['Fuzzy_Score'] < 0.5) & (df['Fuzzy_Score'] >= 0.4),  # Consider for funding
    df['Fuzzy_Score'] < 0.4   # Do not fund
]
choices = ['Strongly Recommend Funding', 'Recommend Funding', 'Consider for Funding', 'Do Not Fund']

df['Nuanced_Decision'] = np.select(conditions, choices, default='Review Further')


# Support Vector Machine (SVM) for Decision Analysis
'''This section focuses on using a Support Vector Machine (SVM) to analyze the relationship between nuanced
decisions and binary decisions. We employ SVM as a classifier to understand how nuanced decisions might align
with the binary decisions made by peer reviewers.'''
```

```
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.preprocessing import LabelEncoder

# Assuming df['Nuanced_Decision'] contains your nuanced decisions and df['Binary_Decision'] the binary ones

## Encoding Nuanced Decisions
'''Firstly, we encode the nuanced decision labels into a numerical format suitable for machine learning models
using LabelEncoder. This encoding is necessary because SVMs and other machine learning algorithms require
numerical input.'''
encoder = LabelEncoder()
nuanced_encoded = encoder.fit_transform(df['Nuanced_Decision'])

# Use encoded nuanced decisions as input for SVM
X = nuanced_encoded.reshape(-1, 1)  # Reshape is needed as we have only one feature
y = df['Binary_Decision']

## Splitting the Dataset
'''We then split the dataset into training and test sets. This step is crucial for evaluating the model's performance
on unseen data, ensuring that we have a robust and generalizable model. '''
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

## Training the SVM Model
'''The SVM model is initialized with a random state for reproducibility and then trained on the training set. Training
involves the model learning to associate the nuanced decisions with the corresponding binary decisions.'''
svm_model = SVC(random_state=42)
svm_model.fit(X_train, y_train)

# Predict using the SVM model
svm_predictions = svm_model.predict(X_test)

## Evaluating the SVM Model
'''After training, we predict the binary decisions on the test set and calculate the accuracy of the SVM model. This
metric tells us how often the model correctly predicts the binary decision based on the nuanced decision.'''
svm_accuracy = accuracy_score(y_test, svm_predictions)
print(f"SVM model accuracy: {svm_accuracy:.2f}")

## Confusion Matrix
'''Finally, we generate a confusion matrix, which provides a detailed breakdown of the model's predictions versus
the actual binary decisions. It helps in understanding the types of errors the model is making (if any) and is a
powerful tool for model evaluation.'''
conf_matrix = confusion_matrix(y_test, svm_predictions)
conf_matrix_df = pd.DataFrame(conf_matrix,
                              index=['Actual Not Fund', 'Actual Fund'],
                              columns=['Predicted Not Fund', 'Predicted Fund'])

print(conf_matrix_df)

# Measure the accuracy, precision, and recall of the SVM
svm_accuracy = accuracy_score(y_test, svm_predictions)  # Calculate the accuracy of the SVM model by
comparing the actual and predicted binary decisions.
svm_precision = precision_score(y_test, svm_predictions)  # Calculate the precision of the SVM model, which is
the ratio of correctly predicted positive observations to the total predicted positives.
svm_recall = recall_score(y_test, svm_predictions)  # Calculate the recall of the SVM model, which is the ratio of
correctly predicted positive observations to all actual positives.

print(f"SVM model accuracy: {svm_accuracy:.2f}")  # Print the accuracy of the SVM model, showing the overall
correctness of the predictions.
```

```
print(f"SVM model precision: {svm_precision:.2f}")  # Print the precision of the SVM model, indicating the quality of
the positive class predictions.
print(f"SVM model recall: {svm_recall:.2f}")  # Print the recall of the SVM model, reflecting the model's ability to
find all the relevant cases within the dataset.


