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DATA-DRIVEN DECISION-MAKING IN PORTUGUESE SOCIAL IMPACT ORGANISATIONS:

EVOLUTIONARY TRENDS AND CATALYTS

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Abstract

Previous research indicated that the Portuguese social sector was lagging behind in the adoption of Data Science, despite its numerous benefits. However, recent years have witnessed several catalysts potentially driving progress, including the COVID-19 pandemic, the emergence of disruptive technologies and their decreasing costs, and competitive pressures. Employing a quantitative approach, this study revealed modest enhancements in Data Science usage, which fell short of expectations. Nevertheless, Portuguese social impact organisations are increasingly recognising the potential value of Data Science, with partnerships, AI, and new software emerging as some of the catalysts for the observed changes.

Keywords: Social-good-oriented organisations; Data-driven decision-making; Unified Theory of Acceptance and Use of Technology; Digital Transformation

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Abbreviations

DDDM	Data-Driven Decision-Making
EU	European Union
EC	European Commission
UTAUT	Unified Theory of Acceptance and Use of Technology
TOE	Technology-Organisation-Environment
DOI	Diffusion of Innovation
AI	Artificial Intelligence
AAG	Association with Altruistic Goal
GDPR	General Data Protection Regulation
RPA	Robotic Process Automation
SESA	Social Economy Satellite Account
GVA	Gross Value Added
DSKC	Data Science Knowledge Centre
CRM	Customer Relationship Management

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1. Introduction

In an era where data proliferation has revolutionized industries worldwide (Aalst, 2020), it is essential to understand the dynamics of data-driven decision-making (DDDM) across various sectors. This research focuses on a significant yet under-explored area: the adoption and evolution of DDDM in Portugal's social sector. Building on a pivotal 2019 study that highlighted a notable resistance within Portugal's social sector to embrace DDDM, this study aims to extend those findings.

Since 2019, the world has undergone unprecedented changes, especially due to the COVID-19 pandemic, which has catalysed shifts in numerous global processes and industries. This research seeks to explore how the approach to DDDM in Portugal's social sector has evolved in response to these global shifts. A key aspect of this transformation is the integration of advanced technologies, such as Artificial Intelligence (AI), chatbots, and large language models, which have the potential to reshape decision-making landscapes (Meissner et al., 2023).

The study aims to answer: how has the current use of data for decision-making in Portugal's social sector changed, and what factors have influenced this evolution? It examines various influencers, including the impact of COVID-19, the integration of AI and digital technologies, shifts in management mindsets, advancements in open-source software, changes in governmental policies, and market competition pressures.

The methodology employs a quantitative approach, revisiting and expanding upon the 2019 survey by targeting the same organisations and incorporating new ones, thus obtaining a broader perspective of the changes over the last five years.

This thesis is based on a comprehensive review of scientific literature, focusing on the evolving perceptions and applications of DDDM in the social economy. These sources highlight the benefits and challenges of adopting DDDM and lay the groundwork for investigating the current state of decision-making practices within Portugal's social sector.

Building on the foundations of earlier studies, this research aims to offer new insights and a fresh perspective on the intersection of technology, data, and social good, especially in a post-pandemic world. By examining the key factors influencing DDDM adoption in this context, the study seeks to significantly enhance the understanding of Data Science's role and potential within the social sector.

The research was developed with the support of the Social Database project, an open data platform designed to promote knowledge about the social economy sector. The project is also part of the Social Equity Initiative, a partnership between the “la Caixa” Foundation, BPI Bank, and Nova School of Business and Economics.

2. Literature Review

2.1. Background

2.1.1. Social Economy Sector

The social economy sector comprises organisations that systematically prioritise people, embracing a social purpose over profit, and whose mission is driven by solidarity values (OECD, 2020). Therefore, most of their surpluses are reinvested into the organisation for further pursuit of their social mission (Farmer et al., 2023). In the European Union (EU), there are a total of 2.8 million social economy entities, with 16.3 million paid employees, accounting for 6.3% of EU employment (European Commission, 2021), but their impact goes far beyond numbers.

In Portugal, the social sector has been gaining recognition since 2013 (Pedroso et al., 2023), with the publication of the Social Economy Framework Law (*Law no. 30/2013, of May 8*). This law establishes the guidelines for social organisations that can assume the following legal forms: i) Cooperatives, ii) Mutual Associations, iii) Holy Houses of Mercy, iv) Foundations, v) Private Institutions of Social Solidarity (IPSS), vi) Associations with Altruistic Goals (AAG), acting in the cultural, recreational, sports, and local development, vii) entities covered by the community and self-managed subsectors integrated under Constitution in the cooperative and social sector, as well as viii) other entities with legal personality that respect the guiding principles of Social Economy (Diário da República, 2013).

2.1.2. Data Science

Data is growing exponentially. Yet, its use is not growing at a comparable rate (Tamburri et al., 2023). This contributes to the increasing interest in Data Science across a wide range of domains and fields. The National Institute of Standards and Technology (2019) provides the following definition of Data Science:

> *Data Science is the methodology for the synthesis of useful knowledge directly from data through a process of discovery or of hypothesis formulation and hypothesis testing.*

Yet, due to its multifaceted nature, arriving at a singular definition of Data Science can be a daunting task (Mike et al., 2023), as it encompasses several fields of knowledge such as mathematics, statistics, advanced analytics, AI, and machine learning, as well as social sciences like sociology. Yet, it is the combination of different domain knowledge that allows Data Science to understand the context and provide understanding (Aparício et al., 2019). For simplicity purposes, one will refer throughout this thesis to Data Science as the “application of quantitative and qualitative methods to solve relevant problems and predict outcomes” (Waller et al., 2013).

As data becomes more detailed and frequent, decision-makers must improve the quality of their decisions. Consequently, they must let go of gut feelings as the basis of their judgments, and, instead, embrace a data-driven approach, with Data Science serving as the fuel for their decision-making process (Brynjolfsson et al., 2011). Data Science, or Data-Driven Decision-Making (DDDM) will be used interchangeably in this thesis.

Achieving a data-driven approach involves a set of processes aimed at reaching an ultimate goal: extract actionable knowledge (NIST. 2019). This includes data collection and storage, encompassing both structured and unstructured data (Dhar, 2013). Past data forms the foundation of this approach, serving as a rich source of historical insights and patterns, while present data can also be integrated, enabling real-time information (Cao, 2017). Subsequently, data must undergo processes of data cleaning and organisation, ensuring its quality and integrity. Once data is organised, analysis techniques will be applied aiming at generating insights and knowledge (NIST, 2019). At this stage, predictive modelling techniques come into play, leveraging both past and present data to forecast future trends and behaviour, and helping organisations anticipate potential scenarios (Cranmer et al., 2016). The resulting knowledge will guide the decision-making process, providing optimal recommendations and actionable measures (Cao, 2017), and, therefore, empowering decision-makers.

Consequently, in the era of data revolution, adopting DDDM strategies has become a standard practice for how for-profit companies manage their operations (Hume et al., 2020). Such adoption has become mandatory for companies that want to remain competitive and profitable (Brownlow et al., 2015). In fact, adopting data-driven strategies is linked to high-performing firms, as there is an increase in productivity that could reach 6% compared to companies that do not employ such strategies (Brynjolfsson et al., 2011).

Although the advantages of DDDM have been extensively analysed and acknowledged in for-profit organisations, the social sector remains under-researched (Cipriano et al., 2023). Traditionally perceived as lacking data at its core and of operating in a low-competitive environment (Kim et al., 2014), the social sector is, in fact, operating in a context that progressively seeks and requires evidence of impact (Fruchterman, 2016).

If one views the social sector as a supply chain, two main groups can be identified: the community the organisation serves, which receives free support, and the donors, who provide funding to enable this support (Dietrich et al., 2017). However, there are many other stakeholders to whom the social organisation reports to, including employees, volunteers, clients, policymakers, and the government (Dicke et al., 2016).

Most of these stakeholders have a need for data. For instance, donors often aim to quantify the impact of the projects they fund. Simultaneously, the organisation must also track donor engagement and churn (Hume et al., 2020). Similar requirements apply to other stakeholders. Hence, a social organisation database stands as one of its most crucial assets (McNutt, 2018), enabling the effective management of stakeholder's information, which should all be factored into decision-making processes (Dicke et al., 2016), while leveraging Data

Science’s predictive capabilities to translate data into actionable insights (Dhar, 2013), ultimately leading to enhanced organisational efficiency and an increase in social impact.

Yet, the social sector is lagging behind when it comes to the adoption of Data Science, and though there is a growing urgency for the social sector to make better use of data to inform decision-making processes (McNutt, 2018) and advance their social missions (Farmer et al., 2023), this transformation is not always an easy one to make (Hume et al., 2020).

With data at the core of decision-making, one of the organisation's main challenges lies in managing it. Unlike for-profit organisations, where metrics are straightforward and mainly focused on financial performance, social organisations must demonstrate not only what they do, but also the impact they create, in financial, social, and environmental terms. This complexity often leaves decision-makers struggling with data: how to get it, how to effectively use it, and how to maintain its privacy (McNutt, 2018).

As most social organisations handle sensitive data, using it becomes a concern for the organisations (Baar et al., 2016), especially when restrictions regarding data collection and data usage keep escalating, such as those imposed by the General Data Protection Regulation (GDPR). This serves as a source of tension in Data Science adoption (European Parliament, 2020), and highlights a gap between optimal data extraction, and addressing the risks of using that data (Farmer et al., 2023).

Moreover, poor data quality can significantly hinder the effectiveness of data-driven approaches, and social organisations frequently struggle with ensuring data quality, which encompasses aspects such as “conformity, accessibility, accuracy, integrity, and consistency” (Baar et al., 2016).

However, challenges in adopting Data Science faced by social organisations extend beyond technical obstacles in how to manage data (Fruchterman, 2016). Repeatedly identified as a barrier to Data Science adoption is the lack of financial resources (McNutt et al., 1999;

Schneider, 2003; Fruchterman, 2016; Brink et al., 2020), along with funder's reluctance to invest in technology, preferring to purchase more activities (Fruchterman, 2016). This results in obsolete equipment (Bobsin et al., 2018), as well as significant repercussions on the organisation's workforce. While an educated staff is linked with enhanced decision-making (Brynjolfsson et al., 2016), numerous authors identify reduced staff resources (McNutt et al., 1999; Nahrkhalaji et al., 2019), limited staff skills (Schneider, 2003; Brink et al., 2020), such as data literacy (Ashby, 2019), lack of staff training (Schneider, 2003; Cipriano et al., 2023), and difficulty in retaining a talented workforce (Saidel et al., 2003) as barriers to technology adoption in social organisations.

Organisational characteristics also significantly influence Data Science adoption, with an organisation's size, age, and structure recognised as potential barriers to technology usage (Eimhjellen et al., 2014). Larger, younger, and more horizontally structured organisations appear to have an easier time adopting technology (Rodríguez et al., 2012; Eimhjellen et al., 2014; Bobsin et al., 2018; Brink et al., 2020). Furthermore, top management support is also highlighted as an accelerator and a key driver of technology adoption (Haderi et al., 2018; Barham et al., 2020).

Competition is also emphasised as a challenge faced by social organisations (Farmer et al., 2023). As the social sector expands, resources are becoming increasingly scarce (Curley et al., 2021), and competition for beneficiaries, staff, grants, or donors, is expected to rise accordingly (Eckerd, et al., 2023). Despite social organisations not fully embracing the idea that they must compete to survive (Curley et al., 2021), comprehending their competitive environment is essential to identify strategies and thrive in the resource acquisition market (Walk et al., 2022). Innovation is mentioned as the best way to remain competitive (Curley et al., 2021), and some larger social organisations are already investing in data professionals to gain competitive advantage (Farmer et al., 2023).

Ultimately, implementing data science is a holistic concept, interconnecting staff roles, skills, technologies, data management, data governance practices, and organisational culture to be optimised (Farmer et al., 2023). Nevertheless, even with all the challenges social organisations face, the data imperative is here to stay (Fruchterman, 2016).

2.1.3. Digital Transformation

Organisations are vulnerable to external shocks, with COVID-19 serving as a prime example (Farmer et al., 2023). During a period of uncertainty, vulnerable communities were heavily impacted (Johnson et al. 2020) and social economy activities spiked during lockdown (European Commission, 2022). COVID-19 also accelerated people's behaviours, experiences, and interactions towards digital channels (Doolitle, 2021), but an Australian study, conducted at the time, revealed that very few social organisations were capable and equipped with the necessary systems for remote work (Farmer et al., 2023). Consequently, social organisations were forced to quickly adapt, and use innovative ways to reach their target audiences, making the use of technology not only vital, but also a crucial measure for survival (Gooyabadi et al., 2024).

In light of the pandemic, as a recognition of social organisations' involvement in supporting society, as well as the barriers they face, the European Commission (EC) established the Social Economy Action Plan. This plan aims to create the right conditions for the social economy to thrive, and to provide opportunities for social organisations to scale up. Additionally, the EC has also established a strategy to guide the social economy towards digital transition, encompassing several action areas such as data maturity, data sharing, data management, and data-driven business models (European Commission, 2022). These measures are aimed at supporting and encouraging the digital transformation of social organisations and are expected to be implemented by 2030. Therefore, during such a critical time as COVID-19, the role of technology was once again acknowledged, enabling social organisations to bridge gaps (Gooyabadi et al., 2024).

Industry 4.0 has also introduced numerous disruptive technologies. The emergence of cloud-based solutions, open-source software, big data, and robotic process automation (RPA) is driving widespread digitalisation (Gooyabadi et al., 2024), giving rise to the concept of digital transformation.

Consequently, while past technologies were expensive and inaccessible for social organisations (Schneider, 2003), the advancement of technology has led to a significant decline in its associated costs, sometimes nearing elimination (Gooyabadi et al., 2024). Moreover, these technologies are becoming increasingly user-friendly (Fruchterman, 2016), allowing improved user experience. Therefore, while resource scarcity is a concern faced by social organisations as explored in the previous section, embracing this digital transformation wave has the potential to solve it (Spelhaug et al., 2019), allowing organisations to do more, with less (Gooyabadi et al., 2024).

When it comes to disruptive technologies, the role of AI is mentioned thoroughly, as a means to deliver social good (Li et al., 2021). Given its increased accessibility, using AI can be a solution for social organisations to increase their efficiency, while on a budget-constraint. First, AI has the promise to allow organisations to focus on more meaningful, mission-centric tasks, as AI takes over the basic tasks, liberating staff and allowing organisations to allocate their resources more strategically (Gooyabadi et al., 2024). Then, it also has the potential to better understand the stakeholders, with improved modelling and predictions, streamlining the interaction with donors and beneficiaries and allowing a high level of customisation and accessibility for each (Metz et al., 2023). As organisations better meet the needs of each stakeholder, they can also achieve their core mission. Then, it also can facilitate staff training, by offering tailored training based on each staff member's needs and performance, allowing a focused skill development (Gooyabadi et al., 2024).

To support the digital transition, social organisations can also enhance their data capability through collaborative efforts. Collaboration not only widens access to resources, but also fosters the exchange of knowledge and expertise (Farmer et al., 2023). Consequently, social organisations can leverage on the growing number of entities committed to supporting this transition. Examples include the Royal Statistical Society, Data Science for Social Good, Solve for Good, and DataKind, all of which facilitate this process. Additionally, the emergence of data-sharing platforms such as the Humanitarian Data Exchange is noteworthy.

Therefore, as the urgency for data increases, it also seems that the social sector finds itself presented with an array of opportunities for its utilisation.

2.1.4. Social Impact Organisations in Portugal

In 2020, there were more than 73 thousand entities in the Portuguese social economy sector, with AAGs accounting for 90% of them. As published in the Portuguese 4th edition of the Social Economy Satellite Account (SESA), aimed at capturing the initial effects of the pandemic on the sector, there was a 0.4% increase in the number of entities compared to 2019, particularly in the health, social, and educational services domains. The pandemic's impact on the social sector was also evident in its contribution to the national gross value added (GVA), which rose by 0.2% compared to 2019, reaching a value of 3.2% in 2020, the highest since the four editions of the SESA report, exceeding 5.5 billion euros. Additionally, social sector entities generated 5% *(+1.8%)* of the compensation of employees and 5.9% *(+0.4%)* of total employment, amounting to €4.1 billion and 243 thousand full-time jobs, respectively. Notably, the social sector underscores its significance by outperforming the national economy in 2020.

While the national gross value added (GVA) decreased by 5.8%, employees by 2.2%, and total employment by 1.4% (Pedroso et al., 2023), the social sector demonstrated resilience.

In Portugal, a study conducted by the Nova SBE Data Science Knowledge Centre (DSKC), in partnership with "la Caixa" Foundation and BPI bank, aimed to assess the level of Data Science adoption in 243 Portuguese organisations in 2019, prior to the onset of COVID-19.

The study revealed that the application of Data Science was minimal to non-existent in Portuguese social organisations, with only 7% considering it as an investment priority. Among those who participated in the study, 77% were unfamiliar with the concept of Data Science. The study also showed that fewer had a dedicated Information Technology (IT) Team, and that data collection habits were outdated, as 82% of social organisations reported still collecting data physically. Moreover, when the concept of Data Science was explained, even though some organisations recognised the benefits it could bring, they perceived a lack of resources as barriers to its implementation. In fact, only 7% reported having the necessary financial resources, and 9% reported having the necessary technical expertise (Bandeira et al., 2020).

This study was an extension of a master's thesis conducted by Mariana Bandeira, under the supervision of Leid Zejnilović, collecting a total of 158 responses from social organisations. The findings of this thesis were consistent with those mentioned above.

