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Research Article

Enabling Data-Driven Innovation in the Third Sector: A Framework for Leveraging Big Data

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Abstract: As digital transformation reshapes sectors worldwide, nonprofit and third sector organizations face increasing pressure to leverage data for impact, accountability, and innovation. This study investigates the factors influencing the adoption, maturity, and sustainability of data-driven approaches in third sector organizations, including nonprofits, Non-Governmental Organizations (NGOs), and social enterprises. The primary contribution of this work is a comprehensive, multi-pillar framework for data-driven innovation in the third sector, extended with a sixth pillar-Impact Evaluation and Sustainability to institutionalize long-term outcome tracking and scalable practices. The study also provides a cross-case synthesis of three representative domains: education (EdNet), healthcare (MIMIC-Extract), and humanitarian response (HUMVI), demonstrating how theoretical principles translate into actionable implementation strategies across diverse organizational contexts. Key results highlight that organizations achieving alignment across vision, infrastructure, data governance, experimentation, stakeholder engagement, and impact perform more effectively. Nevertheless, valuation consistently show higher predictive accuracy, operational efficiency, and social impact. For instance, EdNet models improved student learning outcomes and reduced dropout rates, MIMIC-Extract enabled clinically actionable predictions with AUROC up to 94.6%, and HUMVI enhanced real-time detection of humanitarian incidents with > 80% precision in critical sectors. By clarifying internal and external enablers-including leadership commitment, data literacy, technological access, and funding-while addressing challenges such as skill gaps, resistance to change, and ethical considerations, this study offers both practical guidelines and policy recommendations. The proposed framework and inter-case insights provide a novel, evidence-based blueprint for third sector organizations to harness data strategically, ethically, and sustainably, ultimately supporting social innovation and improved decision-making.

***Keywords*:** data-driven innovation, third sector, nonprofit organizations, non-governmental organizations, big data

1. Introduction

The term third sector broadly refers to organizations and activities that operate between the public and private sectors. These entities typically take the form of not-for-profit, voluntary, or non-governmental organizations [1]. While third sector organizations are generally characterized by their non-profit orientation, independence from direct state control, and diverse funding sources-including social enterprise, donations, grants, and other non-commercial means-they are not driven primarily by financial gain and are not subject to the same profit-distribution mechanisms as for-profit enterprises [2].

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Despite the increasing availability of digital data and analytic tools, there remains a critical gap in understanding how third sector organizations can leverage these resources effectively for social impact. Existing literature provides descriptive accounts of data usage in nonprofits but lacks a systematic framework that links organizational, technological, and cultural factors to successful data-driven outcomes.

The nonprofit sector now has access to unprecedented data resources, ranging from automated analytics to sophisticated visualization tools [3]. This offers new opportunities for enhancing social impact through data-driven decision-making [4]. However, many organizations struggle with limited data literacy, fragmented infrastructures, and a lack of clear strategies, which prevent the translation of data into meaningful, measurable outcomes.

Case studies from Austin, New Orleans, and New York City illustrate how communities, governments, and businesses are beginning to collaboratively generate, share, and visualize data to foster social innovation [5]. These initiatives reveal that value arises not only from data availability but also from its contextualization, purpose-driven design, and strategic deployment.

As digital transformation reshapes the nonprofit landscape, the third sector-including nonprofits, Non-Governmental Organizations (NGOs), social enterprises, and voluntary organizations-is increasingly expected to adopt data-centric practices that enhance service delivery, improve accountability, and stimulate innovation [6-7]. Nevertheless, many organizations remain in the early stages of data maturity. Existing models for data-driven transformation often fail to account for sector-specific constraints, such as limited funding, volunteer-based staffing, or ethical considerations unique to socially oriented missions.

Evaluation serves multiple functions, including responsibility to donors and recipients, measuring performance, and the marketing of third-sector organizations to potential donors and the public [8]. Moreover, in recent decades, there has been a surge in the quantity and variety of civil society or third sector sustainability organizations [9]. Therefore, this paper seeks to explore the potential benefits of applying the six-pillar framework to achieve such remarkable outcomes in the third sector.

This study aims to address these gaps by developing a comprehensive, multi-pillar framework for data-driven innovation in the third sector, including a novel sixth pillar focused on Impact Evaluation and Sustainability.

The objectives of this research are fourfold:

• To examine internal and external factors that facilitate or hinder the adoption of data-driven practices in third sector organizations;

• To analyze technological, organizational, and cultural dimensions that shape data maturity and sustainability;

• To provide practical insights from representative case studies (education, healthcare, and humanitarian response) that illustrate successful implementation strategies;

• To propose actionable recommendations and a transferable framework to support nonprofits, NGOs, and social enterprises in building sustainable, data-literate ecosystems.

By bridging insights from empirical cases and theoretical perspectives, this study contributes a novel evidence-based approach to data-driven transformation in the third sector. It explicitly differentiates itself from previous work by integrating cross-sector synthesis, operational guidelines, and an evaluation-oriented pillar that addresses long-term impact-elements often missing in existing models.

Definitions used in this study: “Third sector” refers to all organizations operating between public and private spheres with a non-profit orientation; “Nonprofit” refers to legally recognized entities that reinvest surpluses into mission-driven activities; “NGO” denotes organizations independent from government control, often engaged in advocacy or humanitarian work.

This study aims to investigate how third sector organizations can effectively adopt and leverage data-driven practices. The objectives are to examine internal and external factors that facilitate or hinder such adoption, analyze technological, organizational, and cultural dimensions that shape data maturity and sustainability, provide practical insights from representative case studies in education, healthcare, and humanitarian response that illustrate successful implementation strategies, and propose actionable recommendations along with a transferable framework to support nonprofits, NGOs, and social enterprises in building sustainable, data-literate ecosystems.

To guide the empirical investigation, the study tests the following hypotheses:

• H1: Organizations with higher data literacy and technological capacity exhibit greater success in implementing data-driven innovation.

• H2: Strong ethical and governance frameworks enhance stakeholder trust and improve the effectiveness of data-driven interventions.

• H3: Cross-sector collaboration and community engagement positively influence the sustainability and social impact of data-driven initiatives.

• H4: Tailored operational frameworks that integrate organizational, technological, and cultural factors result in more consistent and scalable outcomes across diverse third sector contexts.

By bridging insights from empirical cases and theoretical perspectives, this study contributes a novel evidence-based approach to data-driven transformation in the third sector. It explicitly differentiates itself from prior work by integrating cross-sector synthesis, operational guidelines, and an evaluation-oriented pillar that addresses long-term impact-elements often missing in existing models.

To guide the reader, the remainder of the article is structured as follows. Section 2 reviews the relevant literature, beginning with an overview of the third sector and moving toward data-driven approaches, including big data architectures and AI-enabled systems. Section 3 outlines the research design and methodological foundations of the study. Section 4 examines the strategic value of data-driven approaches in third-sector organizations, focusing on decision-making, accountability, and innovation. Section 5 analyzes the organizational and system-level factors that facilitate or hinder successful data initiatives. Section 6 introduces the proposed theoretical framework and its core components. Section 7 presents three case examples-EdNet, MIMIC-Extract, and HUMVI-that illustrate how the framework applies across diverse contexts. Section 8 provides an integrated discussion of the findings, including implications, strengths, and ethical considerations. Finally, Section 9 concludes the article by summarizing key contributions and outlining avenues for future research.

2. Related work

2.1 *Understanding the third sector*

The "third sector" refers broadly to organizations and activities that exist between the public and private sectors. Third sector organizations can take many forms but are typically defined as "not-for-profit", "voluntary", or "non-governmental" organizations [1]. These definitions accordingly state that third sector organizations do not act primarily for pecuniary gain; are not subject to the same profit-distribution controls that govern for-profit organizations; and are funded through enterprise, donations, grants, or other means that are typically less controllable than public funding.

However, the term "third sector" is broader than "nonprofit" or "NGO". In this paper, we use: (i) "third sector" as an umbrella term covering all mission-oriented, non-profit-distributing entities; (ii) "nonprofit" to refer to legally registered organizations that reinvest surpluses into mission activities; and (iii) "NGO" to refer to independent organizations, typically engaged in humanitarian, advocacy, or development work. Social enterprises are also included within the third sector when their primary purpose is social rather than commercial.

Defining clear boundaries around the sector has proved notoriously difficult [10]. This ambiguity reflects the diversity of organizational forms within the third sector, which include charities focused on service delivery and fundraising; NGOs that operate with transnational mandates, advocacy missions, or humanitarian goals; and social enterprises that blend market-based models with explicit social objectives.

Importantly, these widely regarded third sector organizations come from different historical, cultural, and operational trajectories [11]. Because these sub-sectors differ markedly in governance models, funding structures, and operational capacities, their ability to adopt and sustain data-driven practices also differs. Charities may rely heavily on donor reporting and volunteer-led data processes, NGOs may require robust Monitoring and Evaluation (M & E) systems for international accountability, while social enterprises may integrate digital tools more naturally due to hybrid business models.

The defining characteristics of third sector organizations are often summarized as "not-for-profit", "voluntary", and "nongovernmental". Let's examine each term in more detail:

• Not-for-profit: Third sector organizations are not driven by the pursuit of profit for private gain. Any surplus revenue generated is reinvested in the organization's mission rather than distributed to shareholders. This criterion applies differently across sub-sectors: charities depend primarily on donations, NGOs on grants and international funding, and social enterprises on earned income, but all maintain mission primacy over profit.

• Voluntary: Refers to the involvement of volunteers in the organization's activities. Volunteers contribute time, skills, and expertise without financial compensation. Volunteer intensity tends to be highest in charities and community groups, moderate in NGOs, and lower in social enterprises, affecting internal capacities for data collection, management, and analysis.

• Non-governmental: Indicates independence from direct government control. NGOs in particular emphasize institutional independence to preserve advocacy roles, while charities and social enterprises may work more closely with public agencies depending on context.

Figure 1 complements this typology by visually illustrating the diverse forms of third sector organizations. It highlights six major categories-charities, NGOs, community groups, social enterprises, foundations, and voluntary associations-each representing a distinct operational model, funding mechanism, and societal role. Making these distinctions explicit is essential for understanding how data-driven approaches can or cannot be transferred across sub-sectors.