# Function to compute similarity between two texts using a Language Model (LLM)
def compute_llm_similarity(text1, text2):
    # This function would ideally call a language model API to compute similarity
    return np.random.rand()  # Returning a random score for illustration

# Sample data setup
proposals = [ ... ]  # List of proposal summaries
reviewer_research_interests = [ ... ]  # List of reviewer research interests

# TF-IDF and cosine similarity computation
tfidf_vectorizer = TfidfVectorizer()
tfidf_matrix = tfidf_vectorizer.fit_transform(proposals + reviewer_research_interests)
tfidf_cosine_scores = cosine_similarity(tfidf_matrix[:len(proposals)], tfidf_matrix[len(proposals):])

# Sentence embeddings and cosine similarity computation
model = SentenceTransformer('all-MiniLM-L6-v2')
proposal_embeddings = model.encode(proposals)
reviewer_embeddings = model.encode(reviewer_research_interests)
embeddings_cosine_scores = cosine_similarity(proposal_embeddings, reviewer_embeddings)

# Compute LLM similarity for each proposal-reviewer pair
llm_similarity_scores = np.array([
    [compute_llm_similarity(p, r) for r in reviewer_research_interests]
    for p in proposals
])

# Output similarity scores for comparison
print("TF-IDF Cosine Scores:\n", tfidf_cosine_scores)
print("Embeddings Cosine Scores:\n", embeddings_cosine_scores)
print("LLM Similarity Scores (Placeholder):\n", llm_similarity_scores)

import matplotlib.pyplot as plt
import networkx as nx

# Sample data representing proposals and reviewers
proposals = [f'Proposal{i+1}' for i in range(10)]
reviewers = [f'Reviewer{i+1}' for i in range(4)]

# Initialize the graph for visualization
G = nx.Graph()

# Adding nodes for proposals and reviewers to the graph
for proposal in proposals:
    G.add_node(proposal, type='proposal', color='grey')
for reviewer, color in zip(reviewers, ['red', 'green', 'blue', 'orange']):
    G.add_node(reviewer, type='reviewer', color=color)

# Assuming similarity scores exist (here represented as placeholders)
# Selecting the LLM similarity scores for graph edges
scores_to_use = llm_similarity_scores  # Placeholder for actual scores

# Add edges between proposals and reviewers with weights based on similarity scores
for i, proposal in enumerate(proposals):
    for j, reviewer in enumerate(reviewers):
```

```
        G.add_edge(proposal, reviewer, weight=scores_to_use[i][j])

# Define node positions using the spring layout for better visualization
pos = nx.spring_layout(G)

# Drawing nodes and edges with customized styles
nx.draw_networkx_nodes(G, pos, node_color=[G.nodes[node]['color'] for node in G])
nx.draw_networkx_edges(G, pos, width=1)

# Annotate nodes with labels
nx.draw_networkx_labels(G, pos)

# Display the resulting graph
plt.show()




#utility score
# Define strategic weights and preference functions for each feature
weights = {
    'ROI':  0.3,  # Assigns a weight of 30% to the Return on Investment
    'Risk':  -0.2,  # Assigns a negative weight to Risk indicating its adverse effect
    'Alignment': 0.1,  # Alignment with strategic goals is given a 10% weight
    'Innovation': 0.25,  # Innovation is highly valued, hence a 25% weight
    'Past_Performance': 0.3  # Past Performance also carries a significant weight of 30%
}

preference_functions = {
    'ROI':  lambda x: np.log(1 + x),  # Logarithmic function for ROI indicating diminishing returns
    'Risk':  lambda x: -np.sqrt(x),  # Square root function for Risk to model its negative impact
    'Alignment': lambda x: 2 * x,  # Linear function for Alignment indicating direct proportionality
    'Innovation': lambda x: (x / 10) ** 2,  # Quadratic function for Innovation to emphasize higher values
    'Past_Performance': lambda x: x,  # Linear function for Past Performance indicating direct impact
}

# Calculate utility scores for high-potential proposals
df_high_potential['Utility_Score'] = df_high_potential.apply(
    lambda row: sum(
        weights[feature] * preference_functions[feature](row[feature]) for feature in weights
    ), axis=1
)
# This computes the utility score for each proposal in df_high_potential by applying the defined weights and
preference functions to the respective features.
# The utility score is a comprehensive measure of a proposal's value and alignment with strategic priorities.