Throughout this literature review, it appears that despite the historical tendency for the social sector to lag behind in DDDM, there are indications that certain catalysts might have contributed to advancing the agenda. Events such as the COVID-19 pandemic, the emergence of disruptive and more accessible technologies, and the growing recognition of the social sector from the EU are just a few examples. While there is emerging evidence indicating a surge in the social sector in Portugal after the pandemic, the precise effects on organisations and their Data Science adoption remain unclear.

Therefore, this research will be an extension of the previous research conducted by Bandeira, seeking to address the following research question: What is the current state of the adoption of DDDM in the Social Impact Economy in Portugal?

The primary objective of this research is to understand whether there has been an evolution in the use of data for decision-making processes in Portuguese social impact organisations.

Secondly, the objective is to identify the primary contributors to any observed changes, should they exist.

2.2. Theoretical Framework

Several theoretical models have been developed with the intent of examining the adoption of technology. Combining more than one theoretical framework is recommended for a deeper understanding of technology use (Martins et al., 2011). Therefore, for the purpose of this thesis, the Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology-Organisation-Environment (TOE) framework, combined with the Diffusion of Innovation (DOI) theory, will be used.

While the UTAUT measures the level of technology adoption, the TOE identifies factors associated with technology adoption. UTAUT can explain up to 70% of the variance in the use of a specific technology (Venkatesh et al., 2003), while the TOE is highlighted as one of the most applicable models for predicting behavioural adoption (Ismail et al., 2016), and is suitable for studying the factors influencing technology adoption at any stage, evaluating their importance and contribution (Lin et al., 2008). The conceptual research model can be found in *appendix 1*.

2.2.1. Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT suggests that the use of technology is dependent on behavioural intention. Therefore, the likelihood of technology adoption relies on four main constructs: i) performance expectancy, ii) effort expectancy, iii) social influence, and iv) facilitating conditions (Venkatesh et al, 2003). The framework is presented in *appendix 2*.

2.2.2. Technology – Organisation – Environment (TOE)

The TOE framework identifies three constructs that influence the process of technology adoption: i) technological context, which describes existing technologies in use and new technologies relevant to the firm, ii) organisational context, which includes characteristics of the organisation, and iii) environmental context, which includes the arena in which a firm conducts its business (Martins et al., 2011).

For each construct, different factors can be considered. In fact, researchers often use slightly distinct sets of factors depending on the context, as various types of technology are influenced by different adoption factors. Additionally, national, cultural, or industry may also play a role (Baker, 2011).

Under the technological context, an integration with DOI theory is made, as it is suggested to increase understanding (Martins et al., 2011). Factors such as relative advantage and compatibility have been strongly supported by diverse studies (Thong, 1999; Chong et al. 2009; Wang et al., 2010, Hsu et al. 2006), and are found to be the most consistent with innovation behaviours (Tornatzky et al., 1982).

As for the other factors, an extensive review of the application of TOE in different case studies was conducted (Kuan et al., 2001; Oliveira et al., 2008; Zhu et al. 2003; Zhu et al., 2005; Lin et al., 2008; Lee et al., 2009). The adopted factors and framework can be found in *appendix 3*.

3. Methodology and Research Design

This thesis extends a previous study conducted by Mariana Bandeira. A quantitative approach was used, incorporating a survey developed with support from the frameworks mentioned in the previous chapter.

3.1. Research Methods and Data Collection

Building upon previous research, a survey was developed, retaining part of the questions from the initial study. Therefore, demographics, elements to evaluate the organisation's perception of Data Science, and items associated with UTAUT have been preserved to measure evolution over time. Additionally, new questions have been incorporated into the survey to assess the TOE framework, aiming to understand factors influencing technology adoption.

Conducted in Portuguese, the survey underwent internal pre-testing with two native speakers: senior researchers with extensive experience in applying Data Science within Portuguese social impact organisations. Subsequently, for the purpose of this thesis, the survey was translated into English and is available in *appendix 4.*

The final survey comprised 52 questions, with 32 being multiple choice, 16 using 5-point Likert scales, and the remaining requiring short answers. It was organised into 11 sections. The initial sections assessed organisation's characteristics and its IT infrastructure level. Section 4 began with a comprehensive explanation of Data Science, presented in simple terms to ensure understanding, with practical examples also included. Following the introduction of the concept, questions were intended to measure the organisation's perceptions of Data Science application. The fifth and sixth sections evaluated the organisation's access to education in Data Science and its data collection practices, respectively. The seventh section centred on Venkatesh's UTAUT, with the list of items used for its estimation available in *appendix 5*. Subsequently, the eighth section assessed the potential barriers to Data Science implementation.

The 9th section evaluated the TOE framework, exploring the organisation's investment in Data Science in recent years, while assessing potential influencing factors. The list of items used to estimate TOE can be found in *appendix 6*. The penultimate section assessed the organisation's path to digital transformation. Finally, the last section allowed participants to provide comments on the topic and optionally share an email address for further research contact.

When it comes to sampling methods, convenience and purposive sampling were both utilised. To cover the entire network of social organisations available, the survey was disseminated to over 1266 social-good organisations through the newsletter of the Portuguese Social Sector Database. Additionally, the survey was distributed to the main representative entities in Portugal's social economy, requesting them to share it with their affiliates, targeting a total of 10,000 organisations. Furthermore, the survey was shared on the Nova SBE DSKC's social media platforms (LinkedIn, Facebook, and Instagram). Regarding purposive sampling, previous participants of the study who expressed interest in being contacted for further developments were reached out via email and phone.

Data collection occurred from April 24th to May 10th. The author used *Qualtrics* to design the survey and subsequently downloaded the results in *Microsoft Office Excel* format. The sample size was of 47 responses, and data was handled anonymously and agglomerated.

3.2. Data Analysis Methods

After collecting survey data, the questions were coded into variables to streamline the analysis process. *Appendix 7* contains the variable names and their corresponding questions. Furthermore, categorical data was converted into nominal and this conversion process is documented in *appendices 8 and 9*. Additionally, questions phrased in the negative form were reversed. Subsequently, the cleaned data was imported into SPSS for further analysis.

Throughout the analysis, two different sets of data were used. The first set originated from the survey collection results, containing 47 responses. The second set combined this data with the 158 responses previously obtained in the 2019 survey, resulting in a total of 205 responses.

Using the combined dataset, the initial step involved identifying the common variables between both studies, as presented in *appendix 10*. Subsequently, to ensure internal consistency, Cronbach's alpha was computed for each of the UTAUT variables in both surveys, and their values are presented in *appendices 11 and 12*, respectively. As Effort Expectancy presented values below the required threshold of 0.6 (Daud et al., 2018) in both studies, its items have been removed from the analysis.

To assess whether the data sample follows a normal distribution, a Shapiro-Wilk normality test was conducted on UTAUT items for both surveys, as well as for the common variables presented in *appendix 10*. Despite all p-values being found to be lower than the significance level (0.05), thus leading to the rejection of the null hypothesis of a normal distribution, it is worth noting that, following Kline's (2011) recommendation, data can still be considered normally distributed when skewness falls within an absolute range of 3, and kurtosis within an absolute range of 10. As this criterion holds true for all the studied variables, a normal distribution has been assumed.

To assess the evolution in Data Science usage and compare before-and-after studies, a t-test was conducted. However, prior to this, the Levene's Test for Equality of Variances was carried out on the UTAUT items and other common variables, evaluating if the assumption of equal variances between groups was met or not. As for the t-test, for the variables where a statistically significant difference was found between the means of the two groups, an evaluation of their effect size was conducted using Cohen's d. Test results are presented in *appendix 13.*

Considering the new survey data only, internal consistency analysis was performed on TOE items, and their values are presented in *appendix 14*. As Size, and Compatibility presented values below the required threshold of 0.6 (Daud et al., 2018), their items have been removed from the analysis. Subsequently, a normality test was conducted on TOE variables, and, once again, Kline recommendation was applied, thus assuming a normal distribution.

At this stage, the proxy variable to evaluate Data Science evolution was created by combining question items related to whether the application of Data Science in day-to-day operations has increased in the last 5 years, as well as the allocation of resources towards its initiatives, including financial, time, staff, among others. Further details on the proxy variable are available in *appendix 15*. Internal consistency, as presented in *appendix 16,* and normality have also been tested and validated.

As a preliminary step towards building the multiple regression model, a correlation analysis was conducted to evaluate the relationship between various variables and the proxy variable, aiding in the selection process of independent variables. Subsequently, the multiple regression analysis was carried out, as a means to investigate the association between the chosen independent variables and the proxy for Data Science evolution. This involved a nested regression using four distinct blocks of variables, resulting in four linear regression models. All models utilised the same dependent variable. The existence of multicollinearity was also tested.

The first block comprises demographic variables, such as the organisation's area of activity, or budget. The second block encompasses organisational practices, such as establishing Data Science partnerships with external parties, or access to education. The third block incorporates UTAUT and TOE variables. Lastly, the fourth block includes potential catalysts for change in Data Science application, such as COVID-19 or AI. Appendix 17 presents all the variables used and the corresponding survey question, and appendix 18 shows all independent variables considered for each block.

4. <u>Research Findings</u>

4.1. Descriptive Statistics

Among 47 organisations, the majority were non-profit associations (55.3%), followed by cooperatives (14.9%), foundations (12.8%), and a mix of other legal formats such as mercies (8.5%), mutualist associations (4.3%), associations with altruistic goals (2.1%) and social enterprises (2.1%). These organisations predominantly operate in social services (53.2%), health (38.3%), and education (36.2%).

In terms of staffing dimensions, the majority of organisations are relatively small in size. Specifically, 63.8% have less than 50 employees, and 74.5% have fewer than 50 volunteers.

The distribution of organisational budgets reveals a spectrum: 17.0% operate with budgets under 100,000 euros, 21.3% within 100,000 to 300,000 euros, and 46.8% surpassing 1,000,000 euros. The organisation structure also varies, with 46.8% adopting a matrix structure, 23.4% having a vertical culture (top management is responsible for the decisions), and the rest employing a horizontal culture (cross-hierarchical decisions).

Regarding IT Infrastructure, 42.6% of organisations disagree with having obsolete technology, including both software and hardware. However, only a minority claim to leverage disruptive technology, such as AI (4.3%), or RPA (12.8%). Moreover, most organisations have websites (83%), but the functionality is primarily informational (61.7%), with limited AI integration (2.1%), automation (2.1%), automatic data storage (17%), or data processing (17%).

Investment in IT infrastructure is modest, with 42.6% not allocating any of their annual budget, and 44.7% investing less than 5% annually. When compared to the investment made five years ago, 46.8% claim that the budget allocation towards IT infrastructure has remained stable, while 36.2% claim it has increased by more than 20%. In terms of having a dedicated IT team, only a minority (16 out of 47) possess such a resource. Among them, 31.2% are externally hired, 50% are internally hired with IT education, and 18.8% are internally hired without any IT education.

Following the introduction of the concept of Data Science and the presentation of concrete examples of its application, organisations were asked about the value of Data Science for their operations. All participants acknowledge some degree of value, with 48.9% identifying it as valuable and 22.2% as extremely valuable. Yet, current Data Science application remains minimal (31.9%) to non-existent (42.6%) in the majority of organisations, with only 14.9% considering it as an investment priority. Moreover, only 10.6% consider their organisations' data literacy to be above average, with almost half of the organisations (46.8%) not having had access to Data Science education in the last 5 years.

When it comes to data collection, 83% of participants have a digital collection process. At the same time, 70.2% also claim to still collect physical data. However, despite this dual approach, 65.9% of organisations claim their data collection process has become more digital in the last 5 years. Moreover, most participants consider their collected data to be of high quality (82.9%), sensitive (70.2%) and confidential (65.9%). However, despite the mandatory nature of GDPR compliance, 8.5% claim that the data collected does not adhere to this regulation, with 10.6% admitting to collecting data without obtaining user consent.

Regarding barriers to Data Science implementation, 85.1% cite the need for additional training on the topic, while 81% claim requiring third-party assistance. Organisations also perceive other challenges, such as funding difficulties (72.3%), lack of qualified staff (63.8%), and insufficient IT infrastructure (51.1%).

When it comes to organisation's digital transformation journey, 74.5% acknowledge that their internal manual processes have transitioned to digital, and nearly 60% claim that they now provide digital services to their stakeholders.

However, engagement with AI remains low, with only 6.4% of organisations incorporating it into their business model. Moreover, more than half of the participants (53.2%) express concerns about AI implementation, particularly regarding data privacy and ethical considerations, with 38.3% remaining neutral on the matter, and only 8.5% disagreeing. Nonetheless, 62% recognise that AI could assist organisations in focusing on more meaningful tasks. Surprisingly, no organisation admits having a plan for AI implementation in the near future.

The descriptive statistics and frequencies are elaborated further in *appendices 19 to 28*.

4.2. Data Analysis Results

After guaranteeing internal consistency, and excluding variables below Cronbach's alpha threshold, as well as confirming normal distribution, an independent sample t-test was employed to compare mean scores between the two surveys. Test results are presented in *appendix 13*.

The analysis unveiled a statistically significant difference in mean scores between participants surveyed in 2019 and those surveyed in 2024 across two UTAUT variables: Performance Expectancy ($t(205) = 4.535$, $p < 0.001$) and Facilitating Conditions ($t(205) = 3.491$, $p < 0.001$). Despite the statistical significance of these differences, it's crucial to evaluate their effect sizes. Cohen's d revealed a substantial difference (0.75) between the groups for Performance Expectancy and a moderate difference (0.57) for Facilitating Conditions.

Concerning the other tested variables, statistically significant differences in mean scores were also observed for some variables. When assessing their effect size, Cohen's d ranged from small differences for variables such as Data Science as an investment priority (0.43) and actively pursued Data Science initiatives (0.4), to moderate differences for variables such as digital data collection (0.52), the importance of Data Science investment for the organisation's future (0.63), and access to Data Science education (0.64).

When considering the new survey data only, internal consistency was assessed for TOE variables and those below the threshold were removed. Normality was also verified.

Subsequently, independent variables were selected through correlation analysis, and a multiple regression model was performed with a single dependent variable, Data Science evolution. Blocks two to four of the model exhibited statistical significance in predicting Data Science evolution. However, the high R-squared values suggest potential overfitting. Given the small sample size and relatively high number of predictors compared to the sample size, adjusted R-squared was used instead for interpreting the results. This approach also penalises the addition of unnecessary predictors and provides a more reliable measure of the model's goodness-of-fit.

Regression 4 yielded the highest adjusted R-squared value (0.605), making it the regression model that best explains the relationship between variables and the evolution of Data Science. The summarised adjusted R-squared values can be found in a*ppendix 29*, and the results of the multivariable analysis are presented in *Table 1*.

In Regression 4, the evolution of Data Science is positively associated with organisations operating in cultural spheres ($\beta = 1.075$; $p < 0.05$) and education ($\beta = 0.802$; $p < 0.05$). Additionally, it exhibits positive associations with the board's age ($\beta = 0.445$; $p < 0.1$), partnerships in data science ($\beta = 0.904$; $p < 0.05$), prioritisation of data science ($\beta = 0.717$; $p < 0.05$), social influence ($\beta = 0.651$; $p < 0.1$), as well as with the use of AI and new software as catalysts ($\beta = 0.428$; $p < 0.05$ and $\beta = 0.572$; $p < 0.1$ respectively).

Conversely, and unexpectedly, the evolution of Data Science is negatively associated with top management support ($\beta = -0.802$; $p < 0.05$), and the influence of COVID-19 as a catalyst (coefficient = -0.262; $p < 0.1$).

Similar to the findings from the previous study, none of the three regressions indicate statistical significance in predicting the evolution of data science usage based on funding or access to education.

Detailed individual regressions for each block addition can be found in *appendix 30.*

Table 1 | Multiple Regression Analysis of Predictors of Data Science Evolution (n = 47)

Independent Variables	**Regression 2**	**Regression 3**	**Regression 4**
Organisation Area (1, yes; 0, no)			
Culture	0.162	0.255	1.075**
Education	0.675**	0.508	0.802**
Human Health	0.185	0.334	-0.079
Social Services	0.038	-0.112	0.216
Others	-0.139	-0.21	-0.196
Organisation's Dimension [a]	-0.258	-0.303	-0.218
Organisation Member's Age [b]	0.162	0.262	0.015
Board's Age [b]	0.042	-0.031	0.445*
Organisation's Budget [c]	0.075	0.066	0.175
Data Science Partnerships (1, yes; 0, no)	0.682**	0.613**	0.904**
Access to Data Science Education [d]	0.052	0.05	-0.264
Digital Data Collection evolution [e]	0.264	0.237	0.184
Data Science Complexity [f]	-0.101	-0.048	-0.084
Funds availability [f]	0.021	-0.207	-0.403
IT Team (1, yes; 0, no)	0.504	0.326	0.477
Data Science as a Priority [f]	0.362**	0.252	0.717**
Performance Expectancy		0.168	-0.248
Social Influence		0.04	0.651*
Facilitating Conditions		0.246	0.424
Behavioural Intention		0.146	0.157
Top Management Support		-0.022	-0.802**
Competitive Pressure		0.019	-0.419
Market Uncertainty		0.236	0.11
Covid-19 [f]			-0.262*
Ai [f]			0.428**
Leadership [f]			-0.515**
New Software [f]			0.572*
Competition [f]			0.474
R^2	0.65	0.689	0.846
Adjusted R^2	0.463	0.377	0.605

****p<0.01, **p<0.05, *p<0.1*

[a] dimension scale; [b] age group scale; [c] budget scale; [d] frequency scale; [e] evolution scale; [f] statement scale

Table 1. Regressions (2-4) are the results from the multiple regression analysis conducted in SPSS, with usage of Data Science evolution as the dependent variable. Each value corresponds to the coefficient of the predictor variables in the different regressions. Adjusted R^2 refers to the statistical significance and respective variation each block of independent variables has in the model.

