A Systematic Review and Taxonomy of Data Analytics in Nonprofit Organisations

Abstract

Nonprofit organisations (NPOs) use data analytics and corresponding visualisations to discover and interpret patterns of donations and donor behaviours, predict future funds, and analyse time series to undertake decisions and resolve issues. Further detailed understanding of these activities in the context of NPOs is required for efficient and effective utilisation of data analytics. This article reports a systematic review of available literature on data analytics applications in NPOs to answer three research questions: (1) What are the proposed approaches and frameworks for adopting and applying data analytics in NPOs? (2) What aspects of data analytics are used for NPO activities and missions? (3) What challenges and barriers face NPOs regarding the adoption and application of data analytics for their missions? We answered the three research questions by collecting and examining data and using it to develop a new taxonomy. The results show the utilisation of data analytics applications by NPOs has not been examined in depth, indicating the need for further research. This study contributes to the literature by providing insights on the existing use of data analytics applications in various domains, and their benefits and drawbacks for NPOs. This study also presents future research directions.

Keywords:
Data analytics applications, data analysis, nonprofit organisations, third sector,
systematic review, bibliometric analysis

1. Introduction

NPOs are distinct from other enterprises as they are private, structured as institutions separate from the government, and self-governing; they manage and control their practices and missions (Anheier, 2005) as cited by Rathi and Given (2017). Mahmoud and Yusif (2012) note that NPOs meet the unique requirements of their beneficiaries, who may not be able to pay for services. The important social purpose of NPOs differs from the market and profitable organisations

(Productivity Commission, 2010). The label "Not-For-Profit" is also used (Productivity Commission, 2010). In some nations, NPOs are called the "third sector" (Anheier, 2005). Examples of NPOs include museums, schools, universities, research institutions, health organisations, human services, human rights organisations, religious organisations, and charitable foundations (Anheier, 2005). Anheier (2005) notes that NPO missions include values and motivations that drive people to engage in activities to benefit society, the environment, and cultural heritage through charities, philanthropy, volunteering, and giving.

Funding sources for NPOs vary considerably. For example, in Australia, 49.1% of NPOs' income is self-generated; the government contributes 33.5%; only 9.5% comes from public donations (Productivity Commission, 2010). Australia has a higher percentage of public donations than Germany, France, and New Zealand, but lower than the United States (Productivity Commission, 2010). NPOs are a significant social and economic force (Anheier, 2005) contributing significantly to national economies (Rathi and Given, 2017). For example, during 2014-15 in Australia, the direct value added by the charity sector was $71.8 billion (Australian Charities and Not-for-Profits Commission, 2017).

NPOs significantly influence government and society and fulfill their missions by attracting volunteers and establishing strong relationships with their clients. These organisations require time, skills, and management resources to examine and receive valuable feedback for improvement. Conducting research activities, exchanging knowledge, and evaluating and assessing current business practices hold necessary roles in NPOs' operations (Productivity Commission, 2010). NPOs also use data to resolve problems and create new service business opportunities (Hou and Wang, 2017; Johnson, 2015; Mayer, 2019). The use of data is only partially applied to add value to the organisations. According to a survey conducted by Everyaction Team (2018), 90% of NPOs collect data from different sources, but utilise only half of this data. Moreover, many NPOs store their data on spreadsheets and process it manually, rather than digitising it (Bopp et al., 2017). The relationship between data, analytics, and technology in NPOs remains uncertain (Mayer, 2019). Data analytics enables monitoring and evaluation of specific situations by determining significant issues, influencing policy through evidence, enhancing fundraising capabilities, and studying donor behaviour (Bopp et al., 2017; Maxwell et al., 2016; Mayer, 2019; Rathi and Given, 2017). The gap between the available resources and actual usage of data analytics by NPOs is considerable (Johnson, 2015).

Although many studies have been conducted on data analytics applications in various domains, this study specifically focuses on applications of data technology by NPOs. Our study of the literature in the NPO sector discovered only such reviews. One systematic literature review by Gupta et al. (2019) focuses on big data and the humanitarian supply chain, particularly on information systems and operations management. Their review provides an understanding of the role played by humanitarian supply chain organisations to facilitate better decision-making. Another review classifies big data utilisation in health, social networking, and governmental and public agencies (Mohamed et al., 2020). This second review relates data-related research to frameworks of big data applications, shows the trends in the research on big data tools, and gives researchers an insight into the most recent research activities. These reviews do not consider NPO-specific issues in sufficient depth.

First, the reviewed papers only dealt with big data applications in different humanitarian and public sectors and did not precisely focus on NPOs. Second, the methodology of the previous reviews did not include any textual analysis of the papers that enables researchers to identify big data research trends in NPOs. Third, the two studies rarely presented a separate section that discussed the implications of data analytics in NPOs, or considered the challenges, the advantages, and any proposed and alternative solutions for NPOs. Despite their limitations, these two literature review studies (Gupta et al., 2019; Mohamed et al., 2020) provided the starting point of our study.

Our systematic literature review differs from earlier studies as it aims to (1) use a developed taxonomy to investigate and synthesise the literature on data analytics as adopted and applied by NPOs, (2) provide insights of publication trends in the field of NPOs through bibliometric analysis of the discovered documents, and (3) encourage researchers to study and NPOs' management to adopt and apply data technologies. As a result, this study provides four specific contributions to the field by (1) developing a new taxonomy of data analytics research in NPOs and identifying issues that need addressing, (2) focusing on the challenges, requirements, and technical tools associated with applying data analytics in NPOs based on the review of 25 publications found in three databases: Scopus, Web of Science, and ProQuest, (3) demonstrating the usefulness of data analytics applications by NPOs by means of case, and (4) presenting a future research agenda by identifying opportunities and directions based on the implications of the findings and their applicability to other domains, such as decision-making systems. Based on our literature study and understanding, this investigation into the applications of data analytics in NPOs is unique as it combines a systematic review with a taxonomy and bibliometric analysis of the literature.

This paper is organised as follows: Section 2 describes the research methodology, the adopted research strategy, and the process used to select the documents. Following that, a bibliometric analysis tool, together with keywords analysis, is used to evaluate the chosen articles in terms of most published and cited. Then, a developed taxonomy of data analytics publications in NPOs is presented to guide the answers to the research questions. Section 3 presents the results and discussions of each paper, including discussions of the research methods applied, frameworks, main ideas, significance, and limitations. Sections 4, 5, and 6 present research gaps and future directions to address these gaps, the limitations of, and the conclusion of the study.

2. Research Methodology

2.1 Definition of Data Analytics

Data analytics is defined as the usage of computer systems to analyse different scales of data sets to support decision making (Thomas, 2020). As a field of study, data analytics has adopted aspects from different disciplines including machine learning, artificial intelligence (AI), systems theory, operations research, and pattern recognition (Thomas, 2020). Hidden information, patterns, and structures for gaining new insights can be discovered through data analytics (Thomas, 2020). Data analytics projects have several stages: assessing and selecting data, cleaning and filtering data, visualising and analysing data, and finally, interpreting and evaluating the results (Thomas, 2020). Value from data analytics applications is enhanced by using methods and models from the fields of statistics, machine learning, and AI (Thomas, 2020).

Big data is a massive amount of data in different forms and from various sources (Kassen, 2018; Klievink et al., 2017) and is difficult to handle by standard data processing technologies (Klievink et al., 2017). According to Mayer (2019), big data has three characteristics: *volume* (size of the data), *variety* (data comes from various sources), and *velocity* (the speed at which data is created or stored) (Costa and Santos, 2017; Kalema and Mokgadi, 2017; Mohamed et al., 2020). Other scholars include two additional characteristics: *value* (the data can be trusted to generate insights) and *veracity* (the quality and credibility of the data) (Henriksen-Bulmer et al., 2019; Ryzhov et al., 2016). The features of big data prompted scholars to consider new methods of analysing it, and to conduct further research on NPOs (Litofcenko et al., 2020).