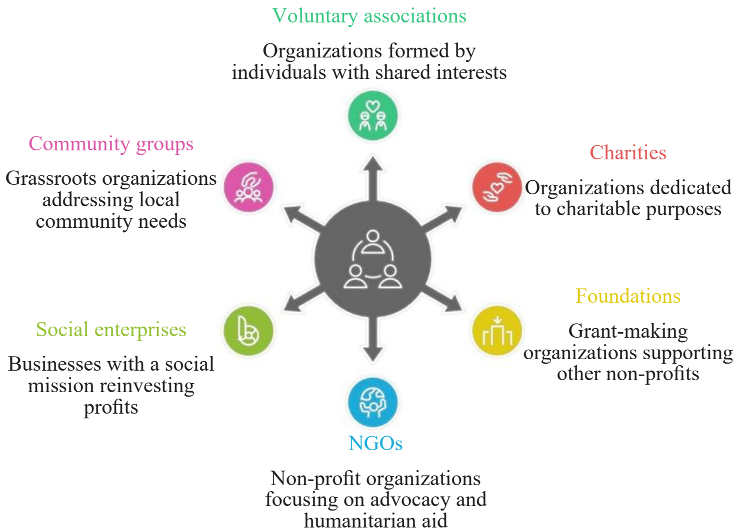

Figure 1. Major types of third sector organizations and their roles

The third sector plays a vital and multifaceted role in contemporary society, contributing significantly to social cohesion, justice, and development [12]. One of its primary functions is to address unmet needs by filling service gaps left by the public and private sectors. These gaps differ by sub-sector: charities often deliver essential services locally, NGOs engage in transnational advocacy or humanitarian response, and social enterprises target systemic issues using market-based mechanisms.

Third sector organizations are uniquely positioned to reach marginalized populations, offer tailored support, and respond flexibly to complex social challenges. Beyond service provision, they are key advocates for social justice and human rights, combatting inequality, discrimination, and exclusion [13]. Their missions are therefore closely aligned with the potential benefits of data-driven strategies-improved targeting, deeper accountability, stronger evidence bases-but the pathways to adoption differ across organizational types.

Moreover, the third sector fosters civic engagement, encourages volunteerism, philanthropy, and active community participation, strengthening democratic values and social capital [12]. It is also a driver of innovation, pioneering creative and scalable solutions to persistent social problems [14]. In particular, social enterprises often serve as experimental platforms for data innovations that later diffuse to charities or NGOs.

Importantly, the third sector serves as a voice for the voiceless, amplifying perspectives of underrepresented communities and influencing policy agendas. Collectively, these contributions underscore the indispensable role of third sector organizations in building inclusive, responsive, and resilient societies [15].

2.2 *Data-driven approaches*

2.2.1 *Big data technologies and architectures*

In the digital age, big data has emerged as a transformative force across industries, reshaping how organizations collect, manage, and analyze vast and complex datasets [16]. Big data refers to massive volumes of heterogeneous, high-velocity data generated from various sources such as social media, smart devices, autonomous systems, sensors, and enterprise platforms. This data is often unstructured or semi-structured, posing significant challenges for traditional data processing tools [17].

Big data is commonly characterized by the three Vs: volume, variety, and velocity, as originally defined by [18]. Volume denotes the scale of data; variety points to the diversity of data types and formats (e.g., text, images, videos, sensor data); and velocity reflects the speed at which data is generated and processed. In some cases, two additional Vs are included: reliability (data uncertainty) and value (usefulness of data) to better encapsulate the complexity of the big data paradigm [19].

Big data originates from a wide array of heterogeneous sources, reflecting the diversity and ubiquity of digital interactions in modern society (Figure 2). These sources can be broadly categorized into structured, semi-structured, and unstructured data streams. Social media platforms (e.g., Twitter, Facebook, Instagram) generate vast amounts of user-generated content, including text, images, videos, and metadata [20]. Sensor networks and Internet of Things (IoT) devices continuously collect environmental, health, and industrial data in real time [21]. Transactional data from e-commerce, banking, and Enterprise Resource Planning (ERP) systems provides structured records of business activities. Healthcare systems produce clinical data, Electronic Health Records (EHRs), diagnostic imaging, and genomic sequences, contributing to healthcare big data [22]. Vehicular data, from connected vehicles and transportation systems, adds to the volume through Global Positioning System (GPS) logs, traffic sensors, and telematics. Additionally, open government data portals, satellite imagery, mobile applications, and streaming services contribute to the ever-expanding ecosystem of big data [23]. These diverse sources present both opportunities and challenges in terms of integration, quality assurance, and real-time processing, necessitating robust data engineering and analytics frameworks.

The Big Data Ecosystem consists of several interdependent technologies that enable large-scale data operations. These include:

- Data processing frameworks (e.g., Apache Hadoop, Apache Spark),
- Analytics and visualization tools (e.g., Tableau, Statistical Analysis System (SAS)),
- Business Intelligence platforms (e.g., International Business Machines (IBM) Cognos),
- Cloud infrastructure providers (e.g., Amazon Web Services (AWS), Google Cloud Platform),
- NoSQL databases (e.g., MongoDB, Cassandra),
- Programming tools (e.g., Python, R).

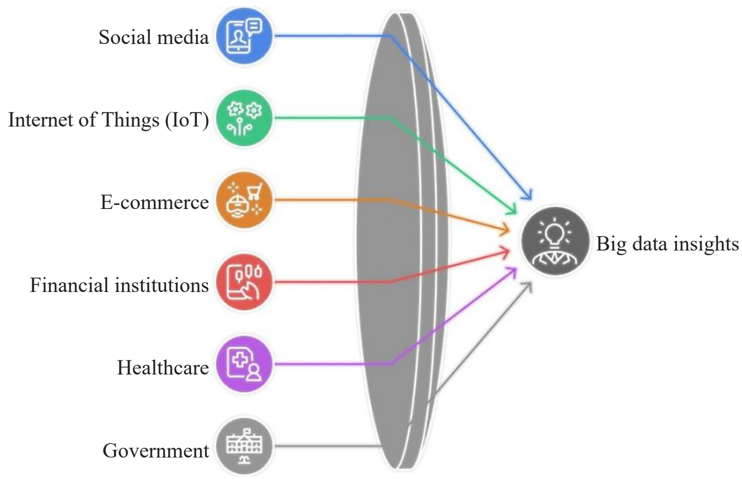

Figure 2. Diverse forms of third sector organizations

This ecosystem supports various tasks such as storage, real-time processing, pattern discovery, prediction, and insight generation. These capabilities make big data applications essential across a wide range of domains, including healthcare, supply chains, smart cities, climate science, cybersecurity, and education.

Technologies for Big Data:

Effectively managing and analyzing big data requires a suite of specialized technologies capable of handling its volume, velocity, and variety, while also highlighting their respective roles and interconnections. Key technologies include:

1. Hadoop [24]: An open-source framework that facilitates distributed storage and parallel processing of massive datasets across clusters of commodity hardware. Hadoop's ecosystem supports scalable and fault-tolerant big data processing.
2. Apache Spark [25]: A fast, general-purpose cluster computing system designed for in-memory processing, which accelerates big data analytics and supports diverse workloads such as batch processing, streaming, machine learning, and graph computation.
3. NoSQL Databases [26]: Unlike traditional relational databases, NoSQL systems are optimized for handling large volumes of unstructured or semi-structured data. Popular examples include MongoDB, Cassandra, and Couchbase, each providing flexible schemas and high scalability.
4. Data Warehouses [27]: Centralized systems that store structured data optimized for query and analysis. They provide a foundation for business intelligence by consolidating data from various sources into a consistent format.
5. Data Lakes [28]: Large, centralized repositories capable of storing all forms of data-structured, semi-structured, and unstructured-in their native format. Data lakes enable organizations to retain raw data for future processing and analysis.
6. Cloud Computing [29]: Offers on-demand access to scalable computing resources including storage, processing power, and software services. Cloud platforms enable flexible, cost-effective big data infrastructure deployment without significant upfront investments.
7. Machine Learning [30]: A set of algorithms and models that automatically learn from data to identify patterns, make predictions, or support decision-making, enhancing the extraction of insights from big data.
8. Data Visualization [31]: Tools and platforms that convert complex datasets into visual formats such as charts, graphs, and dashboards, facilitating intuitive understanding of trends, correlations, and anomalies.

2.2.2 *Artificial intelligence in data-driven systems*

Artificial Intelligence (AI) refers to the branch of computer science that focuses on creating systems capable of performing tasks that normally require human intelligence, such as reasoning, learning, perception, and decision-making. In data-driven systems, AI leverages large volumes of data to automate processes, extract insights, and support intelligent decision-making.

Technical AI models (Figure 3) encompass a broad range of algorithms and architectures designed to perform specialized tasks, including classification, Natural Language Processing (NLP), computer vision, and recommendation systems. These models enable automated decision-making, pattern recognition, and intelligent interactions across multiple domains.

Classification models represent a core category of supervised learning algorithms [32], specifically designed to assign data points to predefined categories or classes. These models operate by learning patterns from labeled datasets during training, which allows them to predict the class membership of new, unseen instances with varying levels of complexity and interpretability. Logistic regression, for example, estimates the probability that an instance belongs to a particular class using a sigmoid function, making it particularly effective for binary classification tasks [32]. Support Vector Machines (SVM) identify optimal separating hyperplanes to distinguish between classes and can manage non-linear relationships through kernel methods. Decision trees recursively partition the feature space based on attribute values, offering intuitive and interpretable models, though they are susceptible to overfitting; ensembles like random forests address this by combining multiple trees to enhance accuracy and robustness. Probabilistic approaches such as Naive Bayes assume feature independence and are highly efficient for tasks like text classification, while instance-based methods like K-Nearest Neighbors classify new data points according to the majority class among nearby instances, albeit at a higher computational cost. More complex architectures, such as neural networks, employ layered structures capable of capturing intricate, non-linear patterns, requiring substantial amounts of data and computational resources. These classification models find widespread applications across domains, including image recognition, medical diagnosis, spam detection, credit scoring, and customer churn prediction, demonstrating their versatility and critical role in modern data-driven decision-making.