5. Discussion

Based on the literature review, numerous supporters and indicators signal an evolution in the application of Data Science within the social sector. The results of this research confirm such evolution in Portuguese social impact organisations since the previous study. However, quantitative data reveals only a slight improvement in the active pursuit of Data Science initiatives, which appears to fall short of the expectations set by the extensive literature review.

Compared to the previous study, the observed changes indicate a notable increase in participants' familiarity with the concept of Data Science and its associated benefits, contrasting with earlier perceptions of reluctance and complexity associated with the term. Quantitative research demonstrated a significant increase in Performance Expectancy, a UTAUT measurement, compared to the previous study. Participants now recognise the potential of Data Science to enhance performance within their organisations. These findings align with the previous study, which identified Performance Enhancement as a critical factor for adopting a data-driven approach in Portuguese social impact organisations.

Yet, despite Data Science being perceived as valuable, and considered a best practice, its actual application within organisations, while improved since the previous study, still falls short, and most organisations still describe their Data Science efforts as minimal to non-existent.

Quantitative research has also indicated a moderate improvement in Facilitating Conditions, another UTAUT measurement. Although funding and skills gaps remain critical factors, they have become less pronounced when compared to 2019. Organisations now possess moderately increased financial and expertise resources for Data Science implementation. The latter align with the previous research findings that identified expertise as a predictor for Data Science application. However, when it comes to financial resources, 73% of survey participants still perceive funding difficulties as one of the primary barriers to Data Science application. Nevertheless, as observed in previous research and confirmed in this study, funding does not exhibit statistical significance concerning Data Science adoption or evolution. The literature also supports this assertion, as the decreasing costs of technology and new disruptive technologies enable organisations to accomplish more with fewer resources, thereby overcoming financial constraints (Gooyabadi et al., 2024).

The same applies to access to Data Science education. Despite organisations increasing their investment in training or workshops since 2019, previous research, as well as findings reaffirmed in this study, demonstrate that access to education does not display statistical significance concerning Data Science application or evolution. This aligns with the perception of participants who had access to education, as the majority perceive minimal (50%) to no change (15%) in Data Science application within their organisations as a result. Yet, it's crucial to highlight that education might not significantly influence Data Science adoption or evolution due to its sporadic nature. For those who did have access to education, the majority participated in no more than three trainings or workshops in the last five years. Therefore, it's reasonable to believe that this limited access to education is insufficient to drive substantial improvements in actual Data Science implementation.

When examining demographic predictors of the exhibited evolution, quantitative research suggested revealed that there is no statistical significance of the organisation's size influencing Data Science evolution. As this contradicts literature which identifies larger organisations as having an easier time adopting technology (Rodríguez et al., 2012), one could attribute this finding to the lack of representation of larger organisations within the survey participants. None of the participants reported having more than 500 employees, and only two (4.3%) claimed to have more than 500 volunteers.

Another surprising finding is the presence of an older board of directors as a predictor for evolution within organisations. As this contradicts theoretical assertions that younger leadership is more inclined to embrace Data Science (Eimhjellen et al., 2014), this observation could once again be attributed to the underrepresentation of younger age groups, thereby skewing the data. Furthermore, as evolution is being measured, one could also argue that younger leaders have already integrated Data Science practices from the outset, thus exhibiting less of a learning curve and progress, whereas older leaders are now in the process of adaptation.

Similarly to UTAUT, the presented results showed that organisations measure their Data Science progress by benchmarking against their peers. Social Influence emerged as a contributor to the evolution over the last five years, mirroring its role as a predictor of Data Science adoption in previous research. As this underscores the importance of social impact organisations to recognise and leverage best practices from their peers, establishing a community for shared knowledge can facilitate this process, enabling the exchange of tools, techniques, and successful Data Science application among organisations. Furthermore, survey data revealed that the majority of organisations tend to perceive themselves as either equal (40.4%) or ahead (19.1%) of their peers in adopting a data-driven approach. This reflects a dynamic landscape where organisations strive to keep pace and remain aware of industry trends.

Another predictor of Data Science evolution over the last five years has been the establishment of partnerships and collaborations with external stakeholders to advance Data Science efforts. This appears to be a crucial focus, as 81% of survey participants claim to require third-party assistance for successfully implementing Data Science into their organisations. In Portugal, organisations such as Data Science for Social Good serve as valuable support in assisting organisations with this transition.

Surprisingly, contrary to the theoretical background and TOE framework, quantitative research found Top Management Support to hinder the evolution of Data Science. One could argue that this could be attributed to response bias, considering that respondents were predominantly top management. There's a possibility that they portrayed their own involvement in a more positive light, potentially biasing the interpretation of results. However, it could also indicate poor change management, where even though top management supports Data Science application, its execution may not translate effectively in practice.

When assessing the impact of COVID-19, quantitative research revealed the perception of the pandemic as a barrier to Data Science evolution, contradicting theoretical expectations. However, this perception may be influenced by the negative context of COVID-19, given its profound impact on people's lives and the tendency to view its effects negatively. An Australian study conducted at the time revealed very few social organisations were equipped to transition to digital operations when lockdown measures were implemented (Farmer et al., 2023), making the adaptation not voluntary, but forced (Gooyabadi et al., 2024). Consequently, the disruption caused by COVID-19 could be perceived as predominantly negative.

On the other hand, quantitative research identified perceptions of AI and new software as predictors of Data Science evolution. This finding is consistent with the widespread availability of technology at more affordable costs and increased user-friendliness (Fruchterman, 2016). As for AI, qualitative research revealed a cautious optimism towards the concept, with organisations recognising its potential and expressing interest in its use. However, they also noted significant barriers, such as concerns over cybersecurity and ethical implications. This cautious approach underscores the critical need for training on AI and its multiple benefits, ensuring responsible and effective adoption by organisations.

This study highlights the discrepancy between the perception of Data Science practices as beneficial and their actual evolution. While the recognition of DDDM potential is growing in a sector focused on impacting people's lives rather than generating profits, this acknowledgment alone is insufficient. Social impact organisations need to witness firsthand the tangible benefits that Data Science can bring to their ultimate mission. This could be achieved through various methods, with support from the academic community. Sharing success stories during seminars or through newsletters can illustrate the practical impacts of Data Science.

Furthermore, partnerships with for-profit companies could be instrumental, as these companies can demonstrate the real-world effects of DDDM and provide guidance on effective implementation strategies. The B Corporation movement and pro bono work as part of corporate social responsibility offers valuable opportunities for social impact organisations to access the expertise they need (Dolan, 2022). This collaborative approach can bridge the gap between perception and practice, helping SIOs fully leverage Data Science to achieve their goals.

This study also reveals a mismatch between the actual barriers to Data Science and those perceived by organisations. Financial constraints are often cited as inhibitors of Data Science application and evolution, yet in reality, they are not significant for the successful application of Data Science. It appears that the primary barrier organisations face is their lack of knowledge on how to proceed and implement data-driven decision-making practices, as many express a need for assistance and support in this transition. As mentioned earlier, partnerships and successful case studies can also play a pivotal role in addressing this challenge.

This research also reveals that although AI is a predictor for organisations experiencing evolution in their Data Science practices, it remains an underutilised technology. Despite being accessible to social impact organisations, they don't seem to leverage it to its full potential. Therefore, it appears crucial to educate organisations on how AI can support them in focusing more on meaningful tasks, liberating staff, and allowing them to allocate their resources more strategically (Gooyabadi et al., 2024).

In summary, this research offers a distinctive and up-to-date perspective on the current state-of-the-art of Data Science application within Portuguese social impact organisations. Its concept has been increasingly recognised and comprehended, signing a positive shift compared to the previous study. Factors such as Social Influence, partnerships, AI, and software solutions emerge as the catalysts for the observed change. However, notwithstanding its growing prioritisation, Data Science continues to be underutilised and often remains in the experimental stages for the majority of organisations.

By offering a comprehensive examination, this research has the potential to inspire future investigations by identifying areas requiring further inquiry, or even by guiding a step-by-step roadmap for success. Additionally, by illuminating challenges and opportunities and shedding light on the current landscape within the Portuguese social sector, this thesis serves as a catalyst for greater understanding and awareness within the academic community. This enhanced understanding can empower organisations to make informed decisions about their data strategies, ultimately leading to greater social impact.

6. <u>Limitations</u>

The present research has several limitations. When considering primary data, the main limitation lies in its sample size, which could be insufficient to draw significant conclusions. Despite nearly three weeks of data collection, there was minimal participation. In total, there were 114 responses received on *Qualtrics*, but only 47 were fully completed, representing just 41% of fully answered questions. Partial responses couldn't be incorporated into the study, as relevant variables for the research were missing. The author attribute this low completion rate mainly to the lengthy nature of the survey, which took over 18 minutes to complete. However, given the need for an extensive overview and comparison, numerous questions were necessary. Consequently, the statistical analysis is influenced by the lack of representation across some categories, and the 47 respondents may not provide adequate insight into the evolution being studied. Furthermore, the length of the survey could introduce acquiescence bias, as participants may become fatigued and select middle options as a shortcut.

Another significant limitation applicable to this study is response bias. Participants may consciously or unconsciously tailor their responses to align with perceived expectations or present their organisation favourably. This can lead to overreporting of positive outcomes and underreporting of challenges or failures, thereby skewing the findings.

Recall bias is also a limitation, as this study relies heavily on participants' accuracy in recalling past events. Participants may not always remember events or actions accurately, or they might portray their organisation in a more favourable light (Hassan, 2006). Conversely, a portrayal in a more negative light may also be observed, as during difficult times, individuals may be more likely to emphasise negative aspects, such as those related to COVID-19.

As this study builds upon findings from previous research, it could also be susceptible to confirmation bias. This bias may occur when researchers, perhaps unwittingly, design studies or interpret findings in ways that confirm established results. Such bias can restrict the investigation's scope, as it may hinder exploration of alternative explanations or contradictory evidence (Hallihan et al., 2013). In this thesis, where previous findings on adopting DDDM are being reassessed, there is a risk of leaning towards interpretations that align with past conclusions rather than challenging them.

By understanding the limitations of this research, subsequent studies can design more robust methodologies that address these issues, and provide a more comprehensive view of the phenomena under study.

7. Conclusion

This thesis investigates the adoption and evolution of data-driven decision-making (DDDM) in Portuguese social impact organizations, aiming to understand how data use has changed and what factors have influenced these changes over the past five years. A survey and quantitative data highlight both minimal progress and ongoing challenges in integrating advanced data practices within the sector.

Data science has become a critical tool for these organizations, increasingly recognized for its potential to revolutionize fundraising, enhance program effectiveness, and drive strategic decisions. However, the actual application of data science techniques remains inconsistent. Quantitative analysis revealed statistically significant variations in Performance Expectancy and Facilitating Conditions over the period. Despite this progress, the evolution was moderate, indicating a gap between the perceived benefits of DDDM and its actual implementation. Additionally, Social Influence, a UTAUT scale measure, plays a significant role in predicting the evolution of data practices. Organizations often use peer comparisons to measure their progress, influencing the future development of Data Science practices. Notably, the rise of AI and new software as significant predictors underscores the profound impact of technological advancements on the progress of Data Science in Portuguese social impact organizations.

In conclusion, while Portuguese organizations have made strides in adopting data-driven practices, the evolution is complex and multifaceted. The sector continues to face significant challenges that hinder the full realization of DDDM's potential. Overcoming these challenges will require a concerted effort to enhance data literacy, improve technological infrastructure, and ensure organizations have the financial and human resources needed to leverage data effectively.

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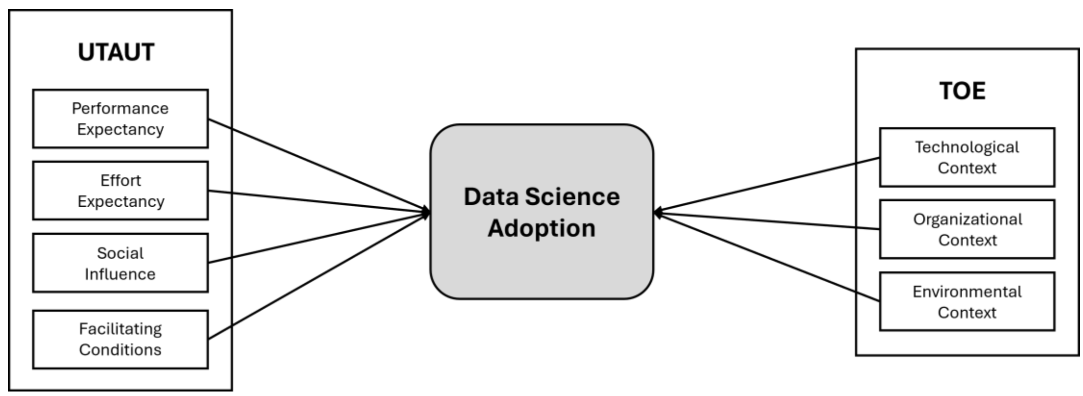
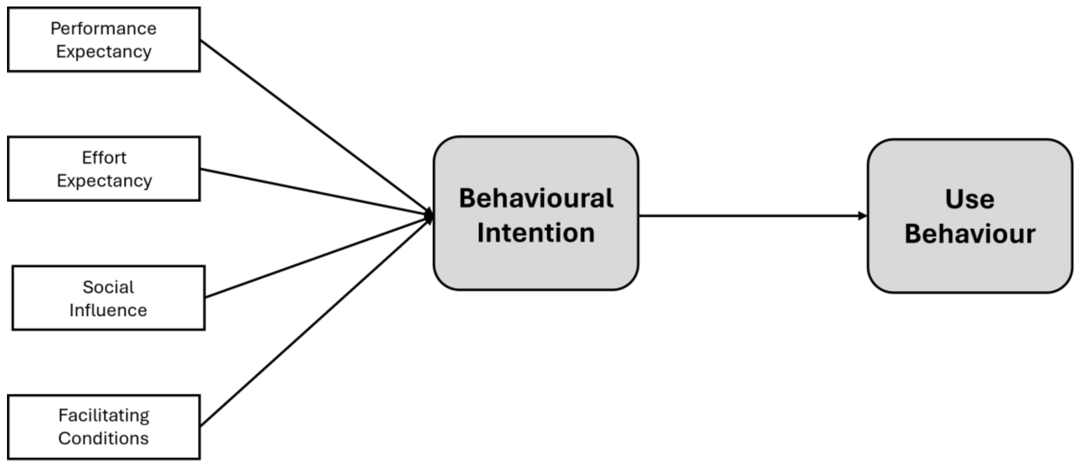
9. Appendices

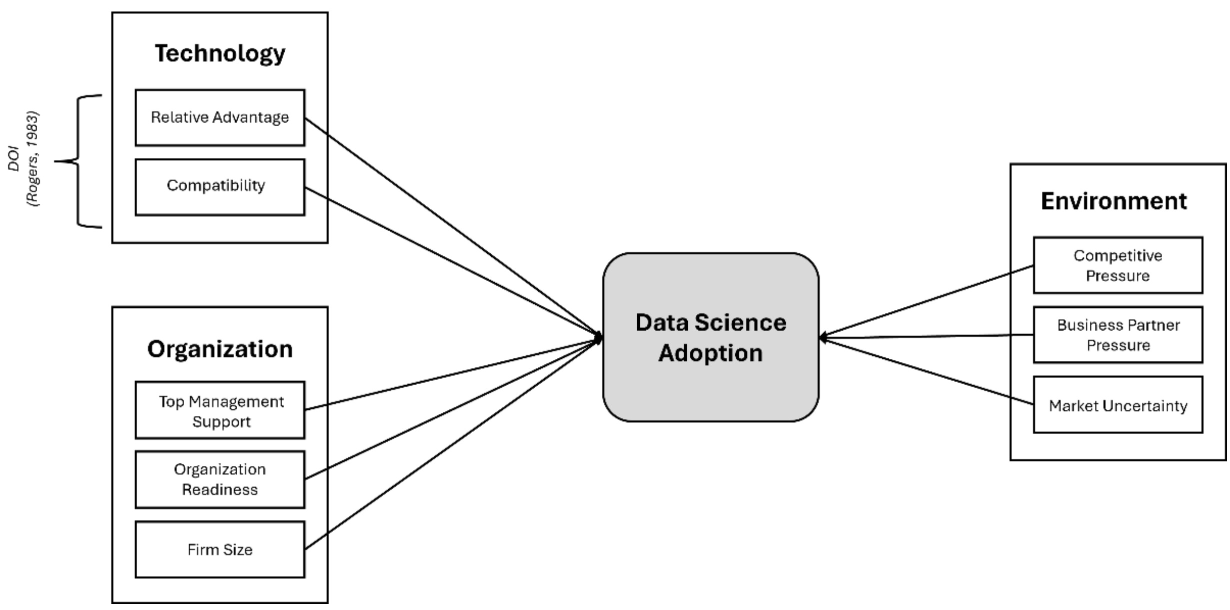
Appendix 1: Conceptual Research Model



Appendix 2: Unified Theory of Acceptance and Use of Technology Model (UTAUT)



Appendix 3: Technology – Organisation - Environment framework (TOE)



Appendix 4: Survey

Together with the Data Science Knowledge Centre (DSKC) at Nova School of Business and Economics (Nova SBE), Master's students in Management, Diana Leitão and Giacomo Testa, are developing a thesis concerning the use of technology in Social Impact Organisations.