2.2 Types of Data Analytics

There are three different types of analytics and the associated techniques (Anitha and Patil, 2018), as summarised in Table 1:

1. Descriptive analytics mines huge amounts of data to discover hidden patterns stored in repositories. Descriptive analytics can be used, for example, to find similarities in customer behaviour. Techniques to generate descriptive analysis include regression of correlated variables and visualising the data by presenting it as charts.
2. Predictive analytics improves decision making by predicting future trends. Predictive analysis is conducted by combining massive amounts of data from various resources. Techniques such as regressions, time series, decision trees, and random forest, among others, can be applied to generate a predictive model of historical data.
3. Prescriptive analytics helps professionals assess the impact of different decisions in the decision-making process. Prescriptive analytics uses optimisation, numerical modelling, and simulation techniques. Anitha and Patil (2018) emphasise that in prescriptive analysis, data is collected continuously to re-predict actions intended to increase the prediction accuracy.

All three types of analytics help organisations establish informed decision-making systems (Pyne et al., 2016). According to the level of analytics, there are certain techniques for conducting descriptive, predictive, and prescriptive analysis.

Type of Analytics	Techniques
Descriptive	Regression analysis, data modelling, visualisation, online analytical processing (OLAP)
Predictive	Time series, naïve Bayes, Bayes Networks, discriminant analysis, decision trees, random forest, CART, clusters
Prescriptive	Optimisation, simulation, decision trees, fuzzy rule-based, neural networks

Table 1. Three Types of Data Analytics

2.3 Methodology: The Systematic Review Process

This section discusses the process and the methodology followed for the systematic literature review. To conduct a systematic review of the literature, researchers must establish a system that allows for efficient detection and searching within articles relevant to the review (Watson, 2015).

Hence, we adopted the process for systematic quantitative literature reviews developed by Pickering and Byrne (2014).

Therefore, the process was modified (Figure 1) to include bibliometric analysis of the collected articles. The bibliometric analysis analyses science as a productive knowledge system by providing a thorough analysis of research trends (Trivedi, 2019). Bibliometric analysis helped discover the most common themes and keywords associated with applications of data analytics in NPOs.

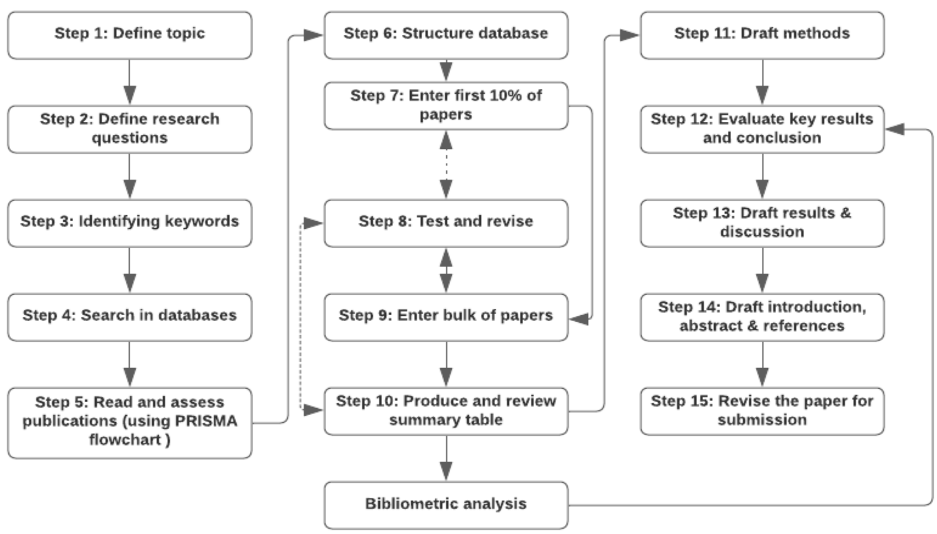

Figure 1. The Modified Systematic Quantitative Approach (Adapted from Pickering and Byrne (2014))

2.3.1 Step 1: Define the Topic

The review process began by stating the topic, aims, and contributions, as described in the previous section. Next, research questions were formulated, keywords for the search were determined, and the databases to be searched for relevant articles were selected (steps 2, 3, and 4, respectively).

2.3.2 Step 2: Define Research Questions

Three research questions were formulated to guide the research and meet the objectives of this study:

RQ.1: What are the proposed frameworks for adopting and applying data analytics in NPOs?

RQ.2: What type of data analytics is utilised for NPO activities and missions?

RQ.3: What challenges and barriers do NPOs face when adopting and implementing data analytics for their business operations and missions?

2.3.3 *Step 3: Identifying the Keywords*

This study deals with two independent domains: computer science (data analytics) and business (nonprofit organisations). Table 2 lists the keywords used to search for documents. Each group in this table represents a relevant keyword. Group A consists of keywords relevant to data concepts, and Group B keywords pertain to the nonprofit domain. In each group, the researchers include the wildcard (*) to provide more results, especially from scientific databases. Keywords from Groups A and B are joined using operator "AND" in the search field, and operator "OR" is used within the same group for a similar keyword; for example, (Big Data AND (Nonprofit OR Non-profitable). The keywords were set to search in the fields of Titles, Abstracts, and Keywords. The completed searching string is shown in Appendix A.

Group A	Group B
"Big Data"	"Nonprofi*" Nonprofit/Nonprofitable
"Data-driven"	"Non-Profi*" (Non-Profit/Non-Profit/Non-profitable/Non-Profitable)
"Data analy*" (Analytics or Analysis or Analysing)	"Not*Profi*" (Not-profitable/Not Profitable)
"Predictive analy*" (Analytics or Analysis)	"Not-for-profit"
	"Charit*" (Charity/Charities/Charitable)
	"Fundraising"
	"Donations"
	"Donors"

Table 2. Keyword Groups

2.3.4 *Step 4: Database Search*

The search was conducted based on all possible matches between the two categories of keywords during a ten-year period from 2010 to 2021 in the Scopus, ProQuest, and Web of Science databases. Research and studies conducted on data analytics applications in NPOs during this ten-year period were sought. According to Khoo-Lattimore et al. (2019), these libraries are comprehensive, used mostly by researchers, and contain more peer-reviewed papers. In addition, these databases are considered the most comprehensive and powerful available (Yang et al., 2017). Other databases, such as Google Scholar and arXiv, were excluded from our search because they provided pointers to publications already contained in our searched databases, or they included non-peer reviewed papers. We concentrated on peer-reviewed articles to obtain evidence of the research's quality. Additionally, the literature review aimed to discover the most recent scholarly works on data analytics applications in NPOs. Recently, NPOs adopted and have become more data-driven in fulfilling their missions (Hou and Wang, 2017).

2.3.5 Step 5: Reading and Assessment

To ensure a comprehensive review, the literature search was conducted on all three databases. Also, to ensure clarity, choices were based on several criteria: the articles had to be written in English, peer-reviewed, and published in journals. These selection criteria were reported in two studies (Gupta et al., 2019; Mishra et al., 2018). The PRISMA flowchart (Page et al., 2021) was used in the systematic review to ensure better reporting and gather the relevant documents during the search process. The PRISMA flowchart shown in Figure 2 consists of four main stages described below:

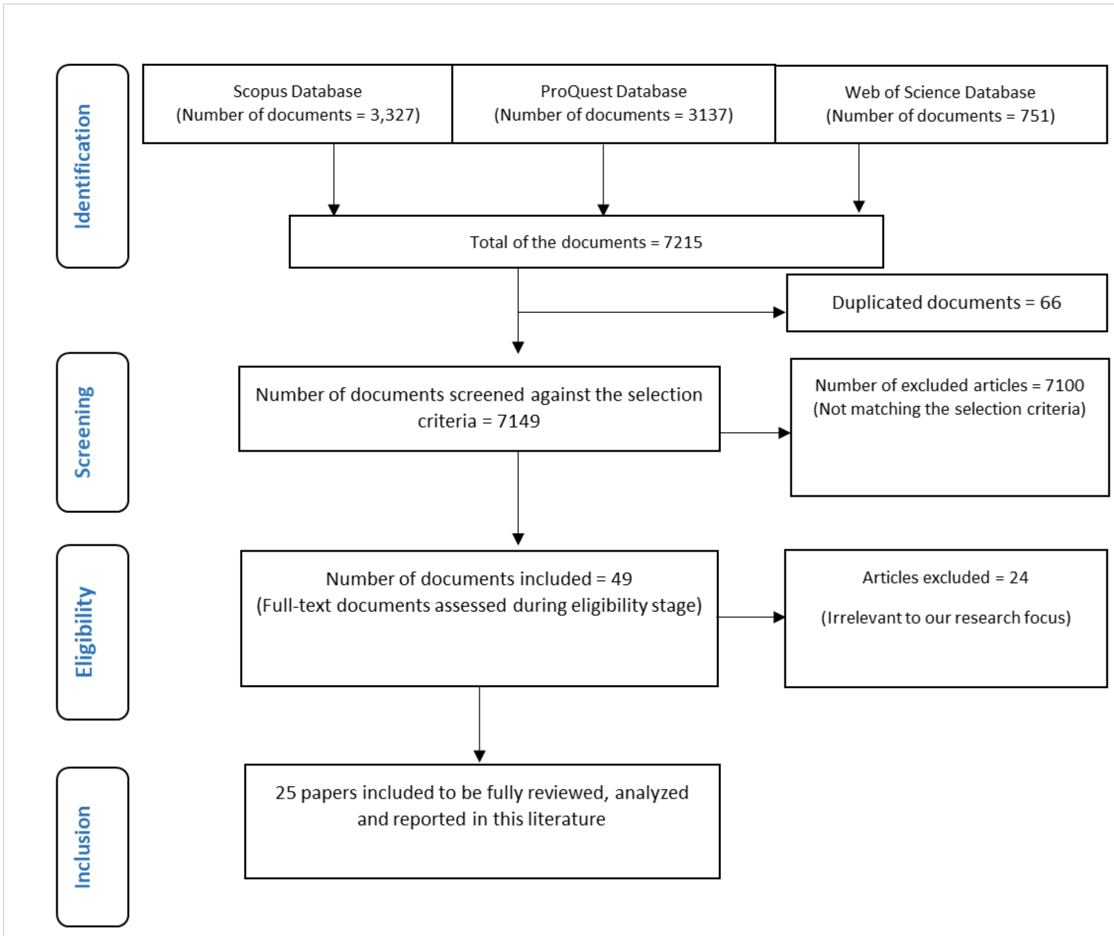

Figure 2. PRISMA Flowchart for Reporting the Literature

Identification Stage

The identification stage yielded 7,215 documents after a search combined the keywords in Group A and Group B. The selection criteria (only English, computer science area, peer-reviewed, and academic journal articles published from 2010 to 2021, and the domain of computer science) were not applied at this stage. The 7,215 documents were comprised of 3,327 articles from Scopus, 3,137 articles from ProQuest, and 751 articles from Web of Science.

Screening Stage

In this stage, 66 duplicate documents were removed, leaving 7,149 articles that were screened against the selection criteria. After choosing only English-language, peer-reviewed journal articles published from 2010 to 2021 in the domain of computer science, 49 publications were eligible for further consideration. Books, book chapters, reviews, conference papers, and surveys were excluded.

Eligibility Stage

The full texts of 49 peer-reviewed articles obtained from the three databases were downloaded, and their abstracts, keywords, and conclusions were analysed to determine the relevance of the contents. The most challenging part of this process was determining whether the research focus of each paper was relevant to the authors' research questions. Irrelevant articles that did not help answer the research questions were excluded. For example, in *New Scientist,* Rutkin (2015) provides only an overview of the blood donation prediction project, but the paper does not describe the research methods or means, or give the data sources, or specify the project's target audience. Hence, it was excluded; it offered no relevant material that could contribute to our research. In total, 25 publications were chosen for closer examination.

Inclusion Stage

In this inclusion stage, the 25 chosen papers were assessed for their relevance to the topic and to this study's research questions. The full text of each article was read, the references were checked, and all references were extracted into Research Information Systems (RIS) files to be stored in Endnote for data management.

2.3.6 Steps 6 to 10

Steps 6 to 10 involved structuring the database, entering the data, and producing a summary table. A database is established (Step 6) to enter essential information for each of the 25 articles. Steps 7, 8, and 9 are entering the papers sequentially, testing and revising them, and finalising all required fields in the database. In Step 10, a summary of the 25 articles with the essential information is produced.

2.3.7 Steps 11 to 15

Steps 11 to 15 were concerned with drafting the systematic review's main parts: methods, results, the introduction, and the abstraction. Most importantly, as the systematic review approach was modified, the results from the bibliometric analysis were evaluated in Step 12.

2.4 Bibliometric Analysis

The bibliometric analysis ensured that all publications were comprehensively examined and to discover more insights (for example, keyword frequency) about the research of data analytics applications in NPOs. Bibliometric analysis is a complex process (Esfahani et al., 2019), thereby motivating lead data scientists (Aria and Cuccurullo, 2017) to develop a bibliometric package in

R language. Their Bibliometrix R-tool supports only Scopus and Web of Science databases, which were used for our search. The final data for the articles sourced from both databases were extracted in Microsoft Excel CSV files for bibliometric analysis. Both CSV files were combined into one file named semi-final records.csv. The Bibliometrix R-tool does not support the records of documents on the ProQuest database. Therefore, the data in Microsoft Excel XLS was extracted and converted to a Microsoft CSV file named "ProQuest data.csv." Finally, the data in the ProQuest file was entered manually using the functions of sim-final records.csv. The Bibliometrix R-package was chosen because it provided several types of metrics for keywords analysis, authors' scientific publications, collaborations of countries and authors, and a conceptual structure (Aria and Cuccurullo, 2017). The Bibliometrix R-package was installed for a variety of analysis.

2.5.1 Citations Analysis

Citation analysis determined the number of citations for each paper and provided relevant information about the popularity of the articles during a certain period (Pilkington and Meredith, 2009). Figure 3 shows the 25 most-cited articles published on data analytics in NPOs during the period of interest. All the most-cited articles shown in Figure 3 were published from 2015 onwards, indicating a growing interest in data analytics applications by NPOs over the last five years.

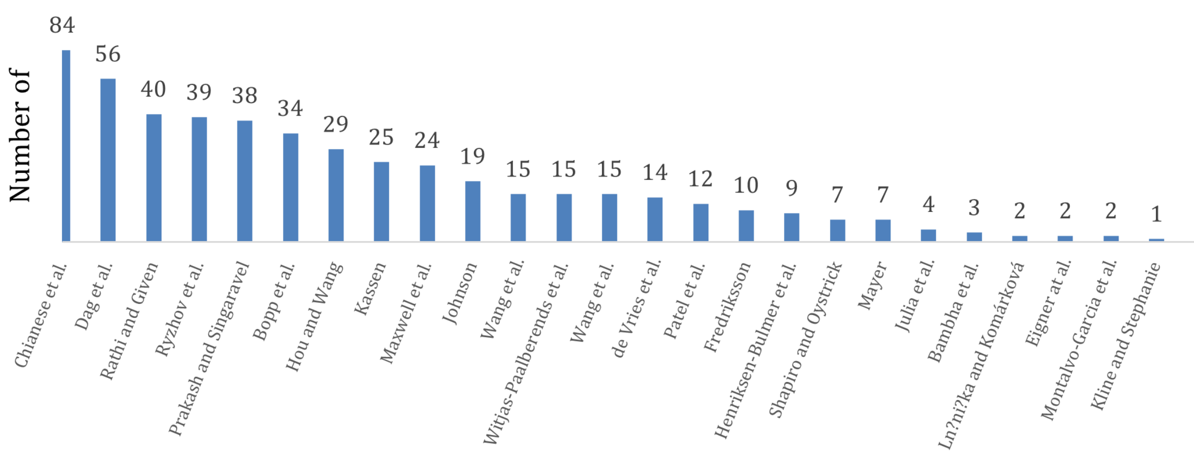

Figure 3. Citations Analysis

Chianese et al. (2017), produced the most frequently cited paper, receiving 84 citations in the Scopus database. They proposed an integrated approach to combine big data, business intelligence, and the Internet of Things (IoT). The approach included using information resources in different forms (structured, unstructured, geospatial, and social network). Their information system was designed to exploit the capabilities of associative in-memory technologies. They aimed to support cultural heritage assets by means of many functions, such as promotions, management, and crowdsourcing. The second most-cited article is from Dag et al. (2017), which received 56 citations in Scopus databases. This work uses analytical models to estimate the graft survival of patients one, five, and nine years after a heart transplant. Notably, Johnson (2015) reviewed the current research state of data analytics practices by NPOs, focusing on community-based organisations (CBOs). Johnson (2015) established concepts to support the usage of data analytics by CBOs. Although this study describes opportunities for specific research projects to design data analysis and information technology solutions, it has had only 19 citations in the last five years.