# Discretizing Continuous Variables
# This converts continuous attributes like ROI into categorical values to prepare for Bayesian analysis.
df_full['discrete_ROI'] = pd.cut(df_full['ROI'], bins=[0, 0.5, 1], labels=[0, 1])
df_full['discrete_Risk'] = pd.cut(df_full['Risk'], bins=[0, 0.5, 1], labels=[0, 1])
df_full['discrete_Alignment'] = pd.cut(df_full['Alignment'], bins=[0, 0.5, 1], labels=[0, 1])
df_full['discrete_Innovation'] = pd.cut(df_full['Innovation'], bins=[0, 0.5, 1], labels=[0, 1])
df_full['discrete_Past_Performance'] = pd.cut(df_full['Past_Performance'], bins=[0, 0.5, 1], labels=[0, 1])

# Discretizing Utility Score
# This prepares the Utility Score for Bayesian analysis by converting it to a categorical variable.
df_full['Utility_Score_discrete'] = pd.cut(df_full['Utility_Score'], bins=[0, 0.5, 1], labels=[0, 1])

# Training Logistic Regression
```

```
# This fits a logistic regression model to predict outcomes based on the discretized and continuous features.
logistic_model = LogisticRegression()
logistic_model.fit(X_train, y_train)

# Predicting Probabilities with Logistic Regression
# This generates success probability estimates for each proposal using logistic regression.
probabilities = logistic_model.predict_proba(X_test[['ROI', 'Risk', 'Alignment', 'Innovation', 'Past_Performance',
'Utility_Score']])[:,1]

# Updating the DataFrame with Logistic Regression Probabilities
# This adds the success probability estimates back to the original dataframe for further analysis.
df_full.loc[X_test.index, 'Success_Probability_Logistic'] = probabilities

# Setting up the Bayesian Network Structure
# This defines the relationships between different features within a Bayesian Network for modeling dependencies.
bn_structure = [
    ('discrete_ROI', 'Utility_Score_discrete'),
    ('discrete_Risk', 'Utility_Score_discrete'),
    ('discrete_Alignment', 'Utility_Score_discrete'),
    ('discrete_Innovation', 'Utility_Score_discrete'),
    ('discrete_Past_Performance', 'Utility_Score_discrete'),
    ('Utility_Score_discrete', 'Success')
]

# Training the Bayesian Network Model
# This step involves fitting the Bayesian Network model to the dataset to learn the conditional dependencies.
bn_model = BayesianNetwork(bn_structure)
df_sample = df_full.dropna(subset=bn_structure)
bn_model.fit(df_sample, estimator=MaximumLikelihoodEstimator)

# Bayesian Inference for Success Probability Estimation
# This function estimates the success probability for each proposal based on the Bayesian Network model.
def estimate_success_probability(row):
    evidence = {k: row[k] for k in bn_structure if not np.isnan(row[k])}
    return bn_infer.query(variables=['Success'], evidence=evidence).values[1]

# Calculating and Assigning Success Probabilities
# This applies the Bayesian inference function to estimate and assign success probabilities for each proposal.
df_full['Success_Probability_Bayesian'] = df_full.apply(estimate_success_probability, axis=1)

# Decision tree
# Defining the features (X) and target variable (y) for the machine learning model.

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Splitting the dataset into training and testing sets to evaluate the model's performance on unseen data.

decision_tree_model = DecisionTreeClassifier(max_depth=3, random_state=42)
decision_tree_model.fit(X_train, y_train)
# Initializing and training a Decision Tree Classifier on the training data.