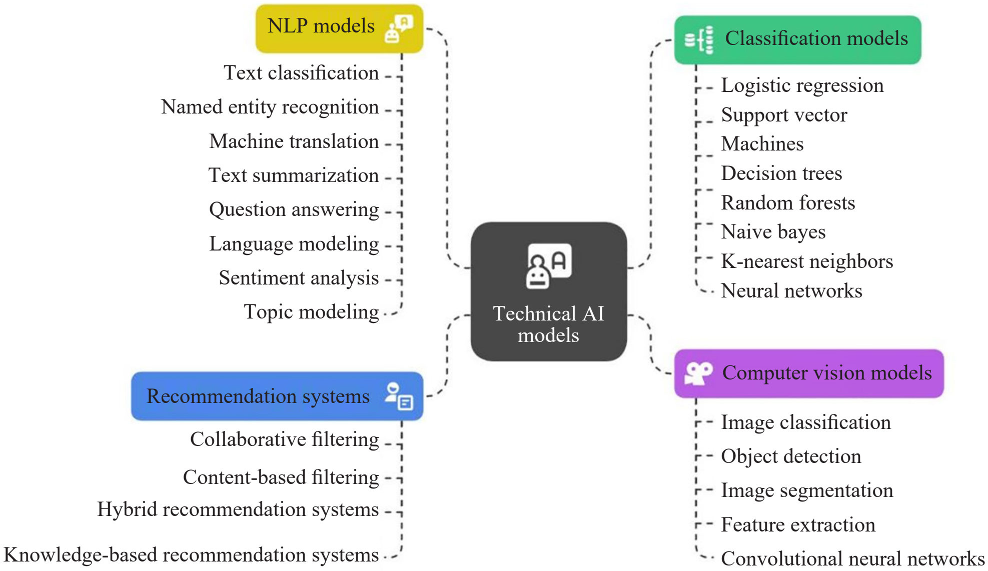

Figure 3. Overview of technical AI models and their representative techniques

Computer vision models [33] empower machines to perceive, interpret, and analyze visual information, enabling a wide range of automated understanding tasks. These models can assign labels to entire images through image classification, detect and localize specific objects within images using object detection techniques, and partition images into meaningful regions for detailed analysis via image segmentation. At the core of these capabilities lies feature extraction, which captures informative patterns such as edges, textures, and keypoints that facilitate accurate interpretation. Convolutional Neural Networks (CNNs), a specialized class of deep learning architectures, have become the foundation for hierarchical feature learning in images, allowing models to progressively detect increasingly complex visual patterns. The practical applications of computer vision are extensive and diverse, spanning autonomous driving systems that detect pedestrians and obstacles, medical imaging for disease diagnosis and treatment planning, security surveillance for anomaly detection, retail analytics to understand customer behavior, and quality control in manufacturing processes to ensure product standards.

Natural Language Processing (NLP) models [34] are designed to process, analyze, and understand human language, enabling machines to perform a variety of language-related tasks. These tasks include text classification, sentiment analysis, and topic modeling to extract meaning and categorize content; Named Entity Recognition (NER) for identifying proper nouns and entities; machine translation for converting text between languages; and text summarization and question answering, which condense information or provide precise responses [34]. Central to these capabilities are advanced architectures such as Rrecurrent Neural Networks (RNNs), which capture sequential dependencies, and transformer-based models like Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer (GPT), which excel at contextual understanding and long-range language patterns. NLP models are applied widely in chatbots and virtual assistants, search engines, social media monitoring, and healthcare analytics, demonstrating their critical role in automating and enhancing language-based tasks [34].

Similarly, recommendation systems leverage computational techniques to predict user preferences and deliver personalized suggestions [35]. Collaborative filtering analyzes patterns among similar users to infer interests, while content-based filtering relies on the attributes of items to recommend comparable options. Hybrid systems integrate both collaborative and content-based strategies to improve recommendation accuracy, and knowledge-based systems use explicit information about user requirements and item characteristics to make informed suggestions. Techniques such as matrix factorization, deep learning, and association rule mining further enhance the precision and relevance of recommendations. These systems are extensively employed in e-commerce platforms, entertainment services, news aggregation, and social media personalization, where they enhance user engagement and satisfaction through tailored experiences [35].

3. Research design and methodology

This study employs a narrative review combined with cross-sector case study analysis to explore Data-Driven Innovation (DDI) practices and their applicability to third-sector organizations. The methodological approach is structured to ensure transparency, rigor, and reproducibility.

3.1 *Search strategy and literature review*

A comprehensive search was conducted in databases including Scopus, Web of Science, and Google Scholar. Keywords included "data-driven innovation", "nonprofit", "NGO", "social enterprise", "ethical AI", and "data governance". The search was restricted to articles published between 2015 and 2025. Inclusion criteria focused on studies reporting on DDI practices, organizational impact, and cross-sector transferability. Exclusion criteria filtered out works lacking methodological details or relevance to organizational implementation.

3.2 *Screening and synthesis approach*

After initial retrieval, articles were screened in two stages: (i) title and abstract review, and (ii) full-text assessment. Data extraction included study objectives, sectoral context, methodology, outcomes, and key lessons. A narrative synthesis was conducted to identify recurring themes, best practices, and gaps in the literature. This synthesis informed the development of the five-pillar framework and the proposal of the sixth pillar (Impact Evaluation and Sustainability).

3.3 *Case study selection and analysis*

Three illustrative cases were selected to exemplify transferable DDI practices: EdNet (education), MIMIC-Extract (healthcare), and HUMVI (humanitarian). While EdNet and MIMICExtract are not third-sector implementations, they were chosen as cross-sector exemplars demonstrating scalable practices relevant to nonprofit and NGO contexts; HUMVI represents a direct third-sector deployment. Selection criteria included data availability, documented implementation processes, and relevance to the framework's pillars. Each case was analyzed using a structured protocol: organizational context, DDI interventions, governance and ethical practices, stakeholder engagement, and measured outcomes. Cross-case synthesis highlighted transferable lessons, context-specific adaptations, and emergent gaps, particularly regarding long-term impact evaluation.

3.4 *Ethics and governance considerations*

Ethical practices were assessed for each case in terms of privacy, consent, bias mitigation, and regulatory compliance. For nonprofit applicability, we emphasize concrete measures such as minimal data collection, Data Protection Impact Assessments (DPIAs), audit practices, and clear data sharing agreements. These considerations are integrated with the framework's pillars to provide actionable guidance for third-sector organizations.

3.5 *Scope and limitations*

This study explicitly positions the selected cases as cross-sector exemplars rather than purely nonprofit applications, ensuring claims are bounded appropriately. Limitations include reliance on secondary data for EdNet and MIMIC-Extract, and the narrative review design, which precludes meta-analytic generalization. Nonetheless, the approach enables identification of transferable practices and the operationalization of the proposed framework within the third sector.

4. The strategic value of data-driven approaches in the third sector

Data-driven approaches are increasingly transforming decision-making processes across sectors, including the third sector. In charities and nonprofit organizations, these approaches provide valuable tools for improving service delivery, assessing impact, strengthening accountability, and fostering innovation. However, their adoption remains uneven due to persistent structural and operational barriers.

As illustrated in Figure 4, nonprofit organizations face a range of interconnected challenges in developing and implementing data-driven practices. These include limited training opportunities, restricted access to appropriate data tools, and low levels of confidence among staff when working with data. Such obstacles are often exacerbated by organizational silos and the absence of a cohesive, organization-wide data strategy-factors that collectively hinder the systematic integration of data into strategic and operational decision-making.

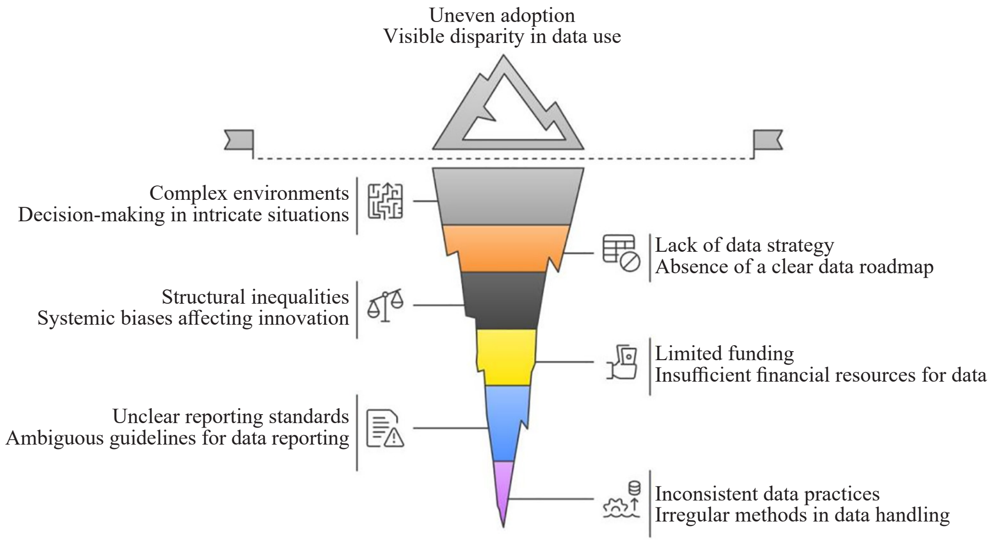

Figure 4. The strategic value of data-driven approaches

4.1 *Enhancing decision-making*

Nonprofits often operate within complex environments where data can help navigate competing priorities, identify service gaps, and optimize resource allocation. Metrics and analytics enable organizations to assess internal operations, monitor outcomes, and make strategic decisions based on evidence rather than assumptions. Access to external datasets-such as demographic trends, social media sentiment, or public health indicators-can further support targeted outreach and adaptive programming. Nevertheless, many organizations lack a coherent data strategy or the necessary infrastructure to collect and analyze relevant data. Bridging this gap requires not only technical tools but also leadership commitment and investment in analytical capacity across all levels of the organization [4].

4.2 *Improving accountability*

Increased public scrutiny and expectations for transparency have pushed nonprofits to expand their understanding of accountability beyond financial reporting. Accountability today includes demonstrating the effectiveness of interventions, the ethical use of data, and responsiveness to stakeholder needs. Data systems can support this shift by enabling more transparent reporting, evidence-backed communication, and continuous performance monitoring. Yet, challenges persist. Many third-sector organizations struggle with inconsistent data practices, fragmented systems, and unclear standards for non-financial reporting. As noted by [36], accountability must be seen as an ongoing dialogue between organizations and their stakeholders, requiring data practices that reflect both technical accuracy and ethical responsibility.