2.5.2 Conceptual Structure

The Bibliometrix R-tool generates a conceptual structure of a framework involving a co-occurrence of words (Zarei and Jabbarzadeh, 2019). The words can be extracted from titles, abstracts, and authors' keywords. In this analysis, two types of conceptual structures were chosen: the thematic map (Figure 4), and co-occurrence of keywords (Figure 5) used by most authors in their publications.

Thematic Map

A thematic map shows the co-word analysis by clustering keywords which are relevant to the main themes of this study. According to the analysis method reported in a bibliometric study (Aria and Cuccurullo, 2017), a thematic map has a vertical axis representing certainty (e.g., the strength between different themes) and a horizontal axis representing density (the strength of the links within the clusters). Figure 4 depicts:

- Quadrant 1: The upper right shows well-discussed and developed themes. For example: "business intelligence" and "challenges."
- Quadrant 2: The lower right shows basic themes discussed in the papers. It indicates that the "big data" theme has not been discussed adequately.
- Quadrant 3: The upper left shows well-developed themes that do not interfere with other themes, such as "privacy" and "crowdfunding."

- Quadrant 4: The lower left shows poorly developed themes; studies of these are emerging, such as “data analysis,” “nonprofit organisations,” and “business analytics.”

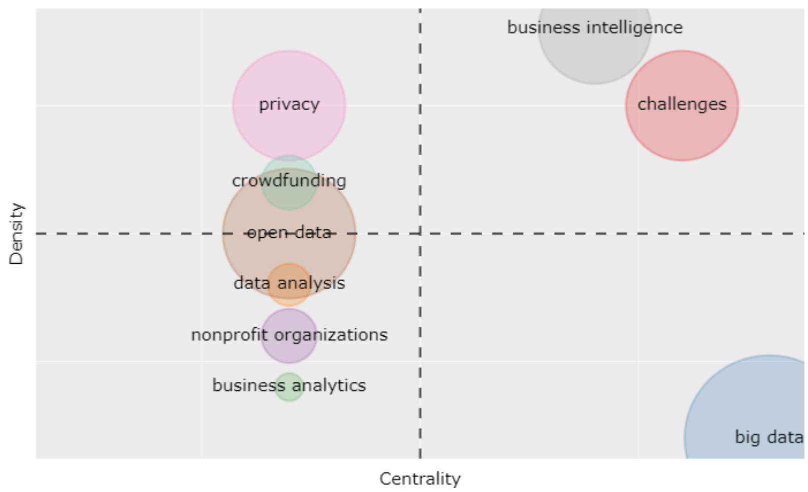

Figure 4. Thematic Map of Keyword Clusters

Co-occurrence Network

The keyword co-occurrence network depicts the relationship between keywords of scientific and technical topics (Aria and Cuccurullo, 2017). In Figure 5, three clusters are shown in three different colours. For clarity of visualisation, 50 words were used for clustering. Keywords such as “data,”

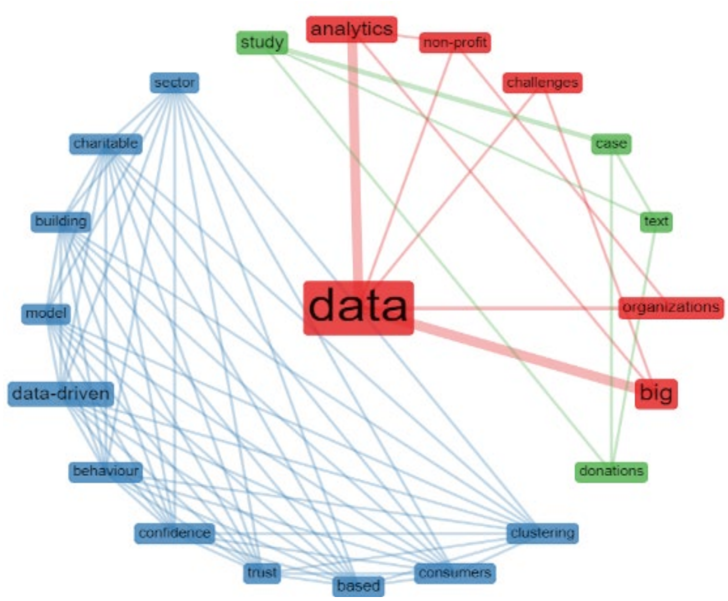

Figure 5. Co-occurrence Network for Keywords

“analytics,” “big,” “non-profit,” and “organisations” were used in the same articles. Another cluster contains words frequently appearing in the same paper, such as “data-driven,” “charitable,” “sector,” and “behaviour.” The third cluster consisted of keywords such as “study,” “case,” “text,” and “donations.”

Overall, from Figures 4 and 5, “big data” seems a popular term in various research fields. However, Figures 4 and 5 show that the term “data analytics” is not well-involved in NPO-related research. This indication inspires scholars interested in researching big data applications in the field of NPOs. For example, further research is needed to understand how big data can be used to align the various stakeholders of humanitarian organisations (Gupta et al., 2019). The bibliometric analysis ultimately contributed to an overview of the chosen topic of study by laying out a research area's structure, utilising multiple indicators (documents, journals, authors, and keywords) and comprehending the underlying relationships between them. These statistics provide a comprehensive overview of the field's research and might be helpful, particularly to early researchers in the field.

2.5 Taxonomy of Found Studies

We identified critical topics in this study based on our examination of the primary data analytics applications for NPOs. Our three research questions’ goals were to provide overviews of (1) proposed frameworks of applying data analytics in NPOs, (2) applied data analytics in NPOs, and (3) challenges that prevent NPOs from applying data analytics. To answer each research question comprehensively, we extracted information by identifying the focus of each study, understanding the research methodology, and highlighting the key findings. We then categorised the topics into the study’s three research questions; Table 3 presents the first part of the taxonomy of the 25 studies. For each research question, we identified relevant answers from the literature as follows:

1. RQ1: Frameworks, approaches, and guidelines for applying and adopting analytics in NPOs.
2. RQ2: Methods, techniques, technology examples, and cases studies of data analytics in NPOs.
3. RQ3: Solutions and alternatives to tackle issues of applying data analytics in NPOs.

Table 3 provides guidance in answering the three research questions with a comprehensive discussion in Section 3 of this review.

RQ #	Authors	Theme of study
RQ1	(Henriksen-Bulmer et al., 2019)	A proposed framework of data analytics application
	(Montalvo-Garcia et al., 2020)	
	(Chianese et al., 2017)	
RQ2	(Fredriksson, 2018)	Data analytics applications: decision-making importance
	(Litofcenko et al., 2020)	Data analytics applications: NPO's data analysis
	(Wang et al., 2019)	
	(Bambha et al., 2020)	Data analytics applications: donor probabilities
	(De Vries et al., 2015)	Data analytics applications: donor segmentations
	(Dag et al., 2017)	
	(Eigner et al., 2017)	
	(Kassen, 2018)	Data analytics applications: showing examples
	(Wang et al., 2010)	
	(Maxwell et al., 2016)	
	(Kline and Dolamore, 2020)	
	(Bopp et al., 2017)	
	(Patel et al., 2017)	
	(Ryzhov et al., 2016)	Data analytics applications: mailing design analysis
RQ3	(Rathi and Given, 2017)	Suggested solutions for tackling challenges of data analytics applications in NPOs
	(Shapiro and Oystrick, 2018)	
	(Lněnička and Komárková, 2015)	
	(Prakash and Singaravel, 2015)	
	(Hou and Wang, 2017)	
	(Johnson, 2015)	
	(Witjas-Paalberends et al., 2018)	

Table 3. Taxonomy of Topics Researched in Data Analytics Applications in NPOs

Table 4 is the second part of the taxonomy, which summarises all 25 relevant articles, clarifying the scope, main work, research methods, and analytics techniques used in each study. According to Table 4, there are few studies that demonstrate the capabilities of data analytics on the decision-making process in NPOs through real examples and case studies (Bambha et al., 2020; Bopp et al., 2017; Fredriksson, 2018; Hou and Wang, 2017; Kassen, 2018; Kline and Dolamore, 2020; Maxwell et al., 2016; Mayer, 2019; Shah et al., 2017). Notably, other studies tackled the challenges of applying data analytics in NPOs (Prakash and Singaravel, 2015; Witjas-Paalberends et al., 2018). This summary helped us discuss the findings in the next section, and identify the research gaps and future directions of research in Section 4.