The project and survey below aim to understand the current state of Data Science Technology and its intended future use for Social Impact.
The data will be used solely for statistical purposes for the presented study and will be treated anonymously.

Organisation

1. What is the name of the organisation you belong to?

2. When was the organisation established?

3. What is the legal structure of the organisation?
    - *Cooperative*
    - *Foundation*
    - *Social Enterprise*
    - *Mutualist Associations*
    - *Holy Houses of Mercy*
    - *Associations with Altruistic Goals and Community and Self-Management Subsectors*

4. In which area does the organisation operate?
    - *Culture, communication, and recreational activities*
    - *Education*
    - *Human health*
    - *Social services*
    - *Environmental protection and animal welfare*
    - *Community and economic development, and housing activities*
    - *Civic, advocacy, political and international activities*
    - *Philanthropic Intermediaries and voluntarism promotion*
    - *Religious congregations and associations*
    - *Business, professional, and labour organisations*
    - *Professional, scientific, and administrative services*
    - *Other:* ____

5. What is the average age of the employees in your organisation?
    - *Less than 25 years*
    - *25-35 years*
    - *36-45 years*
    - *46-55 years*
    - *55-65 years*

- *More than 65 years*

6. What is the average age of the organisation's leadership team?
- *Less than 25 years*
- *25-35 years*
- *36-45 years*
- *46-55 years*
- *55-65 years*
- *More than 65 years*

7. How many paid employees does your organisation have?
- *Less than 50*
- *50-250*
- *251-500*
- *501-750*
- *More than 750*

8. How many members/volunteers does your organisation have?
- *Less than 50*
- *50-250*
- *251-500*
- *501-750*
- *More than 750*

9. In terms of organisation decision-making, which of the statements is the most accurate?
- *Our organisation is vertical, with rigid hierarchical structures, where management makes most decisions, and the employees execute them*
- *Our organisation is horizontal, where employees/volunteers have autonomy to make decisions, and the strategic choices are set in an agreement among the member*
- *Our organisation follows a matrix structure, where decision-making authority is distributed across different functional areas or projects.*

10. What is the annual budget of your organisation?
- *< 100,000 € (less than 100 thousand EURO)*
- *100,000 € - 300,000 € (between 100 and 300 thousand EURO)*
- *300,000 € - 700,000 € (between 300 and 700 thousand EURO)*
- *700,000 € - 1,000,000€ (between 700 thousand and 1 million EURO)*
- *> 1,000,000 € (greater than 1 million EURO)*

IT Infrastructure and Technology Investment

11. In terms of your technological infrastructure, which of these does your organisation have (select all that apply)?
- *Desktop Computers*
- *Laptops*

- *Servers*
- *Specialised program/software for a type of operation within the organisation (e.g. CRM or ERP system)*
- *Integrated communication platform (e.g. Microsoft Teams)*
- *Website*
- *App*
- *AI Language Model (e.g. chatbots like ChatGPT used for specific purposes such as virtual assistants, or data analysis)*
- *Robotic Process Automation*
- *APIs*
- *Cloud Software (e.g. Amazon Web Services, Azure, Google Cloud Platform)*
- *Other*

12. In terms of equipment and technologies:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *The equipment of the organisation is old fashioned/outdated (computers, IT Infrastructure)*
- *The technology used in the organisation is outdated*

13. Which of the following is true:

- *The technology used now by the organisation has been donated by 3rd parties.*
- *The technology used now by the organisation has been bought by the organisation.*
- *The technology used now by the organisation has been partially donated by 3rd parties and partially bought from our funds.*

14. What percentage of your annual budget is allocated towards technological infrastructure (software, hardware)?

- *There's no allocation*
- *Less than 5% of the annual budget*
- *Between 5% and 10% of the annual budget*
- *Between 10% and 30% of the annual budget*
- *More than 30% of the annual budget*

15. How has the budget towards technological infrastructure (software, hardware) evolved in the last 5 years?

- *Decreased significantly (e.g. decreased by more than 50%)*
- *Decreased moderately (e.g. decreased by more than 20%)*
- *Remained stable*
- *Increased moderately (e.g. increased by more than 20%)*
- *Increased significantly (e.g. increased by more than 50%)*

16. The organisational website/platform:

- *Is merely informative*
- *Has cookies*

- *Hosts crucial operations to the functioning of the organisation (e.g. schedules appointments)*
- *Provides online services (e.g. personalised information for end users, automated payments)*
- *All the website functions imply human intervention to function (zero automation)*
- *Has automatic functions (e.g. sales ticket)*
- *Has e-commerce services*
- *Has AI functionalities (e.g. chatbot)*
- *Automatically stores data (collect and stores data inserted by users)*
- *Has data processing (statistics, generates results)*
- *The organisation does not have any website/platform*
- *Is outdated*
- *Has undergone restructuring (e.g. aforementioned features) within the past five years*

IT Team

17. Do you have a dedicated IT team?

- *Yes*
- *No*

18. In the organisation, the IT team is:

- *Part of the organisation (employees), with education in IT*
- *Part of the organisation (employees), without education in IT*
- *Externally hired*

19. What percentage of your annual budget is allocated towards the IT Team's operations and resources?

- *There's no allocation*
- *Less than 5% of the annual budget*
- *Between 5% and 10% of the annual budget*
- *Between 10% and 30% of the annual budget*
- *More than 30% of the annual budget*

20. How has the allocation of funds towards the IT Team evolved in the last 5 years?

- *Decreased significantly (e.g. decreased by more than 50%)*
- *Decreased moderately (e.g. decreased by more than 20%)*
- *Remained stable*
- *Increased moderately (e.g. increased by more than 20%)*
- *Increased significantly (e.g. increased by more than 50%)*

Data Science and its applications

Data Science is a multidisciplinary concept and is very related to other technologies such as Big Data, Artificial Intelligence (AI), Machine Learning, among others. One of its common uses is to predict future outcomes based on past data.

Data Science for prediction or estimation involves the analysis of data. The development of methods for collecting, storing, and analysing data to extract useful information. Its main objective is to generate insights and knowledge from any type of data, both structured and unstructured.

Example 1: Fundraising - with data collected from past fundraising efforts, it is possible to estimate types of donors and amounts donated for a future fundraising event, and thereby know who to approach for a new fundraising campaign.

Example 2: Chatbot - pop-up chat windows that simulate human conversation and are based on a computer program that operates through voice commands, text conversations, or both. It uses Artificial Intelligence (AI) and can be incorporated into messaging applications, such as websites.

Example 3: Churn - with information about employees, it is possible to predict how many and who the expected employees are to leave their participation in the organisation and estimate the reasons. This information can include: absences, evaluations, feedback, among others.

21. Do you perceive any distinction between the concepts of Data Science and AI?

- *No difference*
- *Little difference*
- *Some difference*
- *Moderately different*
- *Extremely different*

22. What's the value that these two concepts hold for your organisation?

1 – No value, 2 – Of little value, 3 – Moderately valuable, 4 – Valuable, 5 – Extremely Valuable

- *Data Science*
- *AI*

23. How would you rate the level of Data Science application within your organisation?

- *Non existent – Data Science techniques are not used*
- *Minimal – Little integration of Data Science techniques*
- *Emerging – Data Science initiatives are beginning to take shape, with some experimentation*
- *Developing – Data Science practices are actively being developed and implemented in the organisation*
- *Established – Data Science is fully integrated into the organisation*

24. In terms of application and implementation of Data Science in the day-to-day of your organisation:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *I see possibilities in applying data science in the day-to-day work*
- *I see benefits in using data science in the day-to-day work*

- *I see constraints in using data science in my organisation*
- *The organisation is interested in the implementation of Data Science*
- *The organisation has the financial resources to proceed with further implementation of data science*
- *The organisation possess the necessary technical expertise to implement Data Science*
- *Implementing Data Science in the organisation would require additional training of staff members*
- *The organisation has identified specific trainings or capacity building needs essential for successfully implementing data science*
- *Before implementing data science, it is necessary for the organisation to recognise and address gaps and areas of improvement.*
- *The application of Data Science in the day-to-day operations has increased in the last 5 years*
- *The allocation of resources towards Data Science initiatives have increased in the last 5 years*
- *The allocation of resources towards Data Science initiatives is expected to increase in the future*
- *We are ready to implement Data Science*

Data Science Education/Training

25. How many times, during these last 5 years, did your organisation have access to some sort of education about Data Science or Digital Transformation? (training sessions, workshops)
- *None*
- *1-3 times*
- *4-6 times*
- *7-10 times*
- *More than 10 times*

26. To what extent have the training sessions resulted in meaningful changes in the organisation's approach to Data Science?
- *No meaningful changes*
- *Few meaningful changes*
- *Some meaningful changes*
- *Significant meaningful changes*
- *Very significant meaningful changes*

27. How would you describe the data literacy among the staff members of the organisation?
- *Very low*
- *Low*
- *Moderate*
- *High*
- *Very High*

Collection, Privacy and Confidentiality of Data

28. In terms of the collection of data performed by the organisation:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *We regularly collect data digitally (e.g. cloud, excel, software)*
- *We regularly collect data in a physical form (e.g. written, books, printed files)*
- *The data stored digitally have important qualities (relevant information for the organisation)*
- *The organisation knows which data to collect*

29. In terms of acting on collected data:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *The organisation knows how to retrieve knowledge from the data collected*
- *The organisation knows how to act accordingly to the results obtained with the digital data collection*
- *The organisation has the habit of taking data driven decisions (digitally or physically stored)*
- *The organisation has the habit of taking decision based on gut feelings*

30. The data stored by the organisation:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *The data that the organisation possesses is highly sensitive*
- *The data that the organisation possesses is highly confidential*
- *The data that the organisation possesses is accessible to all employees*
- *The data collected have all been consented to by the users*
- *Data collection complies with the General Data Protection Regulation (GDPR)*
- *Users willingly provide their personal data*
- *Users question the sharing of their personal data*

31. How has the organisation's transition to digital data collection and storage evolved over the past 5 years?

- *Deteriorated*
- *Limited, we don't have capacity*
- *No change, we consider our current system adequate*
- *Somehow improved*
- *Fully optimised and streamlined*

Acceptance of Data Science

32. In terms of Data Science and its organisational impact:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *Implementing Data Science requires more effort than the benefits it brings*
- *Data Science increases the social impact of the organisation*
- *Data Science would involve effort for the organisation*

- *Data Science is a good idea for the organisation*
- *Data Science is easy to understand*
- *Data Science its easy to work with*
- *Data Science is an intuitive concept*
- *Data Science is too complex to implement*
- *Implementing Data Science requires significant resources*
- *Implementing Data Science requires the aid of 3rd parties*
- *The organisation plans to invest more in using Data Science in the next years*
- *The organisation foresees to invent more in using Data Science in the next years*
- *Data Science can be seamlessly integrated into the organisation*
- *Implementing Data Science would disrupt the organisation's current process*
- *Data Science increases the organisation's efficiency*
- *Implementing data science would yield superior results compared to our current processes.*
- *Investing in Data Science would divert the organisation from its main goals*
- *Data Science can aid in better understanding and serving our beneficiaries and communities*
- *Data Science can assist in identifying new funding opportunities and enhancing donor engagement. .*
- *Data Science can bring cost savings and resources optimization.*
- *The organisation's top management implements new initiatives to the organisation*
- *Similar organisations to ours that already use Data Science influence our intention to use it*
- *Reference organisations influence our intention to use Data Science*
- *Reference organisations encourage our use of Data Science*
- *People outside the organisation encourage the implementation of Data Science*

Barriers towards Data Science Implementation

33. Regarding the implementation of Data Science in the organisation, what are the biggest barriers?

- *Lack of technological structure (computer, website)*
- *Lack of qualified personnel in Data Science*
- *Difficulty in attracting qualified people in Data Science*
- *Difficulty in maintaining qualified people in Data Science*
- *Lack of interest by the leadership team*
- *Lack of time to new projects*
- *Financing difficulties*
- *Lack of financial support by the government*
- *We don't know what Data Science is and what benefits it can brings*
- *We don't have an interest in the implementation of Data Science*

Organisational Investment

34. In terms of the organisation's structure and capacity:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *The organisation's size poses challenges in adopting Data Science*
- *The organisation's size positively impacts the ability to scale and sustain Data Science in the long-term*
- *The organisation's size enables a quick adaptation to changes in the technological landscape*

35. In terms of leadership and management:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *Management actively encourages employees to enhance their data skills*
- *Top management allocates sufficient resources (budget, personnel, time) towards Data Science implementation*
- *Top management establishes goals and standards to monitor Data Science usage.*
- *Top Management is committed in leveraging Data Science.*

36. In the past 5 years, how much has the organisation invested in partnerships or collaborations with external stakeholders to advance its Data Science efforts?

- *Not at all*
- *Bellow 5% of the annual budget*
- *Between 5% to 10% of the annual budget*
- *Between 10% and 30% of the annual budget*
- *More than 30% of the annual budget*

37. In the past 5 years, in how many Data Science projects has your organisation been involved?

- *None*
- *1-2*
- *3-4*
- *5*
- *>5*

38. When it comes to investing in Data Science:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *The investment in Data Science is a priority in the organisation*
- *The investment in Data Science is crucial to the future of the organisation*
- *The investment in Data Science, if it happens, will be a consequence of other decisions*
- *The organisation is actively searching for the use of Data Science*

39. When compared to the usage of Data Science with other social organisations, your organisation is:

- *Far below*
- *Below*
- *Equal*
- *Above*
- *Far above*

40. In terms of maintaining competitiveness:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *The organisation observes and learns from the practices of other organisations regarding the adoption of Data Science*
- *Failing to integrate Data Science will result in the organisation falling behind compared to other similar organisations*
- *Adopting Data Science will enhance the organisation's competitiveness*

41. In terms of stakeholder engagement:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *Failing to integrate Data Science will deteriorate the relationship with our stakeholders*
- *The organisation's capacity to attract donors or funding is impacted by its use of Data Science*
- *Stakeholders anticipate that the organisation remains current and leverages Data Science*
- *Inadequate investment in Data Science limits the organisation's ability to communicate with stakeholders and address their concerns*

Digital Transformation

42. To what extent have manual processes shifted to online platforms within your organisation?
- *Not at all*
- *Minimal transition*
- *Moderate transition*
- *Significant transition*
- *Complete transition*

43. In the past 5 years, the number of online services provided by the organisation to either members, beneficiaries, or other interested parties:
- *Decreased significantly*
- *Decreased moderately*
- *Remained stable*
- *Increased moderately*
- *Increased significantly*

44. Which of the following AI models do you use in your organisation?
- *ChatGPT*
- *LLaMa*
- *Amazon AI*
- *Gemini*
- *Microsoft Co-Pilot*
- *Poe*

- *Perplexity*
- *Other*

45. Is the organisation subscribed to any of these AI models?
- *Yes*
- *No*

46. How much is the organisation spending on monthly licenses?
- *20€*
- *20-100€*
- *100-500€*
- *500-1000€*
- *>1000€*

47. In terms of AI Models and its capabilities in data management, automation and predictive analysis:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *Implementing AI would raise multiple concerns (e.g. data privacy, security, ethical considerations)*
- *Incorporating AI would facilitate process automation within the organisation*
- *Adopting AI would enhance the organisation's efficiency*
- *AI can simplify an organisation's tasks*
- *Implementing AI would enable the organisation to focus on more meaningful activities*
- *Implementing AI could reduce the number of staff within the organisation*
- *The organisation has a strategic plan in place for future AI adoption or expansion within the organisation*

48. In terms of analytical tools usage (e.g. data visualization):

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *The organisation often creates reports with visual representations of their activities (e.g., the total contributions and the types of entities contributing to fundraising)*
- *The organisation is tracking the progress of their activities also with basic statistics and visualisation (e.g. repeated donations and the churn in terms of donors and their types)*
- *The organisation uses algorithms to optimize their performance (e.g., predict the likelihood of donating or predict which beneficiaries are more likely to benefit from the activities)*
- *The organisation employs data segmentation techniques to categorize donors based on their unique attributes and preferences*

49. When considering the period during and after the pandemic, the challenges posed by COVID-19:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *Made the organisation increase the number of services provided online.*
- *Facilitated the organisation's transition to online platforms.*

- *Made the organisation reassess its operational strategy, leading to a more data-driven decision-making process.*
- *Made the organisation rely more on data-driven insights to allocate resources efficiently and optimize the impact on communities.*

50. Regarding the improvements and changes in the strategic use of Data Science observed in the organisation in the past 5 years, to what extent do you attribute the main catalyst to be:

1 - Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

- *COVID-19 and its effect on organisational adaptation to a new reality (remote work, online presence, digital data collection, cybersecurity…)*
- *Increased accessibility of AI models (e.g. ChatGPT) and their impact*
- *A shift in management mindset embracing data-driven decision-making and digital transformation*
- *The emergence of new technologies and open-source softwares*
- *Government regulations or policies influencing technology adoption.*
- *Market competition and the need to gain more fundraising from donors*

Conclusion

51. Leave us a comment about the topic of Data Science in the social sector.

52. Leave us an email if you would like to be contacted for future questions related with this topic.

Appendix 5: Items used in estimating UTAUT

Performance Expectancy
"Degree to which an individual believes that using the system will help him or her to attain gains in job performance"(Venkatesh et al. 2003)

- I see possibilities in applying data science in the day-to-day work
- I see benefits in using data science in the day-to-day work
- Data Science increases the social impact of the organisation
- Data Science increases the organisation's efficiency
- Investing in Data Science would divert the organisation from its main goals