4.3 *Driving innovation*

Data-driven innovation in the third sector is facilitated by advances in digital technologies, open data initiatives, and the growing demand for social impact measurement [14]. Nonprofits increasingly leverage data to design user-centered services, experiment with new delivery models, and collaborate with tech partners or research institutions. To avoid ambiguity in terminology, this paper adopts the following definitions: the “third sector” refers to the overall ecosystem of mission-driven organizations; “nonprofits” and “charities” denote organizations primarily funded by donations; “Non-Governmental Organizations (NGOs)” operate internationally or across policy domains; and “social enterprises” combine social missions with market-based models. This differentiation is crucial because the drivers, constraints, and innovation pathways vary significantly across these sub-sectors. For instance, charities often innovate around donor engagement and service delivery, NGOs around cross-border coordination and data governance, and social enterprises around impact-linked business models. However, structural inequalities in data access and capacity mean that smaller or grassroots organizations are often excluded from these innovations. Factors such as limited funding, legacy systems, and concerns over data privacy contribute to a widening “data divide” between well-resourced and under-resourced organizations. From a theoretical standpoint, this work contributes to the literature by extending existing data-maturity and digital-transformation frameworks through the introduction of a sixth pillar focused explicitly on ethical and community-centered data governance. This addition is supported by cross-case synthesis, which reveals that innovation in the third sector cannot be decoupled from ethical imperatives and local power dynamics. The ethical dimension of innovation is further developed through three lenses: (1) algorithmic fairness, ensuring that automated decision-making does not reinforce existing inequalities; (2) community consent, emphasizing participatory approaches to data collection and use; and (3) responsible AI, promoting transparency, accountability, and context-specific risk assessment. These ethical components emerge as critical determinants of sustainable and trustworthy innovation across charities, NGOs, and social enterprises. Closing the data divide requires systemic investment in capacity-building, equitable access to digital tools, and cross-sector partnerships that center inclusivity and data justice [14]. This study shows that organizations integrating these ethical and structural considerations tend to achieve higher levels of sustained, mission-aligned innovation.

5. Factors influencing data-driven approaches in the third sector

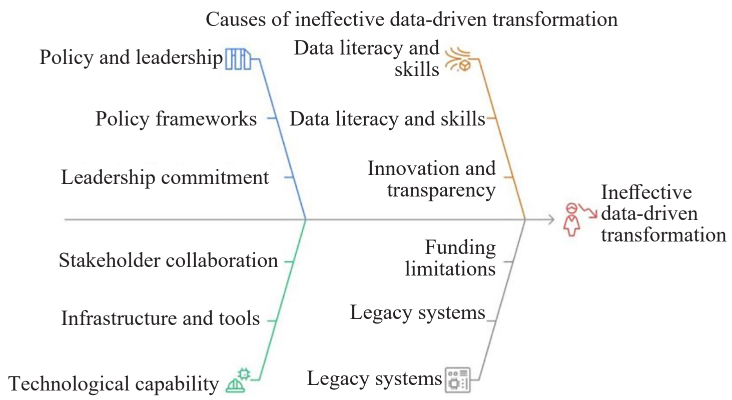

Figure 5. Drivers and constraints of data-driven approaches in the third sector

This section analyzes a diverse and evolving body of literature to identify and synthesize the key factors shaping the adoption, implementation, and sustainability of data-driven approaches in the third sector. These factors span organizational, technological, systemic, and contextual dimensions and are categorized into two overarching domains: organization-level enablers and barriers, and system-level influences. As illustrated in Figure 5, these include policy and leadership, data literacy, stakeholder collaboration, and resource constraints, among others.

5.1 *Organizational-level factors*

5.1.1 *Data characteristics and availability*

The availability, quality, and accessibility of data form the cornerstone of any data-driven transformation. In the third sector, organizations increasingly have access to demographic and administrative datasets at both individual and regional levels. However, the utility of these datasets often varies depending on their alignment with specific organizational missions and social objectives. Many nonprofit organizations lack access to domain-specific or disaggregated data that is directly applicable to their operations. Even when relevant data exists, it is often underutilized due to poor data quality, limited interoperability, or inadequate metadata documentation [37].

A significant barrier to effective data utilization is the scarcity of well-documented, sector-relevant use cases. This absence of practical examples limits organizational learning and inhibits the development of a clear vision regarding the benefits of data-driven approaches. Consequently, many nonprofits remain in an observational stage-monitoring initiatives in adjacent sectors while hesitating to initiate their own data transformation processes [38]. In addition to data-related challenges, organizational capacity plays a crucial role. A lack of skilled personnel in data analysis, data governance, and digital strategy often limits the ability of organizations to acquire, interpret, and apply data meaningfully. Furthermore, capital constraints related to software procurement, Information Technology (IT) infrastructure, and training investments exacerbate this gap, particularly for small and mid-sized organizations.

5.1.2 *Organizational culture*

Organizational culture plays a pivotal role in shaping how data is valued, interpreted, and integrated into everyday decision-making processes. In the third sector, where public accountability and mission-driven outcomes are paramount, a supportive culture can significantly enhance the adoption and sustainability of data-driven initiatives [38].

A positive data culture is typically marked by openness to innovation, commitment to Continuous Improvement (CI), cross-functional collaboration, and a willingness to experiment. These cultural attributes create an environment in which data use is normalized, insights are valued, and learning is ongoing. In contrast, entrenched habits, fear of transparency, or resistance to organizational change can act as powerful inhibitors, particularly when staff perceive data initiatives as top-down, punitive, or misaligned with core values [39].

In nonprofit environments, culture serves not only as an internal compass but also as a strategic resource for navigating external pressures-such as donor expectations, regulatory compliance, and performance evaluation. A strong organizational culture can act as a buffer during times of transformation, providing psychological safety, guiding ethical conduct, and enhancing adaptability.

5.1.3 *Leadership commitment*

Strong and sustained leadership commitment is essential for successful data-driven transformation in third sector organizations. Leadership sets the strategic direction, mobilizes resources, and legitimizes data as a core asset in decision-making. Executive champions play a key role in articulating a clear vision for data use, aligning it with the organizational mission, and fostering a culture of accountability and continuous learning [40]. This commitment is reflected in actions such as integrating data initiatives into strategic plans, allocating dedicated budgets for infrastructure and skills development, and promoting the use of data in program design, performance evaluation, and advocacy. When leaders actively engage with data and model evidence-informed thinking, they reinforce organizational norms and motivate staff to follow suit.

External pressures, such as funding constraints, competitive grant environments, and growing demands for transparency, can also catalyze leadership engagement. These factors often create a sense of urgency that compels organizations to adopt data-driven approaches, not always as a proactive strategy but as a necessary response to survive and remain relevant [40].

Yet, leadership commitment must extend beyond symbolic support. Transformation efforts falter when lacking follow-through in areas like policy alignment, capacity building, and system integration. Effective leaders maintain ongoing advocacy for data use, remain involved throughout implementation, and adapt strategies in response to organizational learning and environmental changes.

5.1.4 *Technological capability and access*

Technological capability is a key factor in an organization's ability to adopt and sustain data-driven approaches. In the third sector, disparities in access to digital infrastructure-from basic hardware and internet connectivity to advanced analytics platforms and cloud services-continue to reinforce the digital divide. Smaller, community-based organizations are especially affected, often constrained by limited budgets, underinvestment, and lack of IT support.

Technology adoption tends to correlate with organizational characteristics such as size, age, governance structure, and prior exposure to digital systems [41-42]. Larger or more established nonprofits are generally better positioned to invest in digital tools and support data integration and remote collaboration. In contrast, grassroots or volunteer-driven organizations often rely on low-cost, less scalable technologies, which can hinder their engagement in digital ecosystems. For example, studies show that community-based organizations are more likely to hold meetings without any technological tools [41], a situation often driven by the high cost of video-enabled equipment and conferencing platforms.

Decisions around technology adoption are shaped not only by financial capacity but also by strategic priorities and prior experience. Organizations with a history of investing in digital systems-often through board-level decisions-are more likely to sustain and expand these capabilities. Conversely, those lacking early exposure may fall into a cycle of technological lag and digital exclusion.

Notably, the relationship between organizational age and digital maturity is complex. While some older nonprofits have successfully modernized, others remain reliant on outdated systems due to legacy constraints or cultural resistance. This challenges the notion of uniform technological diffusion within the sector.

5.1.5 *Data literacy and analytical skills*

Data literacy-understood as the ability to access, interpret, evaluate critically, and communicate data effectively-is a foundational competency for advancing data-driven practices in the third sector. It encompasses not only technical skills but also critical thinking, contextual understanding, and the capacity to translate insights into action [43-44]. Yet, many nonprofit organizations face challenges in building these capabilities, often relying on a small number of skilled staff or external consultants.

Recent studies and international stakeholder workshops have emphasized the multidimensional nature of data literacy. It goes beyond statistical or coding proficiency to include understanding data in context: identifying sources, assessing relevance and limitations, and applying insights to address specific organizational or societal issues. True data literacy involves both critical data consumption (e.g., questioning who produced the data, for what purpose, and how reliable it is) and creative data production (e.g., designing indicators, building visualizations, and crafting data-driven narratives) [44].

Stakeholders report engaging with diverse datasets, quantitative and qualitative, including economic indicators (e.g. GDP, employment), public health metrics (e.g. disease prevalence), political data (e.g. voting behavior) and digital sources such as social media sentiment or behavioral analytics. This variety calls for a flexible understanding of data types, sources, and associated ethical considerations.

However, many organizations lack structured opportunities for staff to build these skills. Traditional training often focuses narrowly on technical tools, neglecting interpretive and applied dimensions. To foster a truly data-informed culture, capacity-building must be integrated across all levels and roles-from frontline staff to senior leadership.

A data-literate organization equips its members to ask informed questions such as: Who created these statistics? What populations do they represent? What indicators best align with our mission? When and where was the data collected? What level of granularity is required? And is the data accessible and reusable under open standards?

5.1.6 *Funding and resource constraints*

Implementing data-driven approaches in the third sector requires sustained investment in skilled personnel, technological infrastructure, and ongoing capacity-building-resources that many organizations chronically lack. Financial constraints are among the most frequently cited barriers, particularly for small and medium-sized nonprofits operating under tight or project-based budgets. These limitations hinder the acquisition of analytics tools, the hiring of data-literate staff, and the development of in-house capabilities for data management and interpretation [45].

Compounding this issue is the fact that many organizations rely on restricted funding from statutory bodies or donors, who may impose specific tools or reporting frameworks that are misaligned with organizational needs or existing workflows. Such externally mandated solutions may fail to support advanced analytics or context-specific insight generation, limiting innovation and adaptability at the organizational level.

Stakeholders widely acknowledge that data work is inherently resource-intensive. Analysis often requires specialized knowledge in statistics, data science, machine learning, and domain-specific performance metrics-expertise that cannot be developed or retained without stable funding. As one practitioner noted, "we are struggling to secure funding to recruit skilled staff and access the right tools for good data." This underscores the broader structural challenge: while expectations for evidence-based reporting and impact measurement are rising, the resource base to meet these expectations is not always keeping pace.

In response, some foundations and funders have begun to adopt a more proactive capacity-building role. Rather than merely financing projects, they increasingly provide shared infrastructure such as data platforms, pre-built analytics dashboards, standardized templates, and toolkits. They also offer in-person or virtual training sessions and foster knowledge-sharing communities to reduce duplication of effort across the sector [45].