y_pred = decision_tree_model.predict(X_test)
# Using the trained Decision Tree Classifier to make predictions on the test set.

accuracy = accuracy_score(y_test, y_pred)
print(f"Decision Tree Classifier Accuracy: {accuracy:.2f}")
# Calculating and printing the accuracy of the model to evaluate its performance.

export_graphviz(decision_tree_model, out_file='funding_decision_tree.dot',
                feature_names=['Utility_Score', 'Success_Prob_Log', 'Success_Prob_Bayesian'],
                class_names=['Low Priority', 'Consider', 'High Priority'],
```

```
rounded=True, proportion=False, precision=2, filled=True)
```

Draft Discussion Guides w/interview participants

Introduction

Revisit informed consent:

Answers will only be identified with a generic title, not individuals (i.e. 'A project manager from a Venture Capital), your name or your employer will not be identified directly or via inference in any study reports.

Purpose of the study, it will be published

No compulsion to answer any questions can end whenever

Confirm whether they are willing to be recorded?

Please walk me through your role and the types of decisions and issues you oversee at your organization when it comes to making funding decisions.

Background and Priorities

The current decision-making process:

Please describe your organization's scope and vision and what type/ stage of research your organization funds?

Please describe the process of decision-making in your organizations.?

Has the process of decision-making evolved over the past few decades/ years, and what were the reasons, if any?

The challenges in the current process:

What are some of the challenges in the current process?

What are some of the potential improvements of the process and some of the missing opportunities?

Can you think of some of the potential sources of human bias judgment in your organization in the process of decision-making?

How do you evaluate the quality of the funding decisions in your organization?

The integration of Artificial Intelligence's capabilities:

Which part of the decision-making process do you think might benefit from integrating it with artificial intelligence capabilities?

Has your organization tried to automate the process and integrate some of the Artificial intelligence's capabilities to improve the quality of the decisions?

What Artificial Intelligence tools applications are you aware of?

Can you list some of the automation efforts that have taken place in your organization?

How do you evaluate the process after implementing and integrating Artificial Intelligence capabilities?

Potential implementation difficulties of Artificial Intelligence in the process

Can you think of some of the potential challenges with implementing and integrating Artificial Intelligence with the process?

How do you anticipate overcoming some of these challenges?

Further Discussion

Who else should I speak with to better understand the potential for application of Artificial Intelligence in funding agencies?

Abbreviations

AI	Artificial Intelligence
ANNs	Artificial Neural Networks
ART	Assisted Referral Tool
CNNs	Convolutional Neural Networks
CSR	Center for Scientific Review
DARPA	Defense Advanced Research Projects
ESG	Environmental, Social and Governance
FNRS	Fund for Scientific Research
GAMs	Generalized Additive Models
GDP	Gross Domestic Product
GERD	Gross Domestic expenditure on Research and Development
GMS	Grant Management Software
IRS	Internal Revenue Service
ISF	Israel Science Foundation
KRB	Korean Research Base
LIME	Local Interpretable Model-Agnostic Explanations
LOI	Letter of Intent
ML	Machine Learning
MCDM	Multi Criteria Decision Making
MISTRA	The Swedish Foundation for Strategic Environmental Research
MRIs	Market Readiness Levels
NFR	National Research Foundation
NGOs	Non-Governmental Organizations
NIH	National Institutes of Health
NNSFC	National Natural Science Foundation of China
NSF	National Science Foundation
OECD	The Organization for Economic Co-operation and Development
R&D	Research and Development
RCC	Responsibility, Credibility, and Contribution
RFPs	Request For Proposals
RSF	Russian Science Foundation
SHAP	SHapley Additive exPlanations
SPW	Research Wallonia Ministry for Public Service
SSF	Swedish Foundation for Strategic Research
SSD	Science Similarity Detection

SVMs	Support Vector Machines
TRLs	Technology Readiness Levels

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