Effort Expectancy
"Degree of ease associated with the use of the system" (Venkatesh et al. 2003)

- I see constraints in using data science in my organisation
- Implementing Data Science requires more effort than the benefits it brings
- Data Science would involve effort for the organisation
- Data Science is easy to work with
- Data Science is an intuitive concept
- Data Science is too complex to implement

Social Influence
"Degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al. 2003)

- Similar organisations to ours that already use Data Science influence our intention to use it
- Reference organisations influence our intention to use Data Science
- Reference organisations encourage our use of Data Science
- People outside the organisation encourage the implementation of Data Science

Facilitating Conditions
"Degree to which an individual believes that an organisation's and technical infrastructure exists to support the use of the system" (Venkatesh et al. 2003)

- The organisation has the financial resources to proceed with further implementation of data science
- The organisation possess the necessary technical expertise to implement data science

Behavioural Intention to use Data Science

- The organisation plans to invest more in using Data Science in the next years
- The organisation foresees to invent more in using Data Science in the next years

Attitude toward using Data Science

- The organisation is interested in the implementation of Data Science
- Data Science is a good idea for the organisation

Appendix 6: Items used in estimating TOE (with DOI integration)

Technological Variables	Items
Relative Advantage	**RA1:** Implementing Data Science would yield superior results compared to our current process. **RA2:** Data Science can aid in better understanding and serving our beneficiaries and communities. **RA3:** Data Science can assist in better identifying new funding opportunities and enhancing donor engagement. **RA4:** Data Science can bring cost savings and resources optimization.
Definition: Innovation is perceived as being better than the idea it supersedes (Rogers, 1995)	
Compatibility	**CA1:** Data Science can be seamlessly integrated into the organisation **CA2:** Implementing Data Science would disrupt the organisation's current process.
Definition: Innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters (Rogers, 1995)	

Organisational Variables	Items
Top Management Support	**TMS1:** Top Management allocates sufficient resources (e.g. budget, personnel, time) towards Data Science implementation. **TMS2:** Top Management establishes goals and standards to monitor Data Science usage. **TMS3:** Management actively encourages employees to enhance their data skills. **TMS4:** Top Management is committed in leveraging Data Science.
Definition: Through business management, time and resources investment and effective execution, to resolve related issues (Chiu et al., 2017)	
Firm Size	**FS1:** The organisation's size poses challenges in adopting Data Science. **FS2:** The organisation's size impacts positively the ability to scale and sustain Data Science in the long-term. **FS3:** The organisation's size enables a quick adaptation to changes in the technological landscape
Definition: Firm size has impact on innovation, as larger firms have more adequate resources to experiment with new innovations (Tran et al., 2022)	
Organisational Readiness	**OR2:** The organisation has identified specific trainings or capacity building needs essential for successfully implementing data science. **OR3:** We are ready to implement Data Science.
Definition: the availability of the needed organisational resources for adoption (IaCovou 1995).	

Environmental Variables	Items
Competitive Pressure	**CP2:** Adopting Data Science will enhance the organisation's competitiveness. **CP3:** Failing to integrate Data Science will result in the organisation falling behind compared to other similar organisations

Definition: The level of pressure from competitors within the same industry *(Chiu et al., 2017)*

Business Partner Pressure	**BPP1:** The organisation capacity to attract donors or funding is impacted by the use of Data Science **BPP2:** Failing to integrate Data Science will deteriorate the relationship with our stakeholders **BPP3:** Inadequate investment in Data Science limits the organisation's ability to communicate with stakeholders and address their concerns. **BPP4:** Stakeholders anticipate that the organisation remains current and leverages Data Science.

Definition: External environmental forces that drive businesses to adapt *(Chiu et al., 2017)*

Market Uncertainty	**MU1:** The challenges posed by COVID-19 made the organisation increase the number of services provided online. **MU2:** The challenges posed by COVID-19 facilitated the organisation's transition to online platforms. **MU3:** The challenges posed by COVID-19 made the made the organisation reassess its operational strategy, leading to a more data-driven decision-making process. **MU4:** Made the organisation rely more on data-driven insights to allocate resources efficiently and optimize the impact on communities.

Definition: Unpredictable situation that takes place without knowing when and how it will occur *(Deelert, 2020).*

Appendix 7: Variable’s names and respective survey questions

Variable Name	Question
Org_name	What is the name of the organisation you belong to?
Org_year	When was the organisation established?
LF_org	What is the legal structure of the organisation?
Area_Culture	Culture, communication, and recreational activities
Area_Education	Education
Area_Human_health	Human Health
Area_Social_Services	Social Services
Area_Environmental_Animal	Environmental protection and animal welfare
Area_Community_Housing	Community and economic development, and housing activities
Area_Civic_Advocacy_Political	Civic, advocacy, political and international activities
Area_Philantrophic_Voluntarism	Philanthropic Intermediaries and voluntarism promotion
Area_Religious	Religious congregations and associations
Area_Business_Professional	Business, professional, and labour organisations
Area_Professional_Administrative	Professional, scientific, and administrative services
Area_Others	Others
Age_org_members	What is the average age of the employees in your organisation?
Age_board	What is the average age of the organisations’s leadership team?
Org_emp	How many paid employees does your organisation have?
Org_vol	How many members/volunteers does your organisation have?
Org_gov_type	In terms of organisation decision-making, which of the statements is the most accurate?
Org_budget	What is the annual budget of your organisation?
IT_Destop_Comp	The organisation has desktop computers
IT_PC	The organisation has laptops
IT_Serves	The organisation has servers
IT_Prog	The organisation has specialised program/software for a type of operation within the organisation
IT_Com	The organisation has integrated communication platform (e.g. Microsoft Teams)
IT_Web	The organisation has website

IT_App	The organisation has app
IT_AI	The organisation has AI Language Model
IT_RPA	The organisation has robotic process automation
IT_APIs	The organisation has APIs
IT_Cloud	The organisation has cloud software
IT_equip_obsolote	The equipment of the organisation is old fashioned/outdated (computers, IT Infrastructure)
Tech_obsolete	The technology used in the organisation is outdated
Tech_donated	The technology used now by the organisation has been donated by 3rd parties.
Tech_bought	The technology used now by the organisation has been bought by the organisation
Tech_mix	The technology by the organisation has been partially donated by 3rd parties and partially bought by the organisation
IT_budget_percentage	What percentage of your annual budget is allocated towards technological infrastructure (software, hardware)?
IT_budget_evolution	How has the budget towards technological infrastructure (software, hardware) evolved in the last 5 years?
Website_inf_only	Is merely informative
Website_cookies	Has cookies
Website_critical_func	Hosts crucial operations to the functioning of the organisation (e.g. schedules appointments)
Website_services	Provides online services (e.g. personalised information for end users, automated payments)
Website_manual	All the website functions imply human intervention to function (zero automation)
Website_automated	Has automatic functions (e.g. sales ticket)
Website_ecommerce	Has e-commerce services
Website_AI	Has AI functionalities (e.g. chatbot)
Website_storage_automated	Automatically stores data (collect and stores data inserted by users)
Website_data_processing	Has data processing (statistics, generates results)
Org_wout_website_yn	The organisation does not have any website/platform
Website_outdated	Is outdated
Website_changes	Has undergone restructuring (e.g. aforementioned features) within the past five years
Dedicated_IT_Team	Do you have a dedicated IT team?
IT_relation	In the organisation, the IT team is:
IT_Team_budget_percentage	What percentage of your annual budget is allocated towards the IT Team's operations and resources?
IT_Team_budget_evolution	How has the allocation of funds towards the IT Team evolved in the last 5 years?
AI_DataScience_diff	Do you perceive any distinction between the concepts of Data Science and AI?

AI_sup	What's the value of AI to your organisation?
DataScience_sup	What's the value of Data Science to your organisation?
Data_Science_level	How would you rate the level of Data Science application within your organisation?
DS_applicable_4ops	I see possibilities in applying data science in the day-to-day work
DS_beneficial_4ops	I see benefits in using data science in the day-to-day work
DS_obstacles_4ops	I see constraints in using data science in my organisation
Interest_4DS_impl	The organisation is interested in the implementation of Data Science
Funds_4DS_available	The organisation has the financial resources to proceed with further implementation of data science
DS_staff_expertise	The organisation possess the necessary technical expertise to implement Data Science
DS_additional_train	Implementing Data Science in the organisation would require additional training of staff members
DS_capacity_needs	The organisation has identified specific trainings or capacity building needs essential for successfully implementing DS
DS_org_assessment	Before implementing DS, it is necessary for the organisation to recognise and address gaps and areas of improvement.
DS_application_evolution	The application of Data Science in the day-to-day operations has increased in the last 5 years
DS_resources_evolution	The allocation of resources towards Data Science initiatives have increased in the last 5 years
DS_resources_expectation	The allocation of resources towards Data Science initiatives is expected to increase in the future
DS_readiness	We are ready to implement Data Science
DS_ed_access	How many times, during these last 5 years, did your organisation have access to some sort of education about Data Science?
DS_ed_result	To what extent have the training sessions resulted in meaningful changes in the organisations's approach to Data Science?
DS_data_literacy	How would you describe the data literacy among the staff members of the organisation?
Data_collection_digital	We regularly collect data digitally (e.g. cloud, excel, software)
Data_collection_physical	We regularly collect data in a physical form (e.g. written, books, printed files)
Data_quality	The data stored digitally have important qualities (relevant information for the organisation)
DigData_needs_understanding	The organisation knows which data to collect
DigData_processing_skills	The organisation knows how to retrieve knowledge from the data collected
Ddriven_actions_knowledge	The organisation knows how to act accordingly to the results obtained with the digital data collection
DDDM_routine	The organisation has the habit of taking data driven decisions (digitally or physically stored)
DM_intuitive_routine	The organisation has the habit of taking decision based on gut feelings
Data_sensitive	The data that the organisation possesses is highly sensitive
Data_confidencial	The data that the organisation possesses is highly confidential
Data_open_access_internal	The data that the organisation possesses is accessible to all employees

Data_collected_with_consensus	The data collected have all been consented to by the users
Data_collected_GDPR	Data collection complies with the General Data Protection Regulation (GDPR)
DataCollected_wout_resistance	Users willingly provide their personal data
Digital_collection_evolution	How has the organisations's transition to digital data collection and storage evolved over the past 5 years?
DS_not_optimal	Implementing Data Science requires more effort than the benefits it brings
DS_impact_aug	Data Science increases the social impact of the organisation
DS_effort	Data Science would involve effort for the organisation
DS_good_idea	Data Science is a good idea for the organisation
DS_easy2work	Data Science its easy to work with
DS_intuitive	Data Science is an intuitive concept
DS_imp_complexity	Data Science is too complicated to implement
DS_help	Implementing Data Science requires the aid of 3rd parties
IntUse_DS	The organisation plans to invest more in using Data Science in the next years
IntUse_DS_pred	The organisation foresees to invent more in using Data Science in the next years
DS_compatibility_ops	Data Science can be seamlessly integrated into the organisation
DS_disruption_ops	Implementing Data Science would disrupt the organisations's current process
DS_aug_eff	Data Science increases the organisations's efficiency
DS_aug_results	Implementing data science would yield superior results compared to our current processes.
DS_investment_focus_dev	Investing in Data Science would divert the organisation from its main goals
DS_aug_stakeholders	Data Science can aid in better understanding and serving our beneficiaries and communities
DS_aug_donors	Data Science can assist in identifying new funding opportunities and enhancing donor engagement
DS_savings	Data Science can bring cost savings and resources optimization.
Boards_likes_new_initiatives	The organisations's top management implements new initiatives to the organisation
Peer_inf_DS_decisions	Similar organisation to ours that already use Data Science influence our intention to use it
Peer_ref_inf_DS_decisions	Reference organisation influence our intention to use Data Science
Peer_ref_incentivize_DS_use	Reference organisation encourage our use of Data Science
Peer_ext_incentivise_DS_use	People outside the organisation encourage the implementation of Data Science
Lack_IT_Infraestrucutre	Lack of technological structure
Lack_Staff_Qualified	Lack of qualified staff
Lack_Attract_Qualified_Staff	Difficulty in attracting qualified staff in Data Science

Lack_Retain_Qualified_Staff	Difficulty in maintaining qualified staff in Data Science
Lack_Interest_Leadership	Lack of interest by board of directors
Lack_Time	Lack of time for new projects
Funding_Difficulty	Funding difficulties
Lack_Government_Support	Lack of financial support by government.
DS_Unknown	We don't know what Data Science is and what benefits it can brings
DS_Uninterest	We don't have interest in Data Science implementation
DS_size_challenges	The organisations's size poses challenges in adopting Data Science
DS_size_ability	The organisations's size positively impacts the ability to scale and sustain Data Science in the long-term
DS_size_adaptation	The organisations's size enables a quick adaptation to changes in the technological landscape
TM_skills	Management actively encourages employees to enhance their data skills
TM_resources	Top management allocates sufficient resources (budget, personnel, time) towards Data Science implementation
TM_monitoring	Top management establishes goals and standards to monitor Data Science usage.
TM_committed	Top Management is committed in leveraging Data Science.
DS_partnerships	In the past 5 years, how much has the org invested in partnerships w/ external stakeholders to advance its DS efforts?
DS_projects	In the past 5 years, in how many Data Science projects has your organisation been involved?
DS_investment_priority	The investment in Data Science is a priority in the organisation
DS_investment_vital_future	The investment in Data Science is crucial to the future of the organisation
DS_side_effect	The investment in Data Science, if it happens, will be a consequence of other decisions
DS_actively_persued	The organisation is actively searching for the use of Data Science
DS_peer_pressure	When compared to the usage of Data Science with other social organisation, your organisation is:
Org_observes_competitors	The organisation observes and learns from the practices of other organisation regarding the adoption of Data Science
Fail_DS_harm_competitiveness	Failing to integrate Data Science will result in the organisation falling behind compared to other similar organisation
DS_aug_competitiveness	Adopting Data Science will enhance the organisations's competitiveness
Fail_DS_deteriorate_stakeholders	Failing to integrate Data Science will deteriorate the relationship with our stakeholders
DS_attract_donors	The organisations's capacity to attract donors or funding is impacted by its use of Data Science
Stakeholders_antecipate_DS	Stakeholders anticipate that the organisation remains current and leverages Data Science
Fail_DS_communicate_stakeholders	Inadequate investment in DS limits the organisations's ability to communicate with stakeholders and address their concerns
Manual_2_Digital	To what extent have manual processes shifted to online platforms within your organisation?
Services_evolution	In the past 5 years, the nr of online services provided by the org to either members, beneficiaries, or other interested parties:

AI	Which of the following AI models do you use in your organisation?
AI_subscription	Is the organisation subscribed to any of these AI models?
AI_subscription_expense	How much is the organisation spending on monthly licenses?
AI_concerns	Implementing AI would raise multiple concerns (e.g. data privacy, security, ethical considerations)
AI_automation	Incorporating AI would facilitate process automation within the organisation
AI_aug_efficiency	Adopting AI would enhance the organisations's efficiency
AI_simplify_task	AI can simplify an organisations's tasks
AI_meaningful_task	Implementing AI would enable the organisation to focus on more meaningful activities
AI_reduce_staff	Implementing AI could reduce the number of staff within the organisation
AI_plan	The organisation has a strategic plan in place for future AI adoption or expansion within the organisation
BA_visual	The organisation often creates reports with visual representations of their activities
BA_progress	The organisation is tracking the progress of their activities also with basic statistics and visualisation
BA_algorithms	The organisation uses algorithms to optimize their performance
BA_segmentation	The organisation employs data segmentation techniques to categorize donors based on their unique attributes and preferences
Covid_online_services	Made the organisation increase the number of services provided online.
Covid_online_transition	Facilitated the organisations's transition to online platforms
Covid_op_strategy	Made the organisation reassess its operational strategy, leading to a more data-driven decision-making process.
Covid_resources	Made the organisation rely on data-driven insights to allocate resources efficiently and optimize the impact on communities.
Catalyst_Covid	COVID-19 and its effect on organisational adaptation to a new reality
Catalyst_AI	Increased accessibility of AI models (e.g. ChatGPT) and their impact
Catalyst_Leadership	A shift in management mindset embracing data-driven decision-making and digital transformation
Catalyst_New_Software	The emergence of new technologies and open-source software
Catalyst_Government	Government regulations or policies influencing technology adoption.
Catalyst_Competitive	Market competition and the need to gain more fundraising from donors
Willingness_to_collaborate	Leave us a comment about the topic of Data Science in the social sector.
W2Collaborate_binary	Leave us a email if you would like to be contacted for future questions related with this topic

Appendix 8: Scales from survey questions and correspondence with each scale variable

	Age Group	Dimension	Budget			
0	Less than 25 years	-	-	-	-	
1	25-35 years	Less than 50	< 100,000€	20€	There's no allocation	
2	36-45 years	50-250	100,000€ - 300,000€	20-100€	Less than 5% of the annual budget	
3	46-55 years	251-500	300,000€ - 700,000€	100-500€	Between 5% and 10% of the annual budget	
4	55-65 years	501-750	700,000€ - 1,000,000€	500-1000€	Between 10% and 30% of the annual budget	
5	More than 65 years	More than 750	> 1,000,000€	>1000€	More than 30% of the annual budget	