Emerging models of support also include pre-analyzed or standardized datasets for commonly measured indicators (e.g., churn rates, engagement clustering), enabling nonprofit organizations to redirect their limited analytical capacity toward more complex or context-specific tasks. In this vision, foundations act as enabling intermediaries-offloading baseline analysis while equipping grantees with resources to perform deeper, mission-aligned data work.

Despite these promising developments, the persistent funding and resource gap continues to constrain the scalability and sustainability of data-driven initiatives. Without systemic changes in how resources are allocated, governed and shared, many third-sector organizations will remain locked in a reactive mode unable to fully harness the potential of data for learning, innovation, and impact.

5.2 *System-level influences*

Beyond the boundaries of individual organizations, several systemic factors shape the third sector's ability to adopt and sustain data-driven practices. These influences operate across organizational networks and define the broader environment in which data initiatives emerge, evolve, and scale. Understanding these system-level dynamics is essential to contextualize both the opportunities and constraints affecting the sector's data maturity [46].

5.2.1 *Stakeholder engagement and ecosystem coordination*

Effective data use in the third sector is rarely the result of isolated efforts; instead, it thrives in collaborative environments where multiple stakeholders contribute to a shared vision [47]. Beneficiaries, funders, academic institutions, government agencies, and technology providers form part of a broader data ecosystem that influences how data is accessed, interpreted, and applied. Trust-based partnerships are crucial to facilitate data sharing, ensure contextual relevance, and foster accountability. Ecosystem-wide platforms for coordination-data collaboratives, learning alliances, or cross-sector working groups-enable knowledge pooling, promote innovation, and reduce duplication of analytical efforts. These collective mechanisms can bridge gaps in capacity and infrastructure, especially for smaller organizations.

5.2.2 *Policy and regulatory frameworks*

The regulatory environment sets the boundaries within which data can be collected, processed, and used. Policies related to data privacy, security, and ethical handling-such as the General Data Protection Regulation (GDPR) in the European context provide essential safeguards for protecting individual rights Toepler and Anheier [48]. However, for many third sector organizations, particularly those with limited legal or technical expertise, such regulations can pose compliance burdens. Navigating consent management, data minimization principles, and cross-border data flows often requires dedicated capacity that small or under-resourced actors may lack. Moreover, ambiguities in regulatory interpretation can lead to risk aversion, discouraging experimentation and data sharing even when legally permissible. A more enabling regulatory environment would balance protection with flexibility and provide clear guidance tailored to the nonprofit and social innovation landscape.

5.2.3 *Evaluation and impact benchmarks*

The pressure to demonstrate effectiveness and social return on investment has intensified the focus on data-driven evaluation. Funders, regulators, and policymakers increasingly demand rigorous evidence of impact, often through standardized frameworks, performance indicators, and reporting requirements. While such benchmarks enhance comparability and transparency, they may inadvertently constrain innovation if they prioritize easily quantifiable outputs over qualitative or long-term outcomes [49]. Moreover, they can lead to mission drift when organizations shape programs primarily around what is measurable rather than what is meaningful. A more inclusive approach to evaluation would accommodate diverse methodologies, encourage participatory assessment, and align metrics with organizational values and contextual realities.

5.2.4 *Platforms for collaboration and knowledge sharing*

Digital platforms and data repositories that support peer learning, best practice dissemination, and technical resource exchange have emerged as key enablers of data capacity-building. These platforms-whether hosted by foundations, academic networks, or sector alliances-allow organizations to access case studies, analytic tools, open datasets, and training materials. By lowering entry barriers and reducing redundancy, such infrastructure enables even resource-constrained actors to engage meaningfully with data. Importantly, these platforms also facilitate feedback loops where insights from practice inform tool refinement and shared learning [50].

5.2.5 *Legacy systems and interoperability*

A major technical barrier to systemic adoption lies in the fragmentation of digital infrastructure across the third sector. Many organizations rely on outdated legacy systems that lack interoperability with modern data architectures. Disparate formats, proprietary software, and inconsistent data standards hinder the seamless integration and aggregation of information across initiatives and institutions. This not only increases administrative burden but also limits the potential for collective impact analysis and sector wide intelligence. Overcoming these challenges requires investment in open standards, Application Programming Interface (API)-based system design, and shared data vocabularies-facilitated by coordinated support from funders, vendors, and policymakers [51].

6. Theoretical framework for successful implementation

Data-Driven Innovation (DDI) is emerging as a transformative force in the third sector, which includes nonprofits, charities, and social enterprises. By leveraging data effectively, these organizations can improve their operational efficiency, increase the impact of their programs, and better fulfill their missions. However, the path toward data-driven transformation is often obstructed by structural constraints, limited resources, and cultural resistance. This section outlines a theoretical framework for enabling DDI in the third sector, combining conceptual steps with practical implementation insights. It highlights critical success factors such as data literacy, infrastructure, ethical governance, and stakeholder engagement.

Compared with existing digital-transformation and data-maturity models, our framework differs in three important ways: (1) it introduces an additional pillar centered on ethical and community-grounded data governance; (2) it explicitly differentiates be-tween subsectors of the third sector (nonprofits, charities, NGOs, and social enterprises) to reflect their distinct constraints and innovation pathways; and (3) it integrates cross-case synthesis findings from our empirical material to refine and validate the proposed pillars.

The successful implementation of data-driven innovation requires a structured and strategic approach. Figure 6 presents a comprehensive framework that delineates five key stages organizations should follow to embed data-centric thinking into their operations and culture.

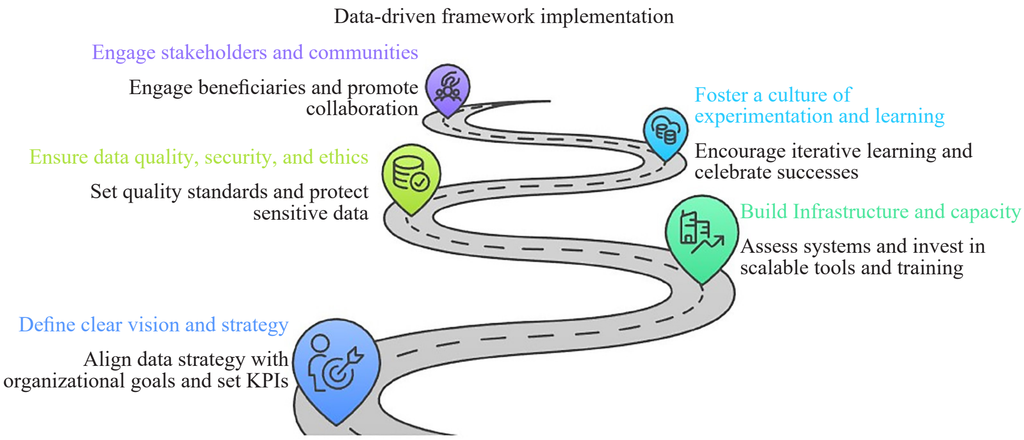

Figure 6. Framework for data-driven innovation. The process is structured around five essential pillars: strategy, capacity, quality, culture, and engagement. A sixth pillar-ethical and community-centered governance-is added in this study to address algorithmic fairness, community consent, and responsible AI practices

6.1 *Define clear vision and strategy*

The first and foundational step in enabling data-driven innovation is to align the organization's data strategy with its overarching mission and strategic objectives. Establishing clear Key Performance Indicators (KPIs) ensures that data initiatives are purposeful and contribute to measurable outcomes. A wellarticulated vision not only guides organizational priorities but also communicates the intended direction to all stakeholders, fostering shared understanding and commitment.

• Integrating Data-Driven Innovation (DDI) into the operations of third sector organizations-nonprofits, charities, and social enterprises-can generate multiple benefits, including:

• Enhancing program effectiveness through evidence-based evaluation and monitoring;
• Optimizing resource allocation by identifying high-priority or high-need areas;
• Improving fundraising and donor engagement through personalized, data-informed campaigns;
• Supporting advocacy efforts with data-backed policy insights;
• Increasing operational efficiency by streamlining workflows and decision-making processes.

Despite these potential benefits, several challenges can hinder the adoption of data-driven strategies in the third sector:

• Limited financial and technological resources;
• Fragmented or siloed data systems that impede integration;
• Low levels of data literacy and analytical capacity among staff;
• Privacy, ethical, and governance concerns related to data handling;
• Organizational resistance to cultural change and innovation adoption.

These constraints highlight the need for a systematic, contextaware, and ethically grounded framework to guide the implementation of DDI initiatives within third sector organizations, ensuring both effectiveness and sustainability.

6.2 *Build infrastructure and capacity*

Once strategic alignment is achieved, the next priority is to assess existing systems and invest in scalable infrastructure and workforce capabilities. This involves adopting appropriate data tools, storage solutions, and analytical platforms, while simultaneously ensuring that staff possess the necessary skills to use these technologies effectively. Capacity-building is not only a prerequisite for operationalizing data strategies, but also essential for sustaining innovation over time.

• Audit existing systems: Conduct a comprehensive assessment of current data assets, tools, and analytical capabilities to identify strengths and gaps.

• Invest in scalable infrastructure: Leverage cloud-based platforms and open-source technologies for data storage, processing, and visualization to ensure adaptability and cost-efficiency.

• Develop data literacy: Implement targeted training programs to enhance staff competencies in data management, analysis, and communication (e.g., data storytelling).

• Recruit or train specialists: Strengthen internal capacity by hiring data professionals or forming partnerships with external experts to build a robust data ecosystem.

6.3 *Ensure data quality, security, and ethics*

High-quality data constitutes the foundation of any successful data-driven initiative. This stage emphasizes the need to establish rigorous standards for data accuracy, completeness, and consistency. Concurrently, protecting sensitive information and adhering to ethical principles-such as transparency, informed consent, and fairness-are essential to maintaining stakeholder trust and ensuring compliance with legal and regulatory frameworks.

• Set quality standards: Establish benchmarks for data accuracy, completeness, consistency, and timeliness tailored to organizational needs.

• Implement quality controls: Apply systematic procedures for data validation, cleaning, and auditing to ensure integrity throughout the data lifecycle.

• Protect sensitive data: Utilize encryption protocols, role-based access controls, and incident response plans to safeguard privacy and mitigate risks.

• Uphold ethical practices: Address algorithmic bias, ensure informed consent, and promote responsible data governance in line with ethical guidelines.

6.4 *Foster a culture of experimentation and learning*

Organizations must foster a learning-oriented culture in which experimentation is both encouraged and normalized. This entails iteratively testing ideas, evaluating outcomes, and continuously refining practices based on data-driven insights. A culture that celebrates success while openly reflecting on failures can strengthen organizational resilience and promote sustainable innovation.