Scope	Authors	Main Work	Research Methods	Analytics Techniques
Big Data	(Witjas-Paalberends et al., 2018)	Explaining the challenges and best practices in managing big data-driven healthcare innovations by public-private partnerships in the Netherlands	Mix-methods: surveys and interviews	Statistical analysis
	(Fredriksson, 2018)	Showing examples of how big data is used in practice in the public sector		Statistical analysis
	(Patel et al., 2017)	Concentrating on how big data and analysis may support good e-governance	Big Data analysis using MongoDB	Data mining, text analytics, and machine learning
	(Mayer, 2019)	Exploration of using big data in NPOs (examples and cases studies)	Comprehensive descriptions of contents related to applications of big data in NPOs	
	(Chianese et al., 2017)	Proposing an integrated approach integrating AI, big data, and the Internet of Things (IoT) and developing an associative in-memory technology information system	Analysing information from heterogeneous sources	Associative in-memory technologies
Business analytics	(Ryzhov et al., 2016)	Identifying designs that have a huge effect on the results of a fundraising campaign through the study of large-scale datasets	Machine learning techniques	Statistical model analysis
Data Analytics	(Wang et al., 2019)	Collecting and analysing call centre data of an NPO for optimisation	Data mining techniques	Data sorting and data association
	(De Vries et al., 2015)	Giving the nonprofit sector an easy-to-understand segmentation method based on a novel unsupervised learning algorithm	Machine learning techniques: unsupervised clustering technique (MST-kNN)	Clustering and a feature saliency
	(Montalvo-Garcia et al., 2020)	Proposing a data analytics methodology for small and medium-sized NPOs	cross-industry standard process for data mining (CRISP-DM)	
	(Johnson, 2015)	Review of data analytics and information technology research and practice, with a focus on community-based organisations	A comprehensive description of contents	
	(Hou and Wang, 2017)	Understanding how civic data hackathons can produce useful data analytics for nonprofits' data-driven efforts	Mix-methods: observations, surveys, and interviews	Statistical analysis
	(Litofcenko et al., 2020)	Classifying NPOs	Machine learning techniques	Classification analysis using rule-based and machine learning
	(Dag et al., 2017)	predicting the 1-, 5-, and 9-year patient's graft survival following a heart transplant surgery	Hybrid data analytic methodology comprising five stages (data preparation, classification method, model assessment, fusing the variables, and differentiation of the variables)	Support vector machines, artificial neural networks, and decision trees
	(Shapiro and Oystrick, 2018)	Proposing a framework model containing three elements:	Qualitative analysis: A case study	Content Analysis

		accessibility, reliability, and adaptability		
	(Wang et al., 2010)	A summary of the current and existing data mining technologies with examples in NPOs	A comprehensive description of contents	
Data Privacy	(Prakash and Singaravel, 2015)	Proposing a personalised anonymisation approach for protecting sensitive data	Data mining techniques	K-anonymity
	(Henriksen-Bulmer et al., 2019)	Presenting Data Protection Impact Assessment (DPIA) framework devised as part of the case study	Qualitative research: Case study	
Decision-Making	(Maxwell et al., 2016)	Investigates how data-driven decision-making (DDDM) activities and culture are perceived in organisations	Quantitative analysis: surveys	Statistical analysis
	(Eigner et al., 2017)	Determining the concerns, behaviours, and requirements for patient release in relation to the risk of readmission and the information provided	Qualitative analysis: focus group	
	(Bopp et al., 2017)	Presenting the importance of data in mission-driven businesses' monitoring and assessment procedures	Qualitative analysis: interviews	Coding and memoing techniques
	(Bambha et al., 2020)	Generating probabilities using US population projections	Machine learning techniques	Machine learning techniques; probabilities
	(Kline and Dolamore, 2020)	Analysing a case study using the cultural dimension of the organisation	Qualitative analysis: Interviews and Case study	Content analysis
Information and knowledge management	(Rathi and Given, 2017)	Investigating the use of tools and technologies for knowledge management (KM)	Quantitative analysis: analysis from Canada and Australia	Statistical analysis
Open Data	(Kassen, 2018)	Studying open data to meet various interests of stakeholders in different sectors	Case study	
	(Lněnička and Komárková, 2015)	Processing data on Apache Hadoop distributed system	Machine learning techniques	Virtual Hadoop cluster

Table 4. Summary of All 25 Articles

3. Research Findings

The literature on data analytics in NPOs evaluated in our systematic literature review enabled us to identify and analyse the practice's investigated aspects, classify existing frameworks to support it, and comprehend how the problems of using data analytics can be addressed. As a result, we answered each research question together with the relevant answer from the 25 connected papers. To provide deep understanding on the current usage of data analytics in NPOs, each research question was followed by a discussion and content analysis of the literature. Content analysis is a systematic method that allows users to make correct inferences from a vocal, graphical, or structured text to define and measure certain occurrences systematically and objectively (Downe-

Wamboldt, 1992). The following subsections (research questions) discuss the findings of these articles to provide a deep understanding on the current usage of data analytics in NPOs.

3.1 What Frameworks are Proposed for Adopting and Applying Data Analytics in NPOs? (Research Question 1)

The literature presents three studies that propose frameworks for adopting, adapting, and implementing data analytics in NPOs. A three-step framework describes the usage of spreadsheets in developing and implementing an accessible, adaptable, reliable, and sustainable system for evaluation practices (Shapiro and Oystrick, 2018). Some NPOs improved their evaluation practices after becoming aware of data analytics (Shapiro and Oystrick, 2018). Spreadsheets can be an easy way to collect demographic information about service users, handle caseload specifications, monitor attendance, and coordinate customer satisfaction data. Moreover, spreadsheets are an easily available, adaptable, and accurate method of data entry and analysis. However, NPOs can use other tools, such as Google Sheets and Open Office (Shapiro and Oystrick, 2018). The three-step framework of Shapiro and Oystrick (2018) is sustainable for evaluation purposes when all three elements are properly integrated into a data analysis system.

The three-step process advocated by this study comprises:

- Accessibility: Ensuring the system captures and produces adequate information to meet NPOs' requirements.
- Adaptability: Ensuring the NPOs can integrate data and analysis of their data.
- Reliability: Data can be obtained and processed consistently over time.

A second framework, a data collection technique, is presented for nonprofit small and medium-sized enterprises (SMSEs) (Montalvo-Garcia et al., 2020). The architecture of this methodology was built on the cross-industry standard process for data mining (CRISP-DM) as a reference system, as defined by the Software Process Engineering Metamodeling (SPEM). CRISP-DM is distinguished by its simplicity, flexibility, and low implementation costs. The proposed methodology aims to reduce the effort required for implementing data analytics, reducing the costs, and minimising the complexity (Montalvo-Garcia et al., 2020).

The privacy of data is addressed by the European Union's General Data Protection Regulation (GDPR) which came into effect in May 2018 (Henriksen-Bulmer et al., 2019). These authors explain that the GDPR covers the scope of the data, gives more rights to individuals, establishes data collection protocols, and requires organisations to justify their data collection. The work of Henriksen-Bulmer et al. (2019) is significant, as it explains how charities and small and medium-sized enterprises (SMEs) should implement GDPR in a structured way.

They established several steps in their application of GDPR using a case study (two managers, 29 staff and volunteers):

1. Data holdings: To understand how the charity stores and processes the data.
2. Analysis of data holdings: To better understand the data.
3. GDPR Process Guidance: To ensure GDPR compliance by assessing the practices and the processes of the data.
4. The DPIA Data Wheel: To assess any privacy risks.