	Rate					Frequency	
0	-	-	-	-	-	-	-
1	Very low	Far below	Non existent	No difference	No value	None	None
2	Low	Below	Minimal	Little difference	Of little value	1-3 times	1-2
3	Moderate	Equal	Emerging	Some difference	Moderately valuable	4-6 times	3-4
4	High	Above	Developing	Moderately different	Valuable	7-10 times	5
5	Very High	Far above	Established	Extremely different	Extremely valuable	More than 10 times	>5

	Statement	Evolution			
0	-	-	-	-	-
1	Strongly Disagree	No meaningful changes	Deteriorated	Not at all	Decreased significantly
2	Disagree	Few meaningful changes	Limited	Minimal transition	Decreased moderately
3	Neutral	Some meaningful changes	No change	Moderate transition	Remained stable
4	Agree	Significant meaningful changes	Somehow improved	Significant transition	Increased moderately
5	Strongly Agree	Very significant meaningful changes	Fully optimised	Complete transition	Increased significantly

Appendix 9: Scales correspondent to each variable within the survey scale items

Variable Name	Scale Type	Variable Name	Scale Type	Variable Name	Scale Type
Age_org_members	Age Group	Data_confidencial	Statement	Peer_ext_incentivise_DS_use	Statement
Age_board	Age Group	Data_open_access_internal	Statement	Funds_4DS_available	Statement
Org_emp	Dimension	Data_collected_with_consensus	Statement	DS_staff_expertise	Statement
Org_vol	Dimension	Data_collected_GDPR	Statement	IntUse_DS_pred	Statement
Org_budget	Budget	DataCollected_wout_resistance	Statement	IntUse_DS	Statement
IT_equip_obsolote	Statement	Digital_collection_evolution	Evolution	Interest_4DS_impl	Statement
Tech_obsolete	Statement	Manual_2_Digital	Evolution	DS_good_idea	Statement
IT_budget_percentage	Budget	Services_evolution	Evolution	DS_aug_results	Statement
IT_budget_evolution	Evolution	AI_subscription_expense	Budget	DS_aug_stakeholders	Statement
IT_Team_budget_percentage	Budget	AI_concerns	Statement	DS_aug_donors	Statement
IT_Team_budget_evolution	Evolution	AI_automation	Statement	DS_savings	Statement
AI_DataScience_diff	Rate	AI_aug_efficiency	Statement	DS_compatibility_ops	Statement
DataScience_sup	Rate	AI_simplify_task	Statement	DS_disruption_ops	Statement
AI_sup	Rate	AI_meaningful_task	Statement	DS_size_challenges	Statement
Data_Science_level	Rate	AI_reduce_staff	Statement	DS_size_ability	Statement
DS_additional_train	Statement	AI_plan	Statement	DS_size_adaptation	Statement
DS_application_evolution	Statement	BA_visual	Statement	TM_skills	Statement
DS_resources_evolution	Statement	BA_progress	Statement	TM_resources	Statement
DS_resources_expectation	Statement	BA_algorithms	Statement	TM_monitoring	Statement
DS_partnerships	Rate	BA_segmentation	Statement	TM_committed	Statement
DS_projects	Frequency	Catalyst_Covid	Statement	DS_capacity_needs	Statement
DS_investment_priority	Statement	Catalyst_AI	Statement	DS_org_assessment	Statement
DS_investment_vital_future	Statement	Catalyst_Leadership	Statement	DS_readiness	Statement
DS_side_effect	Statement	Catalyst_New_Software	Statement	Org_observes_competitors	Statement
DS_actively_persued	Statement	Catalyst_Government	Statement	Fail_DS_harm_competitiveness	Statement
DS_peer_pressure	Rate	Catalyst_Competitive	Statement	DS_aug_competitiveness	Statement

Appendix 10: Common variables between 2019 and 2024 surveys

Org_name	Website_AI	DigData_needs_understanding	DS_obstacles_4ops
Age_org_members	Website_storage_automated	DigData_processing_skills	DS_not_optimal
Age_board	Website_data_processing	Ddriven_actions_knowledge	DS_effort
Org_gov_type	Org_wout_website_yn	DDDM_routine	DS_easy2work
IT_Destop_Comp	Dedicated_IT_Team	DM_intuitive_routine	DS_intuitive
IT_Prog	IT_relation	Data_sensitive	DS_imp_complexity
IT_Com	DS_investment_priority	Data_confidencial	Peer_inf_DS_decisions
IT_Web	DS_investment_vital_future	Data_open_access_internal	Peer_ref_inf_DS_decisions
IT_App	DS_side_effect	Data_collected_with_consensus	Peer_ref_incentivize_DS_use
IT_equip_obsolote	DS_actively_persued	Data_collected_GDPR	Peer_ext_incentivise_DS_use
Tech_obsolete	DS_peer_pressure	DataCollected_wout_resistance	Funds_4DS_available
Website_inf_only	DS_ed_access	DS_applicable_4ops	DS_staff_expertise
Website_cookies	Boards_likes_new_initiatives	DS_beneficial_4ops	IntUse_DS_pred
Website_critical_func	Data_collection_digital	DS_impact_aug	IntUse_DS
Website_manual	Data_collection_physical	DS_aug_eff	Interest_4DS_impl
Website_automated	Data_quality	DS_investment_focus_dev	DS_good_idea

Appendix 11: UTAUT variables and respective Cronbach's alpha for 2019 survey

	n	Items	Cronbach's α
Performance Expectancy	158	5	0.634
Effort Expectancy	158	6	0.020
Social Influence	158	4	0.914
Facilitating Conditions	158	2	0.791
Behavioural Intention to use Data Science	158	2	0.979
Attitude Towards using Data Science	158	2	0.762

Note: required minimum value of 0.6 (Daud et al., 2018)

Appendix 12: UTAUT variables and respective Cronbach's alpha for 2024 survey

	n	Items	Cronbach's α
Performance Expectancy	47	5	0.785
Effort Expectancy	47	6	0.335
Social Influence	47	4	0.888
Facilitating Conditions	47	2	0.601
Behavioural Intention to use Data Science	47	2	0.983
Attitude Towards using Data Science	47	2	0.690

Note: required minimum value of 0.6 (Daud et al., 2018)

Appendix 13: T-test for Equality of Means and Cohen’s d

	t-test for Equality of Means			Size Effect	Group Statistics		
	t	*df*	*sig*	*Cohen's d*	*Survey*	*Mean*	*Std.Dev*
Performance Expectancy (UTAUT)	-4.535	205	<0.001	0.75	2019	3.18	0.389
					2024	3.48	0.458
Facilitating Conditions (UTAUT)	-3.491	205	<0.001	0.57	2019	2.75	0.944
					2024	3.30	0.958
DS_investment_priority	-2.639	205	0.009	0.43	2019	2.09	0.989
					2024	2.53	1.039
DS_investment_vital_future	-3.797	205	<0.001	0.63	2019	2.63	1.164
					2024	3.36	1.187
DS_actively_persued	-2.437	205	0.016	0.40	2019	2.28	1.004
					2024	2.70	1.159
DS_ed_access	-4.451	95.81	<0.001	0.64	2019	3.48	0.951
					2024	4.06	0.734
Data_collection_digital	-3.581	94.605	<0.001	0.52	2019	3.53	1.171
					2024	4.11	0.914

Appendix 14: TOE variables and respective Cronbach's alpha for 2024 survey

	n	Items	Cronbach's α
Relative Advantage	47	4	0.903
Compatibility	47	2	0.441
Size	47	3	0.257
Top Management Support	47	4	0.825
Organisational Readiness	47	2	0.710
Competitive Pressure	47	2	0.771
Business Partner Pressure	47	4	0.920
Market Uncertainty	47	4	0.859

Note: required minimum value of 0.6 (Daud et al., 2018)

Appendix 15: Variables considered for Data Science Evolution's proxy and respective survey questions

Variable Name	Question
DS_application_evolution	The application of Data Science in the day-to-day operations has increased in the last 5 years
DS_resources_evolution	The allocation of resources towards Data Science initiatives have increased in the last 5 years

Appendix 16: Proxy variable (Data Science Evolution) and respective Cronbach's alpha

	n	Items	Cronbach's α
Data Science Evolution	47	2	0.881

Note: required minimum value of 0.6 (Daud et al., 2018)

Appendix 17: Variables used in the multiple regression analysis and corresponding survey questions

Variable Name	Question
Area_Culture	The area of operation of the organisation is culture, communication, and recreational activities
Area_Education	The area of operation of the organisation is education
Area_Human_health	The area of operation of the organisation is human health
Area_Social_Services	The area of operation of the organisation is social services
Area_Others_Combined[a]	The area of operation of the organisation is environmental protection and animal welfare, **or** community and economic development, and housing activities **or** civic, advocacy, political and international activities, **or** philanthropic intermediaries and voluntarism promotion, or religious, **or** business, professional, and labour organisations, **or** professional, scientific, and administrative services, **or** others
Age_org_members	What is the average age of the employees in your organisation?
Age_board	What is the average age of the organisations's leadership team?
Org_dimension[b]	How many paid employees does your organisation have? How many members/volunteers does your organisation have?
Org_budget	What is the annual budget of your organisation?
DS_partnerships	In the past 5 years, how much has the organisation invested in partnerships or collaborations with external stakeholders to advance its Data Science efforts?
DS_investment_priority	The investment in Data Science is a priority in the organisation
DS_ed_access	How many times, during these last 5 years, did your organisation have access to some sort of education about Data Science or Digital Transformation? (training sessions, workshops)
Digital_collection_evolution	How has the organisations's transition to digital data collection and storage evolved over the past 5 years?
DS_imp_complexity	Data Science is too complicated to implement

Funds_4DS_available	The organisation has the financial resources to proceed with further implementation of data science
Dedicated_IT_Team	Do you have a dedicated IT team?
Catalyst_Covid	COVID-19 and its effect on organisational adaptation to a new reality (remote work, online presence, digital data collection,…)
Catalyst_AI	Increase accessibility of AI models (e.g. ChatGPT) and their impact
Catalyst_Leadership	Shift in management mindset embracing data-driven decision-making and digital transformation
Catalyst_New_Software	Government regulations or policies influencing technology adoption.
Catalyst_Competitive	Market competition and the need to gain more fundraising from donors
Performance Expectancy	Details on items used available in *appendix 5*
Social Influence	Details on items used available in *appendix 5*
Facilitating Conditions	Details on items used available in *appendix 5*
Behavioural Intention	Details on items used available in *appendix 5*
Top Management Support	Details on items used available in *appendix 6*
Competitive Pressure	Details on items used available in *appendix 6*
Market Uncertainty	Details on items used available in *appendix 6*

[a] *A combination of variables was carried out to address the underrepresentation of other areas of organisational operations, and avoid biased outcomes.*
[b] *The combination of variables was implemented to incorporate the organisational dimension, encompassing both employees and volunteers.*

Appendix 18: Blocks of independent variables used in the multiple regression model

Block 1 – Demographic Variables	**Block 2 - Organisation Practices**	**Block 3 - UTAUT & TOE**	**Block 4 - Catalysts**
Area_Culture	DS_partnerships	Performance Expectancy	Catalyst_Covid
Area_Education	DS_investment_priority	Social Influence	Catalyst_AI
Area_Human_health	DS_ed_access	Facilitating Conditions	Catalyst_Leadership
Area_Social_Services	Digital_collection_evolution	Behavioural Intention	Catalyst_New_Software
Area_Others_Combined	DS_imp_complexity	Top Management Support	Catalyst_Competitive
Age_org_members	Funds_4DS_available	Competitive Pressure	
Age_board	Dedicated_IT_Team	Market Uncertainty	
Org_dimension			
Org_budget			

Appendix 19: Frequencies – Sociodemographic Characteristics of Organisations

Organisational Characteristics	Full Sample	
	n	*%*
LF_org		
Cooperative	7	14.9%
Foundation	6	12.8%
Association	26	55.3%
Mutualist Association	2	4.3%
Social Enterprise	1	2.1%
Holy Houses of Mercy	4	8.5%
Associations with Altruistic Goals and Community and Self-Management Subsectors	1	2.1%
Area_Culture		
Yes	9	85.4%
No	38	14.6%
Area_Education		
Yes	17	36.2%
No	30	63.8%
Area_Human_Health		
Yes	18	38.3%
No	29	61.7%
Area_Social_Services		
Yes	25	53.2%
No	22	46.8%
Area_Environmental_Animal		
Yes	2	4.3%
No	45	95.7%
Area_Community_Housing		
Yes	7	14.9%
No	40	85.1%
Area_Civic_Advocacy_Political		
Yes	2	4.3%
No	45	95.7%
Area_Philantropic_Voluntarism		
Yes	4	8.5%
No	43	91.5%
Area_Religious		
Yes	1	2.1%
No	46	97.9%
Area_Business_Professional		
Yes	1	2.1%
No	46	97.9%
Area_Professional_Administrative		
Yes	1	2.1%
No	46	97.9%
Area_Others		
Yes	2	4.3%
No	45	95.7%
Age_org_members		
Less than 25 years	1	2.1%
25-35 years	5	10.6%
36-45 years	28	59.6%

46-55 years	13	27.7%
55-65 years	0	0.0%
More than 65 years	0	0.0%
Age_board		
Less than 25 years	1	2.1%
25-35 years	1	2.1%
36-45 years	15	31.9%
46-55 years	20	42.6%
55-65 years	8	17.0%
More than 65 years	2	4.3%
Org_emp		
Less than 50	30	63.8%
50-250	15	31.9%
251-500	2	4.3%
501-750	0	0.0%
More than 750	0	0.0%
Org_vol		
Less than 50	35	74.5%
50-250	9	19.1%
251-500	1	2.1%
501-750	0	0.0%
More than 750	2	4.3%
Org_budget		
< 100,000€	8	17.0%
100,000€ - 300,000€	10	21.3%
300,000€ - 700,000€	4	8.5%
700,000€ - 1,000,000€	3	6.4%
> 1,000,000€	22	46.8%
Org_gov_type		
Horizontal	14	29.8%
Vertical	22	46.8%
Matrix	11	23.4%

Appendix 20: Frequencies - IT Infrastructure

IT Infrastructure	Full Sample	
	n	*%*
IT_Desktop_Comp		
Yes	36	76.6%
No	11	23.4%
IT_PC		
Yes	43	91.5%
No	4	8.5%
IT_Servers		
Yes	25	53.2%
No	22	46.8%
IT_Prog		
Yes	29	61.7%
No	18	38.3%
IT_Com		
Yes	27	57.4%
No	20	42.6%
IT_Web		

Yes	39	83.0%
No	8	17.0%
IT_App		
Yes	8	17.0%
No	39	83.0%
IT_AI		
Yes	2	4.3%
No	45	95.7%
IT_RPA		
Yes	6	12.8%
No	41	87.2%
IT_APIs		
Yes	6	12.8%
No	41	87.2%
IT_Cloud		
Yes	26	55.3%
No	21	44.7%
IT_equip_obsolete		
Strongly Disagree	6	12.8%
Disagree	14	29.8%
Neutral	14	29.8%
Agree	9	19.1%
Strongly Agree	4	8.5%
Tech_obsolete		
Strongly Disagree	6	12.8%
Disagree	19	40.4%
Neutral	9	19.1%
Agree	11	23.4%
Strongly Agree	2	4.3%
IT_budget_percentage		
There's no allocation	20	42.6%
Less than 5% of the annual budget	21	44.7%
Between 5% and 10% of the annual budget	4	8.5%
Between 10% and 30% of the annual budget	1	2.1%
More than 30% of the annual budget	1	2.1%
IT_budget_evolution		
Decreased significantly (e.g. decreased by more than 50%)	3	6.4%
Decreased moderately (e.g. decreased by more than 20%)	1	2.1%
Remained stable	22	46.8%
Increased moderately (e.g. increased by more than 20%)	17	36.2%
Increased significantly (e.g. increased by more than 50%)	4	8.5%
Website_info_only		
Yes	29	61.7%
No	18	38.3%
Website_cookies		
Yes	15	31.9%
No	32	68.1%
Website_critical_func		
Yes	5	10.6%
No	42	89.4%
Website_service		
Yes	6	12.8%
No	41	87.2%
Website_manual		

Yes	17	36.2%
No	30	63.8%
Website_automated		
Yes	1	2.1%
No	46	97.9%
Website_ecommerce		
Yes	8	17.0%
No	39	83.0%
Website_AI		
Yes	1	2.1%
No	46	97.9%
Website_storage_automated		
Yes	8	17.0%
No	39	83.0%
Website_data_processing		
Yes	8	17.0%
No	39	83.0%
Org_wout_website_yn		
Yes	3	6.4%
No	44	93.6%
Website_outdated		
Yes	11	23.4%
No	36	76.6%
Dedicated_IT_Team		
Yes	16	34.0%
No	31	66.0%
IT_Relation		
Externally hired	5	31.3%
Part of the organisation (employees), with education in IT	8	50.0%
Part of the organisation (employees), without education in IT	3	18.8%
IT_Team_budget_percentage		
There's no allocation	3	18.8%
Less than 5% of the annual budget	11	68.8%
Between 5% and 10% of the annual budget	2	12.5%
Between 10% and 30% of the annual budget	0	0.0%
More than 30% of the annual budget	0	0.0%
IT_Team_budget_evolution		
Decreased significantly (e.g. decreased by more than 50%)	0	0.0%
Decreased moderately (e.g. decreased by more than 20%)	1	6.3%
Remained stable	9	56.3%
Increased moderately (e.g. increased by more than 20%)	5	31.3%
Increased significantly (e.g. increased by more than 50%)	1	6.3%