• Encourage iterative learning: Promote small-scale pilot initiatives, rapid feedback loops, and agile development cycles to enable responsive adaptation.

• Celebrate successes: Share compelling impact narratives to build organizational momentum, stakeholder trust, and support for data-driven initiatives.

Facilitate internal knowledge-sharing: Break down organizational silos and foster cross-functional collaboration to accelerate learning and innovation.

• Continuously adapt: Evolve the data strategy in response to contextual feedback, emerging challenges, and shifting stakeholder needs.

6.5 *Engage stakeholders and communities*

Inclusive engagement with both internal and external stakeholders-particularly beneficiaries-is crucial for ensuring that data initiatives are contextually relevant, socially responsible, and aligned with community needs. Cross-sector collaboration introduces diverse perspectives, facilitates access to complementary resources, and enhances the legitimacy and credibility of data-driven initiatives. Moreover, active community involvement strengthens the social value of innovation efforts, promotes accountability, and supports equitable outcomes for all stakeholders.

• Involve beneficiaries: Co-design data initiatives in partnership with community members to ensure alignment with their priorities, lived experiences, and consent regarding data use.

• Collaborate across sectors: Establish partnerships with academic institutions, funders, governmental agencies, and peer organizations to facilitate knowledge exchange, capacity building, and resource pooling.

• Communicate transparently: Clearly report how data is collected, analyzed, and applied, thereby reinforcing accountability, informed participation, and trust in organizational processes.

• Build trust: Practice ethical storytelling and ensure the respectful, non-extractive, and culturally sensitive representation of vulnerable or marginalized groups.

7. Case examples of successful implementation

7.1 *Case study A: Big data-driven innovation in education using EdNet*

To illustrate the proposed framework in practice, we present a case study based on the EdNet dataset [52], one of the largest publicly available collections of student interaction data from a real-world AI-powered education platform. EdNet was developed by Riiid! and contains over 131 million student-system interactions collected from more than 780,000 learners using the Santa TOEIC self-study application over a two-year period.

• Define Clear Vision and Strategy: The EdNet initiative was launched to support data-driven personalization in language education, with the strategic goal of improving TOEIC preparation outcomes. The project's vision was to harness big data analytics to model student learning behaviors and optimize their learning trajectories. Key Performance Indicators (KPIs) included prediction accuracy of student performance, dropout rates, and time-to-proficiency.

• Build Infrastructure and Capacity: Developed a scalable infrastructure capable of capturing fine-grained learning interactions across multiple platforms (Android, iOS, and web). The platform collected diverse behavioral data such as video lecture views, question responses, time spent per item, choice eliminations, and purchase events. These data were structured hierarchically into four levels (KT1-KT4) to support various analytical tasks. In parallel, the organization built a research team skilled in machine learning, natural language processing, and educational data mining.

• Ensure Data Quality, Security, and Ethics: Data quality was maintained through standardized logging protocols, preprocessing pipelines, and continuous auditing. The dataset was anonymized and made available under a non-commercial license, with safeguards to protect student privacy. Ethical considerations were embedded through transparency in data usage and a commitment to non-exploitative research practices.

• Foster a Culture of Experimentation and Learning: EdNet enabled iterative experimentation through large-scale training of AI models such as Deep Knowledge Tracing (DKT), Self-Attentive Knowledge Tracing (SAKT), and Transformer-based architectures like SAINT. Researchers continuously refined models by benchmarking against student performance and exploring novel pre-training strategies for label-scarce prediction tasks. The open release of EdNet fostered a collaborative research ecosystem and innovation across institutions.

• Engage Stakeholders and Communities: The EdNet initiative engaged a broad network of stakeholders including educators, researchers, and developers. Partnered with academic institutions (e.g., Yale, UC Berkeley, University of Michigan) to co-author research and develop new models. The public release of EdNet encouraged community-driven innovation, knowledge sharing, and ethical dialogue about AI in education.

• Outcomes and Impact: The EdNet dataset has significantly advanced the field of AI in Education (AIEd), enabling breakthroughs in knowledge tracing, dropout pre-diction, and personalized learning path recommendation. Models trained on EdNet achieved state-of-the-art performance, and the dataset continues to serve as a benchmark for future research. Importantly, EdNet exemplifies how big data can drive educational innovation while maintaining ethical standards and stakeholder inclusivity.

The EdNet case study demonstrates the practical applicability and effectiveness of the proposed theoretical framework for enabling data-driven innovation in the third sector-specifically Dataset Availability: The EdNet pipeline is openly accessible at: https://github.com/riiid/ednet.

7.2 *Case study B: Implementing data-driven healthcare innovation with the MIMIC-extract pipeline*

Data-Driven Innovation (DDI) is revolutionizing healthcare by enabling evidence-based decision-making, improving patient outcomes, and optimizing resource allocation. The MIMIC-Extract pipeline exemplifies how a structured, ethical, and collaborative approach can overcome challenges in working with complex Electronic Health Record (EHR) data. This section integrates a theoretical framework for successful DDI implementation with the concrete steps taken in the MIMIC-Extract project [53], highlighting best practices and lessons learned.

• Define Clear Vision and Strategy: A clear vision aligned with clinical goals is critical. This includes defining measurable objectives and addressing domain-specific challenges such as data heterogeneity and reproducibility. MIMIC-Extract was designed to standardize heterogeneous raw EHR data from the MIMIC-III database into hourly timeseries suitable for machine learning tasks. Its strategic goals focused on enabling reproducible prediction of key clinical outcomes such as mortality, length-of-stay, and intervention forecasting. Key performance indicators included model accuracy metrics (e.g., Area Under the Receiver Operating Characteristic curve (AUROC)) on welldefined clinical tasks.

• Build Infrastructure and Capacity: Robust infrastructure and capacity-building ensure scalable and accessible data processing. This involves cohort and variable selection, tool integration, and support for diverse analytical workflows. The pipeline filtered Intensive Care Unit (ICU) patients based on stay duration (12 hours to 10 days), aggregated 104 time-series features plus 10 demographic variables, and outputted standardized datasets as Pandas Data Frames. The open-source repository provides Jupyter Notebooks for bench marking and supports both fixed- and sliding window dynamic prediction frameworks. The development team includes clinicians and data scientists skilled in machine learning and time-series analysis.

• Ensure Data Quality, Security, and Ethics: Data must be accurate, consistent, and privacy-preserving. Ethical governance includes transparency, consent, and responsible use. Data units were standardized (e.g., Celsius, kilograms), outliers filtered based on clinical ranges, and missing data imputed with clinically informed methods. Patient privacy was maintained following MIMIC-III deidentification protocols. The pipeline avoids including prescription data to prevent confounding and provides comprehensive documentation to promote transparency and reproducibility.

• Foster a Culture of Experimentation and Learning: Continuous experimentation and collaboration accelerate innovation. Benchmark tasks, flexible feature engineering, and open contributions are encouraged. Researchers used the pipeline for multiple prediction tasks-mortality, length-of-stay, and intervention onset/offset-evaluating models including logistic regression, random forests, CNNs, and Long Short-Term Memory networks (LSTMs) (see Section 7.2.1). Random forests achieved top macro AUROC scores (94.6% for ventilation prediction, 90.7% for vasopressors). The open-source community contributes improvements, shares best practices, and updates features as new clinical insights emerge.

• Engage Stakeholders and Communities: Successful DDI requires broad collaboration with clinicians, researchers, policymakers, and the public. Stakeholder input ensures relevance and trust. Clinical experts guided feature selection to ensure medical relevance. The pipeline has been used to reproduce studies published in leading conferences and journals, reinforcing research rigor. Public availability promotes adoption by diverse stakeholders, including clinicians using high-quality data for decision support and policymakers leveraging benchmarks for healthcare evaluation.

• Outcomes: demonstrated the feasibility of real-time intervention forecasting, emphasized preventing temporal leakage by using appropriate gap times, and provided a standardized baseline for the community.

The MIMIC-Extract pipeline illustrates how integrating a clear strategy, robust infrastructure, data quality safeguards, an innovation culture, and stakeholder engagement enables effective data-driven healthcare innovation. This combined theoretical and practical approach reduces barriers and accelerates clinically impactful research. The lessons learned are transferable to other healthcare domains and more broadly to third-sector organizations seeking to harness data for social good.

Dataset Availability: The MIMIC-Extract pipeline is openly accessible at: https://github.com/MLforHealth/MIMIC_ Extract.

7.2.1 *Results*

Models and Benchmarks. The study presented in [53] benchmarked a variety of models: Logistic Regression (LR), Random Forest (RF), Convolutional Neural Networks (CNN), and Long Short-Term Memory networks (LSTM). Hyperparameters for LR and RF were optimized via random search, while CNN and LSTM settings were adopted from prior studies. This diversity of models enables evaluation of both classical machine learning and deep learning approaches in a time-series, clinically actionable setting.

Results. Table 1 summarizes performance metrics for mechanical ventilation and vasopressor prediction. Overall, RF models achieved the highest AUROC for most outcomes, with macro AUROC scores of 94.6 for mechanical ventilation and 90.7 for vasopressors. Accuracy and macro F1 scores show that both classical and neural network models perform reliably, even without incorporating clinical notes used in prior work. These findings highlight the robustness of the pipeline and demonstrate how structured preprocessing supports effective predictive modeling in clinical settings.

Table 1. Performance results on mechanical ventilation and vasopressor prediction using MIMIC-Extract. AUROC, accuracy, F1, and AUPRC metrics are reported [53]

Model	Vent. onset	Vaso. onset	Vent. wean	Vaso. wean	Vent. stay on	Vaso. stay on	Vent. stay off	Vaso. stay off
RF	87.1	71.6	94	94.2	98.5	98.5	99	98.3
LR	71.9	68.4	93.2	93.9	98.4	98.2	98.3	98.5
CNN	72.2	69.4	93.9	94	98.6	98.4	98.4	98.1
LSTM	70.1	71.9	93.1	93.9	98.3	98.3	98.4	98.1

To address these, HUMVI partnered with Insecurity Insight to define operational labels and curated 17,497 news articles in English, French, and Arabic. Models were evaluated on two tasks: relevance classification and multilabel sector impact prediction

The results in Table 1 illustrate the practical impact of the DDI framework when applied to clinical intervention prediction. Random Forest models consistently achieved the highest AUROC scores across both mechanical ventilation and vasopressor tasks, demonstrating the effectiveness of classical ensemble methods when combined with well-structured, preprocessed data. CNN and LSTM models performed comparably, showing that deep learning approaches can capture temporal dependencies in ICU time-series even without unstructured clinical notes. Accuracy and macro F1 scores confirm that predictions are sufficiently reliable for operational use, supporting real-time decision-making in high-stakes clinical settings.