GDPR is suitable for NPOs whose staff might lack technical and analytical skills. The only critical point is that these regulations and policies presented in GDPR might not apply to non-European NPOs. This algorithm is easy and can be applied by anyone who specialises in data mining and data privacy techniques. This framework may assist NPOs in tackling the challenges of data privacy and data accessibility in NPOs (as discussed in RQ3 below). However, NPOs have different missions and different characteristics; this framework might not apply to all NPOs globally. Table 5 summarises the three frameworks reported to adopt and apply data analytics in NPOs associated with the relevant data scope.

Scope	**Framework's purpose**
Data analytics	A data analytics methodology for small and medium-sized NPOs (Montalvo-Garcia et al., 2020)
Data analytics	A model containing three elements: accessibility, reliability, and adaptability (Shapiro and Oystrick, 2018)
Data privacy	Data Protection Impact Assessment (DPIA) framework (Henriksen-Bulmer et al., 2019)

Table 5. Summary of Data Analytics Applications in NPO Frameworks

3.2 What Type of Data Analytics is Applied to NPO Activities and Missions? (Research Question 2)

The answer requires exploration of different data analytics techniques applied to NPO activities and missions. NPO missions vary in their objectives, such as attracting donors, predicting donations, and improving the decision-making process. There are different applications of large and medium-size data analytics for different research problems related to NPOs and other charitable sectors. For example, NPOs have business problems, such as attracting donors, predicting donations, and managing financial resources. Different data analytics techniques applied, for different research problems related to NPOs missions, are summarised in Figure 6[1].

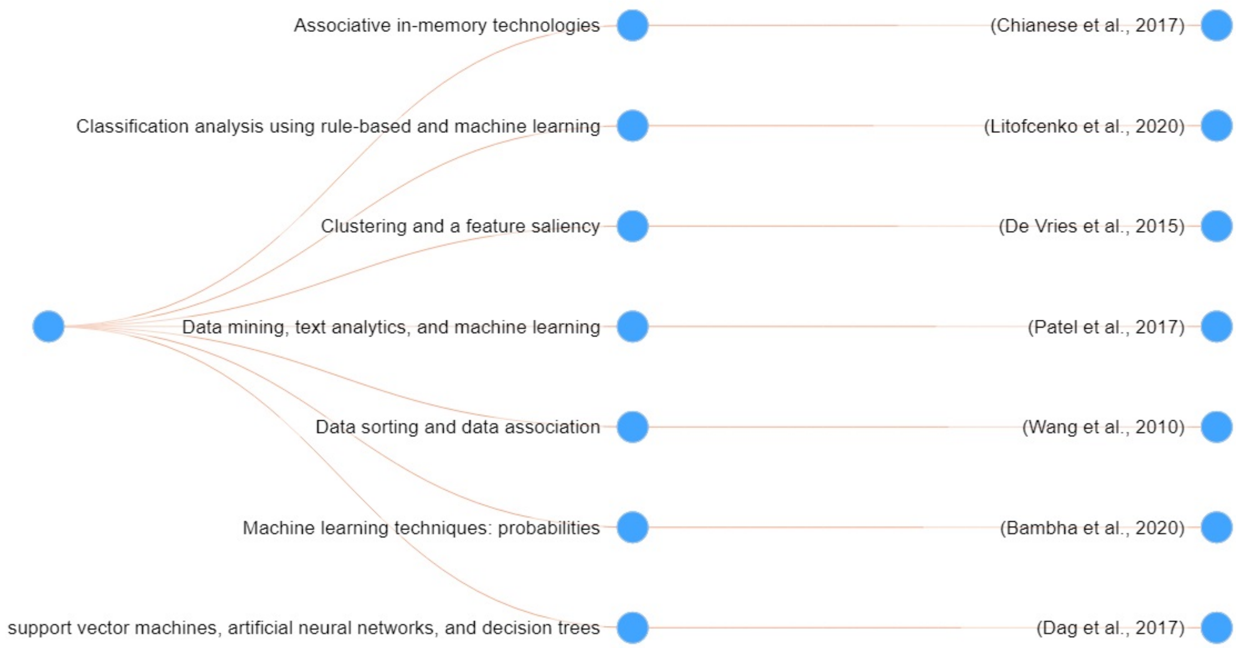

Figure 6. Summary of Different Applied Analytics for Different Problems and Missions in NPOs

Not surprisingly, the process of analysing data in NPOs is known as "knowledge discovery in databases" (Mayer (2019). The process involves data capture and cleansing, aggregation, data mining, and interoperation. Two data analytic techniques applicable to NPO's activities are data mining and text analytics (Patel et al., 2017). Data mining is a common type of analytic in NPOs because it is used to predict customer behaviours (Wang et al., 2010). It involves statistical analytics and machine learning technologies to extract hidden patterns from the data, which are difficult to extract manually (Wang et al., 2010). Data mining based on historical data can optimise the decision-making process (Wang et al., 2010).

Rule-based classification uses textual data to organise Austrian NPOs according to their areas of activity, such as education and research, health, and religion (Litofcenko et al., 2020). International Classification of Nonprofit Organisations (ICNPO) classifies NPOs according to economic growth, political, cultural, and legal structures, and their scale, scope, and function (Salamon and Anheier, 1996). The rule-based method is a type of classification (semi-structured requires manual creation of IF-THEN rules) that can generate data-driven rules. This classification

[1] Figure 6 was created using a visual (Pie charts tree) on Microsoft Power BI. More details: http://www.aritzfb.com

method solves the ongoing research issue that needs quantitative information on the activities and missions of NPOs, but that administrative data is not readily accessible. Long, high-quality texts detailing the activities of NPOs are often unavailable, and there are limited human resources (Litofcenko et al., 2020). This ICNP classification approach is significant as it classifies NPO missions; the framework is appropriate for any number of NPOs.

A study predicting the survival of heart transplant patients was conducted by Dag et al. (2017). The researchers applied data mining methods to discover and analyse raw data from the United Network for Organ Sharing transplant databases, which is classified as an NPO in the United States. The study aims to predict the probability of survival of patients after heart transplant surgery. Four analytical models were used: artificial neural networks, decision trees, support vector machines, and logistic regression. The researchers adopted a hybrid data analytics methodology comprised of five stages: data preparation, classification, model assessment, a fusion of variables, and differentiation of variables. The authors claim the decision tree model produces the best classification outcomes. This paper demonstrates the capability of big data analytics to generate valuable information in the field of health research.

In a similar approach, and demonstrating another application of data analytics by NPOs, an application of data analytics is conducted on organ donors who are individuals waiting for organ transplant donors (dd-SoT), and dd-SoT recipients (Bambha et al., 2020). The study provides a statistical analysis of organ donations, the dd-SoT waiting list, and deceased organ donors in the United States to ascertain (1) a deceased organ donor, (2) dd-SoT organs and (3) the organ recipient required for dd-SoT. They used datasets from United Network for Organ Sharing (UNOS). Their results show that individuals are more likely to require dd-SOT in the United States than to become organ donors following death. This study provides predictive analysis using an NPO dataset in the field of health.

An information system designed exploiting associative in-memory technologies to analyse the behaviours of visitors to social networks (e.g., Twitter's feedback from visitors) for an NPO (Chianese et al., 2017). The integrated approach combines business intelligence, big data, and IoT. Data, such as georeferenced tweets, was collected from social media. The outcomes were: new types of visitor profiles that consider the importance of the digital content provided to tourists and the effect of physical constraints on potential routes, relations between local and territorial visits, and strong support for social business intelligence.

Another research proposes a simply understandable segmentation strategy for the nonprofit sector, based on a unique, unsupervised clustering technique (MST-kNN), followed by a feature saliency method, the CM1 score (De Vries et al., 2015). The MST-kNN clustering method identifies groups of related responders with similar traits. A specific distance or similarity (correlation) metric is used to measure these related qualities. A sample of more than 15,000 responses were collected and analysed to reveal donor segmentations. The strategy used in this study provides a basis for nonprofit organisations to better cluster, segment, comprehend, and target their donor base (De Vries et al., 2015). The clusters discovered in this study provide a first look at the distinct donor segments of the Australian market. This research helps charities identify how donors behave and may be applicable amongst some NPOs.