Appendix 21: Frequencies - Data Science

Data Science	Full Sample	
	n	*%*
AI_DataScience_diff		
No difference	2	4.3%
Little difference	7	14.9%
Some difference	10	21.3%
Moderately different	15	31.9%
Extremely different	13	27.7%
DataScience_sup		
No value	0	0.0%
Of little value	5	11.1%
Moderately valuable	8	17.8%
Valuable	22	48.9%

Extremely valuable	10	22.2%
AI_sup		
No value	3	6.7%
Of little value	4	8.9%
Moderately valuable	16	35.6%
Valuable	9	20.0%
Extremely valuable	3	6.7%
Data Science_level		
Inexistent	20	42.6%
Minimal	15	31.9%
Emerging	10	21.3%
Developing	2	4.3%
Established	0	0.0%
DS_additional_training		
Strongly Disagree	1	2.1%
Disagree	2	4.3%
Neutral	4	8.5%
Agree	19	40.4%
Strongly Agree	21	44.7%
DS_application_evolution		
Strongly Disagree	15	31.9%
Disagree	6	12.8%
Neutral	12	25.5%
Agree	12	25.5%
Strongly Agree	2	4.3%
DS_resources_evolution		
Strongly Disagree	18	38.3%
Disagree	9	19.1%
Neutral	14	29.8%
Agree	5	10.6%
Strongly Agree	1	2.1%
DS_partnerships		
There was no investment	32	68.1%
Less than 5% of the annual budget	13	27.7%
Between 5% and 10% of the annual budget	1	2.1%
Between 10% and 30% of the annual budget	1	2.1%
More than 30% of the annual budget	0	0.0%
DS_projects		
None	34	72.3%
1-3 times	11	23.4%
4-6 times	2	4.3%
7-10 times	0	0.0%
More than 10 times	0	0.0%
DS_investment_priority		
Strongly Disagree	10	21.3%
Disagree	10	21.3%
Neutral	20	42.6%
Agree	6	12.8%
Strongly Agree	1	2.1%
DS_investment_vital_future		
Strongly Disagree	3	6.4%
Disagree	9	19.1%
Neutral	12	25.5%
Agree	14	29.8%
Strongly Agree	9	19.1%
DS_side_effect		
Strongly Disagree	1	2.1%
Disagree	5	10.6%
Neutral	14	29.8%

Agree	21	44.7%
Strongly Agree	5	10.6%
DS_actively_persued		
Strongly Disagree	8	17.0%
Disagree	12	25.5%
Neutral	17	36.2%
Agree	6	12.8%
Strongly Agree	4	8.5%
DS_peer_pressure		
Very low	7	14.9%
Low	12	25.5%
Equal	19	40.4%
Above	9	19.1%
Far above	0	0.0%
DS_data_literacy		
Very low	7	14.9%
Low	17	36.2%
Moderate	18	38.3%
High	4	8.5%
Very high	1	2.1%
DS_ed_access		
None	22	46.8%
1-3 times	18	38.3%
4-6 times	3	6.4%
7-10 times	2	4.3%
More than 10 times	2	4.3%
DS_ed_result		
No difference	4	15.4%
Little difference	13	50.0%
Some difference	7	26.9%
Moderately different	1	3.8%
Extremely different	1	3.8%

Appendix 22: Frequencies - Data Collection and Privacy

Data Collection and Privacy	Full Sample	
	n	*%*
Data_collection_digital		
Strongly Disagree	1	2.1%
Disagree	2	4.3%
Neutral	5	10.6%
Agree	22	46.8%
Strongly Agree	17	36.2%
Data_collection_physical		
Strongly Disagree	3	6.4%
Disagree	5	10.6%
Neutral	6	12.8%
Agree	21	44.7%
Strongly Agree	12	25.5%
Data_quality		
Strongly Disagree	1	2.1%
Disagree	2	4.3%
Neutral	5	10.6%
Agree	23	48.9%
Strongly Agree	16	34.0%
DigData_needs_understanding		
Strongly Disagree	0	0.0%

Disagree	4	8.5%
Neutral	6	12.8%
Agree	26	55.3%
Strongly Agree	8	17.0%
DigData_processing_skills		
Strongly Disagree	2	4.3%
Disagree	6	12.8%
Neutral	12	25.5%
Agree	23	48.9%
Strongly Agree	4	8.5%
Ddriven_actions_knowledge		
Strongly Disagree	4	8.5%
Disagree	6	12.8%
Neutral	8	17.0%
Agree	25	53.2%
Strongly Agree	4	8.5%
DDDM_routine		
Strongly Disagree	5	10.6%
Disagree	5	10.6%
Neutral	9	19.1%
Agree	25	53.2%
Strongly Agree	3	6.4%
DM_intuitive_routine		
Strongly Disagree	4	8.5%
Disagree	12	25.5%
Neutral	13	27.7%
Agree	17	36.2%
Strongly Agree	1	2.1%
Data_sensitive		
Strongly Disagree	0	0.0%
Disagree	5	10.6%
Neutral	9	19.1%
Agree	19	40.4%
Strongly Agree	14	29.8%
Data_confidential		
Strongly Disagree	1	2.1%
Disagree	3	6.4%
Neutral	12	25.5%
Agree	16	34.0%
Strongly Agree	15	31.9%
Data_open_access_internal		
Strongly Disagree	12	25.5%
Disagree	20	42.6%
Neutral	6	12.8%
Agree	5	10.6%
Strongly Agree	4	8.5%
Data_collected_with_consensus		
Strongly Disagree	0	0.0%
Disagree	5	10.6%
Neutral	3	6.4%
Agree	23	48.9%
Strongly Agree	16	34.0%
Data_collected_GDPR		
Strongly Disagree	0	0.0%
Disagree	4	8.5%
Neutral	3	6.4%
Agree	20	42.6%
Strongly Agree	20	42.6%
DataCollected_wout_resistance		
Strongly Disagree	1	2.1%
Disagree	6	12.8%

Neutral	8	17.0%
Agree	25	53.2%
Strongly Agree	7	14.9%
Digital_collection_evolution		
Deteriorated	1	2.1%
Limited	7	14.9%
No change	8	17.0%
Somehow improved	30	63.8%
Fully optimised	1	2.1%

Appendix 23: Frequencies - Digital Transformation

Digital Transformation	Full Sample	
	n	*%*
Manual_2_Digital		
Not at all	6	12.8%
Minimal transition	6	12.8%
Moderate transition	17	36.2%
Significant transition	13	27.7%
Complete transition	5	10.6%
Services_evolution		
Decreased significantly	3	6.4%
Decreased moderately	1	2.1%
Remained stable	15	31.9%
Increased moderately	24	51.1%
Increased significantly	4	8.5%
AI		
Yes	3	6.4%
No	44	93.6%
AI_concerns		
Strongly Disagree	0	0.0%
Disagree	4	8.5%
Neutral	17	36.2%
Agree	17	36.2%
Strongly Agree	8	17.0%
AI_Automation		
Strongly Disagree	1	2.1%
Disagree	2	4.3%
Neutral	21	44.7%
Agree	17	36.2%
Strongly Agree	6	12.8%
AI_aug_efficiency		
Strongly Disagree	1	2.1%
Disagree	2	4.3%
Neutral	18	38.3%
Agree	20	42.6%
Strongly Agree	6	12.8%
AI_simplify_task		
Strongly Disagree	1	2.1%
Disagree	2	4.3%
Neutral	15	31.9%
Agree	20	42.6%
Strongly Agree	9	19.1%
AI_reduce_staff		
Strongly Disagree	7	14.9%
Disagree	13	27.7%
Neutral	21	44.7%
Agree	3	6.4%

Strongly Agree	3	6.4%
AI_plan		
Strongly Disagree	20	42.6%
Disagree	12	25.5%
Neutral	15	31.9%
Agree	0	0.0%
Strongly Agree	0	0.0%
BA_visual		
Strongly Disagree	1	2.1%
Disagree	9	19.1%
Neutral	7	14.9%
Agree	21	44.7%
Strongly Agree	9	19.1%
BA_progress		
Strongly Disagree	6	12.8%
Disagree	16	34.0%
Neutral	6	12.8%
Agree	12	25.5%
Strongly Agree	7	14.9%
BA_algorithms		
Strongly Disagree	18	38.3%
Disagree	14	29.8%
Neutral	13	27.7%
Agree	2	4.3%
Strongly Agree	0	0.0%
BA_segmentation		
Strongly Disagree	0	0.0%
Disagree	13	27.7%
Neutral	11	23.4%
Agree	10	21.3%
Strongly Agree	1	2.1%

Appendix 24: Frequencies - Catalysts

Catalysts	**Full Sample**	
	n	%
Catalyst_Covid		
Strongly Disagree	10	21.3%
Disagree	5	10.6%
Neutral	10	21.3%
Agree	14	29.8%
Strongly Agree	8	17.0%
Catalyst_AI		
Strongly Disagree	12	25.5%
Disagree	12	25.5%
Neutral	14	29.8%
Agree	9	19.1%
Strongly Agree	0	0.0%
Catalyst_Leadership		
Strongly Disagree	5	10.6%
Disagree	8	17.0%
Neutral	14	29.8%
Agree	19	40.4%
Strongly Agree	1	2.1%
Catalyst_New_Software		

Strongly Disagree	3	6.4%
Disagree	5	10.6%
Neutral	13	27.7%
Agree	23	48.9%
Strongly Agree	3	6.4%
Catalyst_Government		
Strongly Disagree	8	17.0%
Disagree	7	14.9%
Neutral	18	38.3%
Agree	12	25.5%
Strongly Agree	2	4.3%
Catalyst_Competitive		
Strongly Disagree	2	4.3%
Disagree	7	14.9%
Neutral	17	36.2%
Agree	15	31.9%
Strongly Agree	6	12.8%

Appendix 25: Frequencies - Barriers towards Data Science Implementation

Barriers towards Data Science Implementation	Full Sample	
	n	%
Lack_IT_Infrastructure		
Yes	24	51.1%
No	23	48.9%
Lack_Staff_Qualified		
Yes	30	63.8%
No	17	36.2%
Lack_Attract_Qualified_Staff		
Yes	12	25.5%
No	35	74.5%
Lack_Retain_Qualified_Staff		
Yes	10	21.3%
No	37	78.7%
Lack_Interest_Leadership		
Yes	6	12.8%
No	41	87.2%
Lack_Time		
Yes	16	34.0%
No	31	66.0%
Funding_Difficulty		
Yes	34	72.3%
No	13	27.7%
Lack_Government_Support		
Yes	12	25.5%
No	35	74.5%
DS_Unknown		
Yes	13	27.7%
No	34	72.3%
DS_Uninterest		
Yes	3	6.4%
No	44	93.6%

Appendix 26: Frequencies - UTAUT Items

UTAUT Items	Full Sample	
	n	%
DS_applicable_4ops		
Strongly Disagree	5	10.6%
Disagree	8	17.0%
Neutral	12	25.5%
Agree	21	44.7%
Strongly Agree	1	2.1%
DS_beneficial_4ops		
Strongly Disagree	2	4.3%
Disagree	5	10.6%
Neutral	9	19.1%
Agree	25	53.2%
Strongly Agree	6	12.8%
DS_impact_aug		
Strongly Disagree	0	0.0%
Disagree	3	6.4%
Neutral	14	29.8%
Agree	19	40.4%
Strongly Agree	11	23.4%
DS_aug_eff		
Strongly Disagree	0	0.0%
Disagree	1	2.1%
Neutral	6	12.8%
Agree	28	59.6%
Strongly Agree	12	25.5%
DS_investment_focus_dev		
Strongly Disagree	1	2.1%
Disagree	5	10.6%
Neutral	15	31.9%
Agree	17	36.2%
Strongly Agree	9	19.1%
DS_obstacles_4ops		
Strongly Disagree	4	8.5%
Disagree	6	12.8%
Neutral	16	34.0%
Agree	20	42.6%
Strongly Agree	1	2.1%
DS_not_optimal		
Strongly Disagree	3	6.4%
Disagree	17	36.2%
Neutral	17	36.2%
Agree	7	14.9%
Strongly Agree	3	6.4%
DS_effort		
Strongly Disagree	0	0.0%
Disagree	3	6.4%
Neutral	14	29.8%
Agree	19	40.4%
Strongly Agree	11	23.4%
DS_easy2work		
Strongly Disagree	4	8.5%
Disagree	8	17.0%
Neutral	23	48.9%
Agree	10	21.3%
Strongly Agree	2	4.3%
DS_intuitive		
Strongly Disagree	4	8.5%
Disagree	12	25.5%

Neutral	20	42.6%
Agree	9	19.1%
Strongly Agree	2	4.3%
DS_imp_complexity		
Strongly Disagree	4	8.5%
Disagree	12	25.5%
Neutral	23	48.9%
Agree	6	12.8%
Strongly Agree	2	4.3%
Peer_inf_DS_decision		
Strongly Disagree	2	4.3%
Disagree	8	17.0%
Neutral	26	55.3%
Agree	10	21.3%
Strongly Agree	1	2.1%
Peer_ref_inf_DS_decisions		
Strongly Disagree	2	4.3%
Disagree	4	8.5%
Neutral	26	55.3%
Agree	13	27.7%
Strongly Agree	2	4.3%
Peer_ref_incentivize_DS_use		
Strongly Disagree	3	6.4%
Disagree	5	10.6%
Neutral	26	55.3%
Agree	12	25.5%
Strongly Agree	1	2.1%
Peer_ext_incentivise_DS_use		
Strongly Disagree	3	6.4%
Disagree	7	14.9%
Neutral	18	38.3%
Agree	17	36.2%
Strongly Agree	2	4.3%
Funds_4DS_available		
Strongly Disagree	17	36.2%
Disagree	13	27.7%
Neutral	8	17.0%
Agree	7	14.9%
Strongly Agree	2	4.3%
DS_staff_expertise		
Strongly Disagree	18	38.3%
Disagree	15	31.9%
Neutral	7	14.9%
Agree	6	12.8%
Strongly Agree	1	2.1%
IntUse_DS_pred		
Strongly Disagree	3	6.4%
Disagree	3	6.4%
Neutral	21	44.7%
Agree	15	31.9%
Strongly Agree	5	10.6%
IntUse_DS		
Strongly Disagree	3	6.4%
Disagree	3	6.4%
Neutral	23	48.9%
Agree	14	29.8%
Strongly Agree	4	8.5%
Interest_4DS_impl		
Strongly Disagree	2	4.3%
Disagree	5	10.6%
Neutral	12	25.5%
Agree	20	42.6%

Strongly Agree	8	17.0%
DS_good_idea		
Strongly Disagree	0	0.0%
Disagree	1	2.1%
Neutral	9	19.1%
Agree	24	51.1%
Strongly Agree	13	27.7%

Appendix 27: Frequencies - TOE Items

TOE Items	Full Sample	
	n	*%*
DS_aug_results		
Strongly Disagree	0	0.0%
Disagree	2	4.3%
Neutral	11	23.4%
Agree	23	48.9%
Strongly Agree	11	23.4%
DS_aug_stakeholders		
Strongly Disagree	0	0.0%
Disagree	0	0.0%
Neutral	6	12.8%
Agree	26	55.3%
Strongly Agree	15	31.9%
DS_aug_donors		
Strongly Disagree	0	0.0%
Disagree	2	4.3%
Neutral	10	21.3%
Agree	23	48.9%
Strongly Agree	12	25.5%
DS_savings		
Strongly Disagree	0	0.0%
Disagree	1	2.1%
Neutral	8	17.0%
Agree	25	53.2%
Strongly Agree	13	27.7%
DS_compatibility_ops		
Strongly Disagree	1	2.1%
Disagree	0	0.0%
Neutral	17	36.2%
Agree	25	53.2%
Strongly Agree	4	8.5%
DS_disruption_ops		
Strongly Disagree	2	4.3%
Disagree	11	23.4%
Neutral	17	36.2%
Agree	15	31.9%
Strongly Agree	2	4.3%
DS_size_challenges		
Strongly Disagree	1	2.1%
Disagree	11	23.4%
Neutral	10	21.3%
Agree	20	42.6%
Strongly Agree	5	10.6%
DS_size_ability		
Strongly Disagree	2	4.3%
Disagree	4	8.5%
Neutral	19	40.4%
Agree	19	40.4%

Strongly Agree	3	6.4%
DS_size_adaptation		
Strongly Disagree	4	8.5%
Disagree	7	14.9%
Neutral	16	34.0%
Agree	19	40.4%
Strongly Agree	1	2.1%
TM_Skills		
Strongly Disagree	1	2.1%
Disagree	3	6.4%
Neutral	7	14.9%
Agree	29	61.7%
Strongly Agree	7	14.9%
TM_resources		
Strongly Disagree	6	12.8%
Disagree	12	25.5%
Neutral	18	38.3%
Agree	11	23.4%
Strongly Agree	0	0.0%
TM_monitoring		
Strongly Disagree	9	19.1%
Disagree	16	34.0%
Neutral	14	29.8%
Agree	8	17.0%
Strongly Agree	0	0.0%
TM_commited		
Strongly Disagree	7	14.9%
Disagree	6	12.8%
Neutral	15	31.9%
Agree	16	34.0%
Strongly Agree	3	6.4%
DS_capacity_needs		
Strongly Disagree	8	17.0%
Disagree	12	25.5%
Neutral	15	31.9%
Agree	9	19.1%
Strongly Agree	3	6.4%
DS_org_assessment		
Strongly Disagree	1	2.1%
Disagree	2	4.3%
Neutral	8	17.0%
Agree	20	42.6%
Strongly Agree	16	34.0%
DS_readiness		
Strongly Disagree	12	25.5%
Disagree	9	19.1%
Neutral	17	36.2%
Agree	7	14.9%
Strongly Agree	2	4.3%
Org_observes_competitors		
Strongly Disagree	5	10.6%
Disagree	8	17.0%
Neutral	17	36.2%
Agree	16	34.0%
Strongly Agree	1	2.1%
Fail_DS_harm_competitiveness		
Strongly Disagree	3	6.4%
Disagree	4	8.5%
Neutral	13	27.7%
Agree	19	40.4%
Strongly Agree	8	17.0%
DS_aug_competitiveness		