From a framework perspective, these outcomes validate several key pillars: (i) a clearly defined strategy aligns predictive tasks with critical clinical objectives, (ii) robust infrastructure and standardized preprocessing facilitate model generalization across patients and outcomes, (iii) attention to data quality and ethics ensures trustworthiness and reproducibility, and (iv) a culture of experimentation allows for comparative evaluation of multiple model architectures. Stakeholder engagement was also central, as clinical relevance guided feature selection and task design, ensuring that models address actionable questions. Overall, the MIMIC-Extract case demonstrates that integrating theoretical principles with concrete data engineering and model evaluation practices can yield robust, clinically actionable insights, offering a replicable blueprint for other domains seeking to operationalize data-driven innovation.

7.3 *Case study C: Implementing data-driven humanitarian innovation with the HUMVI dataset*

Data-Driven Innovation (DDI) is transforming humanitarian response by enabling real-time monitoring of violent incidents, improving aid delivery, and informing policy decisions. The HUMVI dataset [54] exemplifies how structured multilingual data, expert-labeled categories, and NLP-driven automation can bridge critical gaps in humanitarian analytics. This case study integrates a theoretical DDI framework with the practical steps of the HUMVI project, emphasizing collaboration, scalability, and ethical governance.

• Define Clear Vision and Strategy: The HUMVI initiative aimed to enable real-time classification of violent incidents impacting humanitarian sectors-such as aid security, health, and food supply-by leveraging multilingual news data. Key challenges included:

-Data scarcity: Lack of labeled data linking violent events to sector-specific impacts.

-Language limitations: Underrepresentation of Arabic and French, crucial for conflict zones.

-Domain expansion: Adding underrepresented categories like food security.

• Build Infrastructure and Capacity: The technical infrastructure integrated multilingual scraping (NewsAPI, Overseas Security Advisory Council (OSAC), Global Database of Events, Language, and Tone (GDELT)), preprocessing (deduplication, anonymization), and annotation pipelines. Annotation followed two modes: On-The-Job (OTJ) labeling embedded in humanitarian workflows and Offline (OFL) expansion for underrepresented labels.

Key features include:

-HUMVI-core: English-only dataset (15,631 articles across 4 categories).

-HUMVI-expansion: Adds Arabic/French and food security (total 17,497 articles).

-Tools: Open-source code and Jupyter notebooks, publicly available via GitHub.

High inter-annotator agreement (Cohen's $\kappa > 0.75$) confirmed labeling reliability.

• Ensure Data Quality, Security, and Ethics: HUMVI prioritized ethical data use and quality through:

-Filtering duplicates and empty articles.

-Standardizing labels (e.g., "food security" includes market or supply disruptions).

-Excluding personal identifiers and restricting to publicly available content.

-Ensuring annotator compensation and transparency on geographic and media biases (e.g., GDELT limitations).

• Foster a Culture of Experimentation and Learning: Bench marking involved both traditional fine-tuned models and LLMs (see Section 7.3.1):

-XLM-RoBERTa achieved F1 scores between 0.83 and 0.88.

-GPT-4o performed well in zero-shot settings but lagged behind fine-tuned models.

-Innovations such as translation augmentation improved Arabic/French performance by 5-10%.

-Masked loss improved English food security classification but showed instability in low-resource settings.

Findings confirmed that domain-specific fine-tuning outperformed general LLMs, especially for underrepresented categories.

• Engage Stakeholders and Communities: Collaboration was central to HUMVI's success. Humanitarian experts helped validate labels and define practical use cases (e.g., tracking attacks on aid convoys). The project also invited contributions from NLP researchers focused on multilingual models for underrepresented SDGs such as Zero Hunger. Public dataset release accelerated community driven improvements while supporting advocacy through empirical evidence.

• Outcomes and Lessons Learned: The implementation of the HUMVI framework yielded measurable improvements in operational efficiency and highlighted critical considerations for deploying data-driven tools in humanitarian contexts.

-Impact: Automated detection achieved > 80% precision in critical sectors like aid security and education.

-Scalability: HUMVI-expansion demonstrated how to integrate new languages and categories with minimal resources.

-Challenges: LLMs require tuning for domain accuracy; indirect impacts (e.g., looted medical supplies) remain hard to detect.

Key Lessons for the Third Sector:

-Align with end-users-operational relevance is critical.

-Promote open science-shared datasets accelerate collective progress.

-Iterate frequently-adapt datasets and models to emerging humanitarian needs.

The HUMVI project highlights how applying a structured data-driven framework-with attention to strategy, ethics, experimentation, and inclusivity-can significantly enhance the effectiveness and accountability of humanitarian interventions.

Dataset Availability: https://github.com/dataminr-ai/ humvi-dataset.

7.3.1 *Results and analysis*

For the HUMVI dataset, the study presented in [54] combined transformer-based models and Large Language Models (LLMs) to perform relevance and category classification. Transformer models such as DistilBERT, Bidirectional Encoder Representations from Transformers (BERT), and Cross-lingual Language Model – RoBERTa (XLM-RoBERTa) were fine-tuned on labeled data to capture semantic patterns and multilingual content effectively. DistilBERT provides a lightweight architecture with faster training, BERT offers deeper contextual understanding, and XLM-RoBERTa extends capabilities to multiple languages, making it suitable for English, French, and Arabic reports. In parallel, proprietary and open-source LLMs (e.g., GPT-4T, GPT-4o, Mistral, Llama3) were evaluated in zero- or few-shot settings to assess their ability to generalize without extensive fine-tuning. These models provide complementary strengths: transformer models excel when finetuned on structured datasets, while LLMs are more flexible for prompt-based inference.

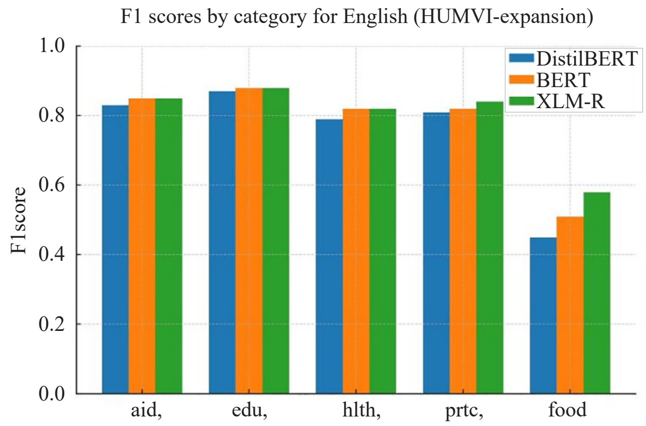

Figure 7. F1 scores by category for English on HUMVI-expansion. Each plot compares DistilBERT, BERT, and XLM-RoBERTa across five categories (aid, education, health, protection, and food security) [54]

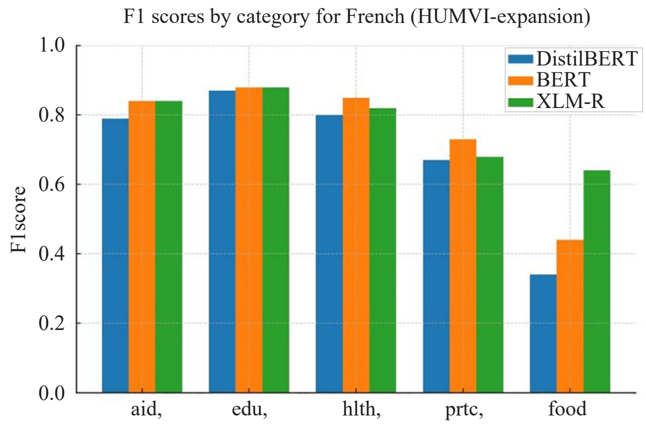

Figure 8. F1 scores by category for French on HUMVI-expansion. Each plot compares DistilBERT, BERT, and XLM-RoBERTa across the five categories [54]

Performance on HUMVI-core. Figures 7, 8, and 9, together with Table 2, summarize model performance using F1 scores across categories and languages. In Figures 7-9, fine-tuned transformers consistently outperform LLMs, achieving the highest F1 scores in English, French, and Arabic for categories such as aid, education, health, and protection. The newly introduced food security category shows lower scores across models, highlighting the challenge of adapting to emerging categories with limited labeled data. Table 2 further shows that translation augmentation improves relevance classification, particularly for French and Arabic, confirming the benefits of multilingual data augmentation. Overall, these results indicate that combining fine-tuned transformers with careful preprocessing and augmentation yields the most reliable performance, while LLMs can serve as a supplementary tool for rapid adaptation or prompt-based inference.

The performance results on HUMVI (Figures 7-9 and Table 2) illustrate the practical value of applying the DDI framework to humanitarian analytics. Fine-tuned transformer models, particularly XLM-RoBERTa, consistently achieved the highest F1 scores across English, French, and Arabic, confirming the advantage of structured multilingual training in capturing semantic patterns relevant to sector-specific impacts. DistilBERT and BERT performed robustly in English, while translation augmentation notably improved performance in underrepresented languages, demonstrating the importance of preprocessing and augmentation for inclusivity. The lower scores observed for the newly introduced food security category underscore the difficulty of adapting models to novel domains with scarce labeled data, reinforcing the need for iterative dataset expansion and continuous refinement.

From a framework perspective, the HUMVI case validates several pillars: (i) a clearly defined vision and strategy ensures operational relevance, (ii) robust infrastructure supports scalable and reproducible model training, (iii) ethical data governance safeguards trustworthiness in sensitive humanitarian contexts, and (iv) fostering a culture of experimentation enables comparison between classical fine-tuning and prompt-based LLM approaches. Stakeholder engagement contributed to label quality and alignment with real-world humanitarian priorities. Overall, HUMVI demonstrates that combining theoretical principles with carefully designed NLP pipelines can produce actionable insights for the third sector, with fine-tuned transformers serving as a reliable backbone and LLMs offering flexibility for rapid adaptation and zero-/few-shot inference.