The importance of data analytics in decision-making processes is underscored by some studies. The decision-making process of NPOs needs growing data, which necessitates efficient management (Fredriksson, 2018). However, managing information in NPOs is a challenging task (Bopp et al., 2017). NPOs will not be able to draw insights and conclusions if the data is not well-collected and organised (Maxwell et al., 2016). To enable data usage, NPOs should adopt strategies that clarify employees' understanding of how to utilise data to achieve their organisation's tasks and mission (Kline and Dolamore, 2020). The literature presents several examples and case studies to demonstrate the importance of using data to drive decision-making by NPOs.

A study investigated the way Family League, a large NPO in Baltimore, Maryland, collects, organises, and utilises data from the perspective of organisational culture (Kline and Dolamore, 2020). The researchers explained the importance of an organisation's values and found that organisational values may vary from one NPO to another. They learned that an internal culture can define and integrate data into the decision-making process. In another interesting study, Bopp et al. (2017) conducted interviews with 13 mission-driven organisations to examine the role of data in evaluating and monitoring practices in NPOs. Their results showed that these 13 NPOs were not empowered by data. They identified three negative consequences of failing to evaluate, monitor, and empower data-driven decision making: data drift, erosion of autonomy, and data fragmentation. These three impacts gave NPOs less control of data, and data is the key to successful decision making.

Another study was conducted using a qualitative approach to determine the factors affecting decision making regarding patient discharge from the hospital (Eigner et al., 2017). Focus groups were conducted at an Australian NPO hospital to gather data. This study aimed to analyse data pertaining to factors influencing patient discharge decisions. The results indicate a growing interest in data analytics and applications to enable faster and more accurate decision making in healthcare. Although this study concludes that data analytics is a valuable tool for decision making, this research's value is limited because the results are interpreted by the authors and have not been evaluated using a data analytics tool.

3.3 What Common Challenges are Faced by NPOs when adopting and applying data analytics? (Research Question 3)

Studies of data applications in the NPO literature are limited. This limitation means that NPOs face major challenges when adopting and applying data analytics. Investigating these challenges and considering them under different sub-headings provides a comprehensive overview of the existing literature to researchers. Ongoing challenges in applying data analytics in NPOs are evident. For example, the literature shows NPO leaders and managers face some significant obstacles, such as a lack of financial resources, ensuring the privacy of data, accessibility of data to authorised personnel, and technical skills required to manage and analyse their data (Gamage, 2016). The challenges are summarised below under different subheadings.

3.3.1 Financial and Technical Resources

NPOs spend less than 2% of their budget on information technology (IT) infrastructures, such as hardware and software, and only 36% on technical training (Hackler and Saxton, 2007). NPOs also face the challenge of selecting the best data analytics tools to respond to their enormous demands (Johnson, 2015). Moreover, the study by Rathi and Given (2017) revealed that NPOs invest in low-cost applications to capture and store data, and may utilise cloud-based computing, such as Google Docs and Microsoft OneDrive (Rathi and Given, 2017). Technical constraints prevent NPOs from making the best use of software, hardware, and professional expertise (Johnson, 2015). However, affordable technologies exist in the form of cloud solutions and large-scale clusters to facilitate big data processing which can improve the performance of these organisations (Lněnička and Komárková, 2015).

MongoDB is one solution that does not require a complex distributed system. Patel et al. (2017) used MongoDB to store the data in an application of data analysis in the public sector for better e-governance. The study is useful as it shows the effective application of a tool to store large-scale data for NPOs. MongoDB is a common-purpose distributed system with features to ensure availability, scalability, and compliance with the most demanding data protection and privacy requirements (Mongodb Atlas, n.d.).

Several software applications, analytics methods, and visualisation tools inspire, show promise and can assist NPO researchers and practitioners in achieving their social missions (Johnson, 2015). The list of technologies and analytics tools are affordable and easy to use by NPOs professionals (Johnson, 2015). One limitation of web-based technologies reported in the list of (Johnson, 2015) is that they have been developed for NPOs in the United States and might not be applicable or beneficial to worldwide NPOs. No details are given regarding the ability of these solutions to handle massive amounts of data, which is another limitation.

3.3.2 Data Privacy

Since NPOs collect data from different sources, including the public, data privacy and accessibility issues present significant challenges to applying data technology (Costa and Santos, 2017; Gamage, 2016). NPOs collect sensitive and private data such as funds, medical research, and donor data, which require an anonymisation mechanism that restricts data access (Prakash and Singaravel, 2015). To overcome the challenge of securing data privacy in non-governmental organisations, a privacy framework was proposed using a top-down greedy algorithm with five stages (Prakash and Singaravel, 2015):

1. Store all data on one single a database.
2. Modify the data through processing such as aggregation and sampling.
3. Apply data mining algorithms.
4. Hide sensitive data.
5. Use data privacy techniques, such as blocking.

This algorithm is easy and can be applied by anyone who specialises in data mining and data privacy techniques. However, NPOs have different missions and different characteristics; this framework might not be applicable to all NPOs globally.

3.3.3 Data Accessibility

The literature shows an ongoing debate around the policies for accessing public data by organisations. NPOs have to ensure full accessibility to the required data (Hackler and Saxton, 2007). Gaining access to any type of data by any organisation involves formal procedures, and all staff must adhere to company policy. It is essential to provide guidelines for data property management and opting-out principles for public data (Witjas-Paalberends et al., 2018). Accessing NPOs datasets helps potential supporters, participants, clients, volunteers, and staff learn about specific business problems, and assist researchers and journalists in evaluating information about

NPOs (Mayer, 2019). However, previous studies have only given examples of data access processes in NPOs; the literature did not discuss strategies, principles, and rules for accessing data.

3.3.4 Human Resources

Several researchers noted that a lack of NPO employees with adequate technical skills was a major challenge. Maxwell et al. (2016) claimed that NPOs struggle to invest in developing employee skills and maintaining a technically skilled workforce. Hou and Wang (2017) highlighted the critical challenge posed by the lack of knowledge in applying analytics to NPOs' data. Developing personnel skills, particularly in data science specialties like analytics, is crucial to improving NPOs' performance and viability (Shah et al., 2017). Moreover, NPOs may rely on volunteers to provide technical support, another human resources limitation (Hackler and Saxton, 2007).

Providing adequate training to extrinsically and intrinsically motivated staff facilitates knowledge transfer and technical skill development (Witjas-Paalberends et al., 2018). Experts who were interviewed suggested best practices to implement when addressing the challenges of applying big data analytics in public-private partnerships (PPPs) (Witjas-Paalberends et al., 2018). These suggestions can be used as guidelines for NPOs seeking solutions. However, the study by Witjas-Paalberends et al. (2018) is limited to the Netherlands. The study also examined the applications of big data from a holistic perspective that focused on PPS in the health sector. Figure 7 summarises the reported solutions by each category of challenges and considers all the drawbacks of applying data analytics.

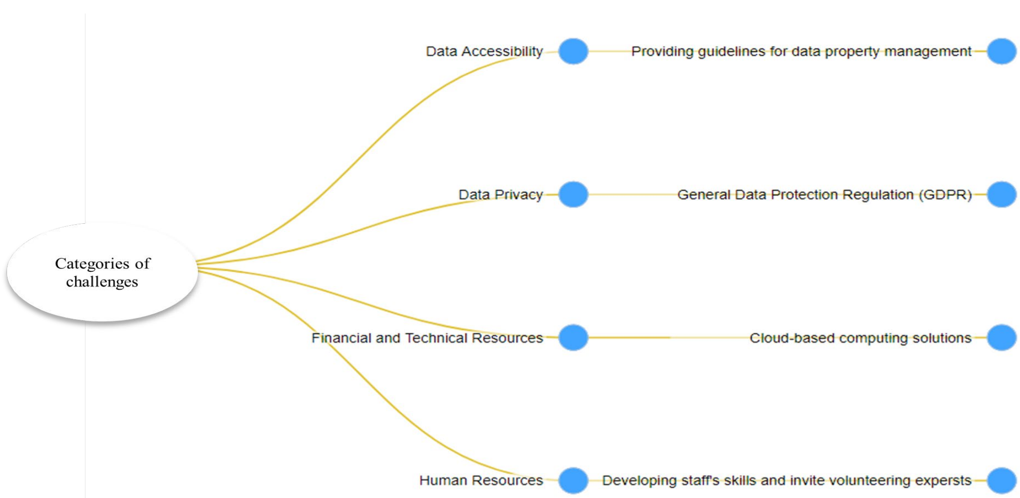

Figure 7. Summary of Suggested Solutions to Data Analytics Challenges in NPOs

4. Research Gaps and Future Directions

There are two specific gaps in the research conducted on the adoption and application of data analytics in NPOs. These gaps are based on the analysis of the documents' records, citations, keywords in subsection 2.4, and the findings in Section 3.