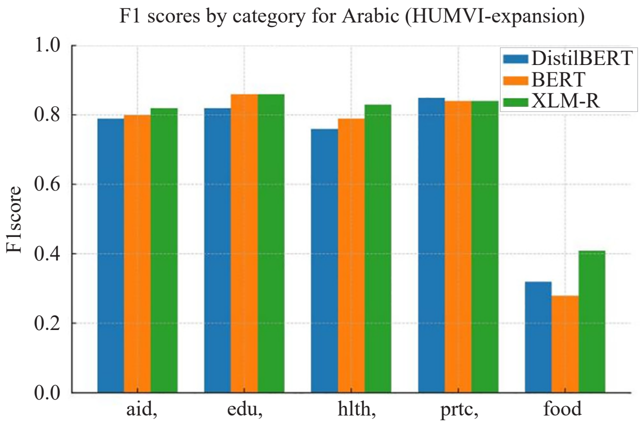

Figure 9. F1 scores by category for Arabic on HUMVI-expansion. Each plot compares DistilBERT, BERT, and XLM-RoBERTa across the five categories [54]

Table 2. F1 scores for relevance classification before (Base) and after translation augmentation (wAug) on HUMVI-expansion [54]

Lang	Mode	DistilBERT	BERT	XLM-RoBERTa
English	Base	0.81	0.82	0.83
	wAug	0.82	0.83	0.82
French	Base	0.69	0.76	0.81
	wAug	0.74	0.76	0.77
Arabic	Base	0.69	0.75	0.81
	wAug	0.79	0.80	0.83

7.4 *Synthesis and framework-case alignment*

Table 3 provides a cross-case synthesis of how the five pillars of the proposed theoretical framework are operationalized across three representative domains: education (EdNet), healthcare (MIMIC-Extract), and humanitarian response (HUMVI). This comparative assessment moves beyond narrative description by systematically evaluating the degree of alignment between expected outcomes and actual implementations.

The comparative analysis of Table 3 reveals several key insights. First, EdNet and MIMIC-Extract demonstrate nearcomplete alignment across all five pillars, particularly excelling in vision and strategy, infrastructure, and data governance. Their systematic use of standardized pipelines, skilled interdisciplinary teams, and clearly defined performance metrics underscores the feasibility of operationalizing the framework in technologically mature environments.

In contrast, HUMVI illustrates the adaptability of the framework in resource-constrained humanitarian settings. While showing partial alignment in infrastructure and capacity due to its lighter technological footprint, it strongly excels in stakeholder engagement and ethical governance. This reflects the contextual prioritization of participatory design, multilingual accessibility, and bias transparency in humanitarian analytics, even when advanced computational infrastructure is limited.

Overall, the cross-case synthesis confirms that the framework is both domain-agnostic and context-sensitive: its core principles remain valid across sectors, while specific emphases vary according to institutional priorities and resource constraints.

Importantly, the analysis also reveals a recurrent gap: none of the case studies demonstrates systematic mechanisms for the long-term tracking of social impact or continuous outcome evaluation. To address this limitation, we propose the addition of a sixth pillar-Impact Evaluation and Sustainability, which would explicitly institutionalize practices for measuring downstream effects, scaling successful interventions, and ensuring sustained alignment with beneficiary needs. This extension would not only strengthen the robustness of the framework but also enhance its capacity to guide real-world, evidence-based innovation across diverse sectors.

8. Discussion

The three case studies-EdNet (education), MIMIC-Extract (healthcare), and HUMVI (humanitarian)-demonstrate the practical applicability and adaptability of the proposed Data-Driven Innovation (DDI) framework across diverse third-sector contexts. Despite differences in technological maturity, data infrastructure, and resource availability, the five core pillars of the framework-vision & strategy, infrastructure & capacity, data quality & ethics, culture of experimentation, and stakeholder engagement-consistently support effective implementation. Across all cases, adherence to these pillars enabled structured planning, operational efficiency, and measurable outcomes. EdNet and MIMIC-Extract exhibited nearly full alignment, combining skilled interdisciplinary teams, standardized pipelines, and clearly defined KPIs to achieve high-performance results. In resource-constrained environments such as HUMVI, the framework's flexibility became evident: stakeholder engagement, multilingual inclusion, and ethical governance were prioritized over technological sophistication, demonstrating that effective DDI can be achieved even with limited resources. Nevertheless, none of the cases implemented systematic mechanisms for long-term social impact evaluation or continuous outcome tracking, highlighting a recurring gap that motivates the addition of an Impact Evaluation and Sustainability pillar. This analysis underscores the main strengths of the proposed framework relative to existing approaches. Unlike prior studies that often focus on isolated aspects of data-driven initiatives, the framework offers a holistic, pillar-based structure that integrates strategic vision, organizational capacity, ethical governance, and stakeholder engagement into a coherent model. Its adaptability across sectors, as demonstrated by the three cases, shows that both resourcerich and resource-constrained organizations can operationalize data-driven innovation effectively. Furthermore, the explicit inclusion of measurable outcomes and the proposed sixth pillar on Impact Evaluation and Sustainability addresses a gap in the literature, providing a replicable and evidence-based pathway for third-sector organizations to achieve long-term social impact while maintaining ethical and operational rigor.

The empirical outcomes of the case studies provide evidence supporting the research hypotheses introduced in Section 1. First, H1 posits that organizational capacity and data literacy enhance DDI success; EdNet and MIMIC-Extract confirm this, with specialized teams and robust infrastructures enabling reliable model development and effective use of complex datasets, while HUMVI shows that targeted capacity-building in low-resource contexts can also yield meaningful results. H2 asserts that ethical and governance practices increase stakeholder trust and operational effectiveness; anonymization in EdNet, de-identification and clinical compliance in MIMIC-Extract, and ethical labeling with bias transparency in HUMVI were critical for establishing trust and ensuring operational relevance. H3 hypothesizes that inclusive stakeholder engagement improves sustainability and impact; HUMVI demonstrates participatory design with humanitarian experts and multilingual considerations, whereas EdNet and MIMIC-Extract engaged researchers, educators, and clinicians to ensure adoption and alignment with real-world needs. Finally, H4 suggests that a clear vision and strategic alignment lead to measurable outcomes; the consistent tracking of KPIs-such as TOEIC scores, AUROC, and F1 metrics-confirms that well-defined objectives are essential for translating data-driven efforts into actionable results. Overall, these findings indicate that the proposed framework operationalizes the research hypotheses effectively, providing a replicable pathway for DDI across diverse third-sector contexts, while allowing sector-specific adaptations to address contextual constraints (see Table 3).

Table 3. Alignment of theoretical framework pillars with case study implementations

Pillar of framework	Expected outcome	EdNet	MIMIC-Extract	HUMVI
Vision & strategy	KPIs clearly defined; alignment with mission	Full alignment-KPIs for TOEIC score improvement, dropout reduction	Full alignment-KPIs for AUROC on clinical tasks	Strong alignment-KPIs for relevance & sector prediction accuracy
Infrastructure & capacity	Scalable tools; skilled workforce	Full-multi-platform logging, ML/NLP team	Full-standardized pipeline, clinician-data scientist team	Partial-open-source tools & annotation infra; smaller tech footprint
Data quality, security, ethics	Standards, anonymization, bias mitigation	Full-standardized logging, anonymization	Full-clinical ranges, imputation, de-ID	Strong-deduplication, ethical labeling, bias transparency
Culture of experimentation	Iterative pilots; model refinement	Full-multiple KT models, open benchmarks	Strong-multiple model classes, open benchmarks	Strong-fine-tuning, translation augmentation, LLM testing
Stakeholder engagement	Cross-sector collab; beneficiary involvement	Strong-partnerships with global universities	Strong-clinician input; adoption by policymakers	Full-humanitarian partners co-design labels and use cases

Building on these insights, several directions for future research and practical development emerge. First, developing scalable and inclusive tools will enable small and grassroots organizations to access data-driven capabilities, reducing the “data divide.” Second, ethical AI and algorithmic governance should be investigated to ensure transparency, fairness, and inclusivity, particularly for marginalized populations, with appropriate governance structures to monitor ethical risks. Third, longitudinal impact assessments are needed to evaluate organizational effectiveness, social impact, and resilience over time, including comparative analyses across different third-sector subgroups such as charities, NGOs, and social enterprises. Fourth, cross-sectoral data collaboratives can explore secure, ethical, and sustainable models for data sharing between nonprofits, public agencies, and private actors, balancing innovation, privacy, and accountability. Fifth, ecosystems for data literacy and capacity building-through participatory training, mentorship programs, and peer-learning networks-can enhance staff and volunteer skills, fostering continuous learning and adaptive innovation. Sixth, context-sensitive framework adaptation should ensure that the proposed framework remains relevant and practical across various organizational sizes, sectors, and socio-cultural environments. Finally, the integration of impact evaluation and sustainability mechanisms is crucial to monitor downstream social impact, scale successful interventions, and ensure long-term alignment with beneficiary needs.

By pursuing these directions, third-sector organizations can move from isolated pilot projects toward a systemic, inclusive, and ethically grounded model of data-driven innovation, capable of responding adaptively to complex societal challenges while maximizing transparency, equity, and social impact.

9. Conclusion

This article, underscores the transformative potential of data-driven approaches in empowering nonprofit organizations, NGOs, and social enterprises. By harnessing big data, these entities can strengthen evidence-based decision-making, enhance transparency and accountability, and foster innovation aligned with their social missions. Nevertheless, the sector continues to face critical barriers, including limited financial resources, insufficient technical expertise, technological constraints, and institutional resistance to organizational change.

The study identifies key enablers that support the successful adoption of data-driven strategies: committed leadership, a data-informed organizational culture, sustained investment in infrastructure and data literacy, and robust ethical and governance frameworks. The proposed theoretical framework, which includes vision alignment, capacity building, data quality assurance, iterative experimentation, and stakeholder engagement, offers a practical roadmap to operationalize data innovation in diverse third-sector contexts.

Empirical illustrations, such as the EdNet initiative in education, the application of MIMIC-Extract in healthcare, and the HUMVI case in humanitarian logistics, provide concrete examples of how this framework can be implemented to achieve measurable social impact. These case studies demonstrate how ethically grounded and context-sensitive data practices can unlock value, even in resource-constrained environments. To strengthen the impact of data-driven approaches in the third sector, several recommendations can be considered. Organizations should prioritize the development of scalable and inclusive tools that offer adaptable, cost-effective data solutions suited to the capacities of small and grassroots nonprofits. Ensuring ethical AI and algorithmic fairness is essential, promoting transparency, inclusivity, and equity, particularly for underserved and marginalized communities. Long-term evaluations of data-driven initiatives can provide valuable insights into their effects on organizational performance, resilience, and social outcomes. Encouraging cross-sectoral data collaborations can help establish sustainable governance models for secure and responsible data sharing among nonprofits, public agencies, and private actors. Finally, fostering ecosystems for data literacy through participatory training programs and peer-learning networks can enhance data skills and capacity across the sector. By implementing these recommendations, the third sector can move toward a more systemic, inclusive, and impactful model of data-driven practice that better addresses complex social challenges.

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Data Availability

All data used for the experiments are publicly available (as indicated by pointers to the literature in the paper).

Conflicts of interest

The author has no competing interests to declare that are relevant to the content of this article.

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