4.1 Research Gaps

First, analysing donor behaviour remains critical and challenging for many NPOs, which is evident from the lack of literature on the topic. Future research can explore applications of data analytics to analyse donors' behaviours. For example, using machine learning and data mining techniques such as regression and classification to investigate and understand donors' behaviours and enhance the decision-making process in NPOs. Therefore, there is a need to design a decision support system to analyse donor behaviour in NPOs. However, little is known on designing a decision support system, due to certain limitations of NPOs, such as technical experience and technical resources.

Second, NPOs may face critical obstacles, technical concerns, and a lack of sufficient resources when adopting data (as discussed in Section 3.3). Challenges have been discovered while applying data analytics in NPOs; developing theoretical frameworks on how NPOs can adopt data analytics may resolve their critical issues. These frameworks could address privacy concerns and the NPO requirements that data analytics tools need to meet. Understanding and predicting users' perceptions (e.g., NPO managers and scholars) can overcome some of these challenges. For example, the technology acceptance model (TAM) (Davis et al., 1989) can provide insights and indications concerning the perception of data in NPOs. Case studies conducted in several countries could validate the framework to ensure its effectiveness, accuracy, and generalisability.

4.2 Future Directions

Recently, a design science research process framework adopted from (Peffers et al., 2007) has started to address the first research gap (Alsolbi et al., 2022). The framework helps design and build a decision support system for analysing donors behaviour by applying different machine learning (ML) in NPOs (Alsolbi et al., 2022). The framework contains six phases and three iterations to conduct specific actions for building the decision support system. The output of this framework is a design theory and an artefact (an AI-enabled decision support system for analysing donors' behaviours in NPOs). The design theory is the instantiation of the decision support system we are building. It creates guidelines for further developments of an AI-enabled decision support system, which will use machine learning techniques to build descriptive and predictive analysis of donor. Since this framework is under development, there could be some limitations of data features or attributes that help analysts perform the analysis intensively.

Investigating factors that influence the adoption of data analytics by NPOs may address the second research gap and offer a future direction to researchers. For example, applying TAM will enable researchers to study challenges and barriers facing NPOs which prevent them from applying data analytics. It will also reveal how aware NPOs' scholars are of applying data analytics and data concepts. Currently, there does not appear to be a study attempting to determine user adoption of data analytics by NPOs.

Investigating the influence of using quantitative or qualitative research methods to apply data analytics in NPOs offers another future research direction. These research methods will answer a range of questions about the characteristics of NPOs, including size, service types, scope, and intensity, which will help develop theories that provide adequacy of information for investing data analytics in NPOs (Johnson, 2015). Also, these methods could help practitioners of data analytics to be aware of NPOs data analytics needs. However, these studies should be conducted in the literature under a collaboration between NPOs and industrial sectors who may volunteer their experience to assist in applying data analytics.

5. Limitations of This Study

The literature review has several limitations. For example, the explorative methodology makes the study prone to subjective bias, although the exploratory review method ensures a comprehensive analysis of the research topic. There is a massive volume of secondary data from numerous databases can be examined to achieve additional research objectives and establish the foundation for future studies. In this study, only three popular databases were used: Scopus, Web of Science, and ProQuest. However, some papers might have been skipped if the source was not in these databases. Another limitation is the restriction of sources to publications appearing only from 2010 to 2021. If the chosen period had been longer, more results could have been obtained. Most importantly, other terms might appear with research focused on NPOs such as "decision making" or "empowered data". However, irrelevant literature might appear in this research scope. Aiming to achieve specific results matching the keywords lists did not allow for extending the time period.

6. Conclusion

The researchers adopted the explorative methodology to conduct the systematic literature review. This systematic literature review aims to (1) investigate and synthesise the literature on data analytics as adopted and applied in nonprofits, based on a developed taxonomy of the literature, (2) provide perspectives into research trends in the field of NPOs via bibliometric analysis and a taxonomy of the discovered documents, and (3) encourage researchers to study and NPOs' management to adopt and apply data technologies in practice. Twenty-five peer-reviewed journal articles were examined in-depth to determine how and where data has been applied in NPOs and offer a comprehensive view of this technology and its current applications. It was found that data is adopted to some extent in NPOs to improve organisational effectiveness.

Nonetheless, the review and discussion of findings revealed two research gaps that require future studies to fill the void and contribute to the knowledge of data applications. Advanced analytics can use data analytics techniques to investigate donor behaviour and predict intentions, motivations, and engagement in NPOs. Frameworks and appropriate analytical models are essential to address technical challenges, privacy, and data accessibility. This study's contribution (1) focuses on challenges, specifications, and technical tools associated with applying data analytics in NPOs, (2) demonstrates the effectiveness of data analytics applications in NPOs using case studies, and (3) presents future research opportunities and directions based on the implications of the findings and their applicability to other domains, such as decision-making systems.

This study identifies implications for data analytics researchers and practitioners. The results of the review show that applications of data analytics are limited in NPOs due to known challenges, such as financial constraints and technical experience. As a result, empirical studies may identify and propose solutions that practitioners can use to help NPOs to develop technical solutions that tackle these challenges. The potential to share lessons about applying data analytics, which may help NPOs worldwide overcome the challenges reported in the literature, is a final and beneficial implication.

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Appendex A

Database	Search string
Scopus	((TITLE-ABS-KEY ("Big Data") OR TITLE-ABS-KEY ("Data-driven") OR TITLE-ABS-KEY ("Data analy*") OR TITLE-ABS-KEY ("Predictive analy"))) AND ((TITLE-ABS-KEY ("Nonprofi*") OR TITLE-ABS-KEY ("Non-Profi*") OR TITLE-ABS-KEY ("non for profit*") OR TITLE-ABS-KEY ("Charit*") OR TITLE-ABS-KEY ("Fundraising") OR TITLE-ABS-KEY ("Donations") OR TITLE-ABS-KEY ("Donors")))
ProQuest: It does not offer a searching field in the keywords	ab((("Big Data") OR ("Data-driven") OR ("Data analy*") OR ("Predictive analy")) AND (("Nonprofi*") OR ("Non-Profi*") OR ("non for profit*") OR ("Charit*") OR ("Fundraising") OR ("Donations") OR ("Donors"))) OR ti((("Big Data") OR ("Data-driven") OR ("Data analy*") OR ("Predictive analy")) AND (("Nonprofi*") OR ("Non-Profi*") OR ("non for profit*") OR ("Charit*") OR ("Fundraising") OR ("Donations") OR ("Donors")))
Web of Science	ti=((("Big data") OR ("Data-driven") OR ("Data analy*") OR ("Predictive analy*"))) AND ti=((("Nonprofi*") OR ("Non-Profi*") OR ("Non-for-Profi *") OR ("Charit*") OR ("Fundraising") OR ("Donations") OR ("Donors"))) OR ab=((("Big data") OR ("Data-driven") OR ("Data analy*") OR ("Predictive analy*"))) AND ab=((("Nonprofi*") OR ("Non-Profi*") OR ("Non-for-Profi *") OR ("Charit*") OR ("Fundraising") OR ("Donations") OR ("Donors"))) OR ak=((("Big data") OR ("Data-driven") OR ("Data analy*") OR ("Predictive analy*"))) AND ak=((("Nonprofi*") OR ("Non-Profi*") OR ("Non-for-Profi *") OR ("Charit*") OR ("Fundraising") OR ("Donations") OR ("Donors")))