Strongly Disagree	0	0.0%
Disagree	1	2.1%
Neutral	14	29.8%
Agree	20	42.6%
Strongly Agree	12	25.5%
Fail_DS_deteriorate_stakeholders		
Strongly Disagree	6	12.8%
Disagree	9	19.1%
Neutral	19	40.4%
Agree	7	14.9%
Strongly Agree	6	12.8%
Stakeholders_antecipate_DS		
Strongly Disagree	4	8.5%
Disagree	5	10.6%
Neutral	20	42.6%
Agree	11	23.4%
Strongly Agree	7	14.9%
Fail_communicate_stakeholders		
Strongly Disagree	4	8.5%
Disagree	4	8.5%
Neutral	22	46.8%
Agree	12	25.5%
Strongly Agree	5	10.6%
Covid_online_services		
Strongly Disagree	4	8.5%
Disagree	11	23.4%
Neutral	11	23.4%
Agree	14	29.8%
Strongly Agree	7	14.9%
Covid_online_transition		
Strongly Disagree	3	6.4%
Disagree	6	12.8%
Neutral	13	27.7%
Agree	16	34.0%
Strongly Agree	9	19.1%
Covid_op_strategy		
Strongly Disagree	5	10.6%
Disagree	14	29.8%
Neutral	19	40.4%
Agree	6	12.8%
Strongly Agree	3	6.4%
Covid_resources		
Strongly Disagree	4	8.5%
Disagree	12	25.5%
Neutral	22	46.8%
Agree	8	17.0%
Strongly Agree	1	2.1%

Appendix 28: Group Statistics of Survey Variables

Variable	Mean	St. Dev
Area_Culture	0.19	0.398
Area_Education	0.36	0.486
Area_Human_health	0.38	0.491
Area_Social_Services	0.53	0.504
Area_Environmental_Animal	0.04	0.204
Area_Community_Housing	0.15	0.36
Area_Civic_Advocacy_Political	0.04	0.204
Area_Philantrophic_Voluntarism	0.09	0.282
Area_Religious	0.02	0.146
Area_Business_Professional	0.02	0.146
Area_Professional_Administrative	0.02	0.146
Area_Others	0.04	0.204
Age_org_members	2.13	0.679
Age_board	2.83	0.963
Org_emp	2.83	0.963
Org_vol	1.4	0.577
Org_gov_type	1.4	0.901
Org_budget	3.45	1.639
IT_Destop_Comp	0.77	0.428
IT_PC	0.91	0.282
IT_Serves	0.53	0.504
IT_Prog	0.62	0.491
IT_Com	0.57	0.5
IT_Web	0.83	0.38
IT_App	0.17	0.38
IT_AI	0.04	0.204
IT_RPA	0.13	0.337
IT_APIs	0.13	0.337
IT_Cloud	0.55	0.503
IT_equip_obsolote	2.81	1.154
Tech_obsolete	2.66	1.109
Tech_donated	0.13	0.337
Tech_bought	0.43	0.5
Tech_mix	0.45	0.503
IT_budget_percentage	1.77	0.865
IT_budget_evolution	3.38	0.922
Website_inf_only	0.62	0.491
Website_cookies	0.32	0.471
Website_critical_func	0.11	0.312
Website_services	0.13	0.337
Website_manual	0.36	0.486
Website_automated	0.02	0.146
Website_ecommerce	0.17	0.38
Website_AI	0.02	0.146

Website_storage_automated	0.17	0.38
Website_data_processing	0.17	0.38
Org_wout_website_yn	0.06	0.247
Website_outdated	0.2	0.428
Website_changes	0.26	0.441
Dedicated_IT_Team	0.34	0.479
IT_Team_budget_percentage	1.94	0.574
IT_Team_budget_evolution	3.38	0.719
AI_DataScience_diff	3.64	1.169
AI_sup	3.82	0.912
DataScience_sup	2.86	1.027
Data_Science_level	1.87	0.9
DS_applicable_4ops	3.11	1.068
DS_beneficial_4ops	3.6	0.993
DS_obstacles_4ops	3.17	0.985
Interest_4DS_impl	3.57	1.037
Funds_4DS_available	2.23	1.22
DS_staff_expertise	2.09	1.12
DS_additional_train	4.21	0.931
DS_capacity_needs	2.72	1.155
DS_org_assessment	4.02	0.944
DS_application_evolution	2.57	1.298
DS_resources_evolution	2.19	1.135
DS_resources_expectation	3.11	1.22
DS_readiness	2.53	1.158
DS_ed_access	1.81	1.035
DS_ed_result	2.31	0.928
DS_data_literacy	2.47	0.929
Data_collection_digital	4.11	0.914
Data_collection_physical	3.72	1.155
Data_quality	4.09	0.905
DigData_needs_understanding	3.68	1.065
DigData_processing_skills	3.45	0.974
Ddriven_actions_knowledge	3.4	1.097
DDDM_routine	3.34	1.109
DM_intuitive_routine	2.98	1.032
Data_sensitive	3.98	0.961
Data_confidencial	3.87	1.013
Data_open_access_internal	2.34	1.221
Data_collected_with_consensus	4.06	0.919
Data_collected_GDPR	4.19	0.9
DataCollected_wout_resistance	3.66	0.962
Digital_collection_evolution	3.49	0.856
DS_not_optimal	2.79	0.999
DS_impact_aug	3.81	0.876
DS_effort	3.81	0.876

DS_good_idea	4.04	0.751
DS_easy2work	3.04	0.955
DS_intuitive	3.15	0.978
DS_imp_complexity	2.79	0.931
DS_help	4.06	0.734
IntUse_DS	3.28	0.949
IntUse_DS_pred	3.34	0.984
DS_compatibility_ops	3.66	0.731
DS_disruption_ops	3.09	0.952
DS_aug_eff	4.09	0.686
DS_aug_results	3.91	0.803
DS_investment_focus_dev	3.6	0.993
DS_aug_stakeholders	4.19	0.647
DS_aug_donors	3.96	0.806
DS_savings	4.06	0.734
Boards_likes_new_initiatives	3.64	0.87
Peer_inf_DS_decisions	3	0.808
Peer_ref_inf_DS_decisions	3.19	0.825
Peer_ref_incentivize_DS_use	3.06	0.845
Peer_ext_incentivise_DS_use	3.17	0.963
Lack_IT_Infraestrucutre	0.51	0.505
Lack_Staff_Qualified	0.64	0.486
Lack_Attract_Qualified_Staff	0.26	0.441
Lack_Retain_Qualified_Staff	0.21	0.414
Lack_Interest_Leadership	0.13	0.337
Lack_Time	0.34	0.479
Funding_Difficulty	0.72	0.452
Lack_Government_Support	0.26	0.441
DS_Unknown	0.28	0.452
DS_Uninterest	0.06	0.247
DS_size_challenges	3.36	1.031
DS_size_ability	3.36	0.895
DS_size_adaptation	3.13	0.992
TM_skills	3.81	0.851
TM_resources	2.72	0.971
TM_monitoring	2.45	0.996
TM_committed	3.04	1.16
DS_partnerships	1.38	0.644
DS_projects	1.32	0.556
DS_investment_priority	2.53	1.039
DS_investment_vital_future	3.36	1.187
DS_side_effect	3.49	0.93
DS_actively_persued	2.7	1.159
DS_peer_pressure	2.64	0.965
Org_observes_competitors	3	1.022
Fail_DS_harm_competitiveness	3.53	1.08

DS_aug_competitiveness	3.91	0.803
Fail_DS_deteriorate_stakeholders	2.96	1.179
DS_attract_donors	3.38	1.054
Stakeholders_antecipate_DS	3.26	1.113
Fail_DS_communicate_stakeholders	3.21	1.041
Manual_2_Digital	3.11	1.165
Services_evolution	3.53	0.929
AI	0.06	0.247
AI_concerns	3.62	0.874
AI_automation	3.53	0.856
AI_aug_efficiency	3.6	0.851
AI_simplify_task	3.72	0.902
AI_meaningful_task	3.68	0.911
AI_reduce_staff	2.62	1.033
AI_plan	1.89	0.866
BA_visual	3.6	1.077
BA_progress	2.86	1.318
BA_algorithms	1.98	0.921
BA_segmentation	2.47	1.158
Covid_online_services	3.19	1.209
Covid_online_transition	3.47	1.139
Covid_op_strategy	2.74	1.031
Covid_resources	2.79	0.907
Catalyst_Covid	3.11	1.402
Catalyst_AI	2.43	1.078
Catalyst_Leadership	3.06	1.051
Catalyst_New_Software	3.38	0.99
Catalyst_Government	2.85	1.122
Catalyst_Competitive	3.34	1.027

Appendix 29: Summarised results of multiple regression models

Model		SS	df	F	Sig.	R^2	R^2_{adj}
1	Regression	14.979	9	1.335	0.253	0.245	0.620
	Residual	46.127	37				
	Total	61.106	46				
2	Regression	39.711	16	3.480	0.002	0.650	0.463
	Residual	21.395	30				
	Total	61.106	46				
3	Regression	42.082	23	2.212	0.031	0.689	0.377
	Residual	19.025	23				
	Total	61.106	46				
4	Regression	51.673	28	3.521	0.004	0.846	0.605
	Residual	9.433	18				
	Total	61.106	46				

Appendix 30: Linear regressions with blocks addition from multiple regression model

Model	Independent Variables	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.456	0.873		1.667	0.104	-0.313	3.225
	4_1_Area_Culture	-0.032	0.46	-0.011	-0.069	0.945	-0.964	0.901
	4_2_Area_Education	0.637	0.374	0.269	1.703	0.097	-0.121	1.396
	4_3_Area_Human_health	0.494	0.379	0.21	1.303	0.201	-0.274	1.261
	4_4_Area_Social_Services	-0.14	0.376	-0.061	-0.371	0.712	-0.902	0.622
	Other_area_sum	-0.126	0.18	-0.109	-0.703	0.486	-0.491	0.238
	5_Age_org_members	-0.12	0.278	-0.071	-0.433	0.667	-0.683	0.442
	6_Age_board	-0.018	0.207	-0.015	-0.087	0.931	-0.437	0.401
	Org_dimension	0.136	0.367	0.062	0.371	0.713	-0.608	0.881
	9_Org_budget	0.22	0.131	0.313	1.68	0.101	-0.045	0.485
2	(Constant)	-1.091	1.076		-1.014	0.319	-3.288	1.106
	4_1_Area_Culture	0.162	0.398	0.056	0.406	0.687	-0.651	0.974
	4_2_Area_Education	0.675	0.29	0.284	2.327	0.027	0.083	1.267
	4_3_Area_Human_health	0.185	0.338	0.079	0.549	0.587	-0.505	0.876
	4_4_Area_Social_Services	0.038	0.294	0.017	0.128	0.899	-0.564	0.639
	Other_area_sum	-0.139	0.148	-0.12	-0.936	0.357	-0.441	0.164
	5_Age_org_members	0.162	0.248	0.095	0.652	0.519	-0.345	0.668
	6_Age_board	0.042	0.158	0.035	0.262	0.795	-0.282	0.365
	Org_dimension	-0.258	0.32	-0.118	-0.806	0.426	-0.912	0.396
	9_Org_budget	0.075	0.109	0.106	0.687	0.497	-0.147	0.296
	36_DS_partnerships	0.682	0.241	0.382	2.832	0.008	0.19	1.174
	26_DS_ed_access	0.052	0.167	0.046	0.31	0.759	-0.289	0.393
	31_Digital_collection_evolution	0.264	0.167	0.196	1.579	0.125	-0.077	0.605
	32_7_DS_imp_complexity	-0.101	0.164	-0.082	-0.618	0.541	-0.436	0.233
	24_4_Funds_4DS_available	0.021	0.143	0.022	0.147	0.884	-0.272	0.314
	17_Dedicated_IT_Team	0.504	0.379	0.209	1.329	0.194	-0.27	1.278
	38_1_DS_investment_priority	0.362	0.16	0.327	2.266	0.031	0.036	0.689

3	(Constant)	-2.485	1.742		-1.427	0.167	-6.089	1.119
	4_1_Area_Culture	0.255	0.502	0.088	0.509	0.616	-0.783	1.294
	4_2_Area_Education	0.508	0.335	0.214	1.514	0.144	-0.186	1.202
	4_3_Area_Human_health	0.334	0.421	0.142	0.793	0.436	-0.537	1.205
	4_4_Area_Social_Services	-0.112	0.406	-0.049	-0.275	0.785	-0.951	0.727
	Other_area_sum	-0.21	0.182	-0.181	-1.152	0.261	-0.587	0.167
	5_Age_org_members	0.262	0.297	0.154	0.882	0.387	-0.352	0.875
	6_Age_board	-0.031	0.196	-0.026	-0.157	0.877	-0.436	0.375
	Org_dimension	-0.303	0.359	-0.139	-0.845	0.407	-1.046	0.439
	9_Org_budget	0.066	0.122	0.093	0.537	0.596	-0.187	0.318
	36_DS_partnerships	0.613	0.281	0.343	2.181	0.04	0.032	1.194
	26_DS_ed_access	0.05	0.203	0.045	0.247	0.807	-0.369	0.47
	31_Digital_collection_evolution	0.237	0.219	0.176	1.079	0.292	-0.217	0.69
	32_7_DS_imp_complexity	-0.048	0.229	-0.039	-0.21	0.835	-0.521	0.425
	24_4_Funds_4DS_available	-0.207	0.331	-0.219	-0.627	0.537	-0.892	0.477
	17_Dedicated_IT_Team	0.326	0.461	0.135	0.707	0.487	-0.627	1.279
	38_1_DS_investment_priority	0.252	0.242	0.227	1.041	0.309	-0.248	0.752
	Performance	0.168	0.313	0.1	0.538	0.596	-0.479	0.816
	Social	0.04	0.282	0.026	0.143	0.887	-0.543	0.623
	Facilitating	0.246	0.4	0.211	0.615	0.545	-0.582	1.074
	Behaviour	0.146	0.31	0.121	0.471	0.642	-0.495	0.787
	TMS	-0.022	0.35	-0.016	-0.064	0.949	-0.746	0.701
	Comp_Pressure	0.019	0.281	0.014	0.067	0.948	-0.563	0.6
	Market_Uncertainty	0.236	0.196	0.185	1.2	0.242	-0.171	0.642
4	(Constant)	-3.045	1.424		-2.138	0.047	-6.037	-0.052
	4_1_Area_Culture	1.075	0.458	0.371	2.345	0.031	0.112	2.038
	4_2_Area_Education	0.802	0.298	0.338	2.695	0.015	0.177	1.427
	4_3_Area_Human_health	-0.079	0.474	-0.034	-0.166	0.87	-1.075	0.917
	4_4_Area_Social_Services	0.216	0.362	0.095	0.596	0.558	-0.545	0.978
	Other_area_sum	-0.196	0.186	-0.169	-1.053	0.306	-0.587	0.195
	5_Age_org_members	0.015	0.273	0.009	0.055	0.957	-0.559	0.589
	6_Age_board	0.445	0.238	0.371	1.871	0.078	-0.055	0.944
	Org_dimension	-0.218	0.316	-0.1	-0.69	0.499	-0.883	0.446
	9_Org_budget	0.175	0.117	0.249	1.495	0.152	-0.071	0.421

	36_DS_partnerships	0.904	0.304	0.505	2.969	0.008	0.264	1.544
	26_DS_ed_access	-0.264	0.196	-0.237	-1.348	0.194	-0.676	0.148
	31_Digital_collection_evolution	0.184	0.221	0.137	0.831	0.417	-0.281	0.648
	32_7_DS_imp_complexity	-0.084	0.187	-0.068	-0.449	0.659	-0.478	0.309
	24_4_Funds_4DS_available	-0.403	0.351	-0.426	-1.149	0.266	-1.14	0.334
	17_Dedicated_IT_Team	0.477	0.454	0.198	1.05	0.307	-0.477	1.431
	38_1_DS_investment_priority	0.717	0.234	0.647	3.062	0.007	0.225	1.21
	Performance	-0.248	0.274	-0.147	-0.905	0.377	-0.822	0.327
	Social	0.651	0.331	0.421	1.968	0.065	-0.044	1.346
	Facilitating	0.424	0.369	0.364	1.148	0.266	-0.352	1.2
	Behaviour	0.157	0.257	0.13	0.609	0.55	-0.384	0.697
	TMS	-0.802	0.353	-0.563	-2.268	0.036	-1.544	-0.059
	Comp_Pressure	-0.419	0.337	-0.312	-1.241	0.231	-1.127	0.29
	Market_Uncertainty	0.11	0.294	0.086	0.375	0.712	-0.507	0.727
	50_1_Catalyst_Covid	-0.262	0.146	-0.319	-1.798	0.089	-0.568	0.044
	50_2_Catalyst_AI	0.428	0.18	0.4	2.376	0.029	0.05	0.806
	50_3_Catalyst_Leadership	-0.515	0.225	-0.47	-2.292	0.034	-0.987	-0.043
	50_4_Catalyst_New_Software	0.572	0.313	0.491	1.826	0.084	-0.086	1.23
	50_6_Catalyst_Competitive	0.474	0.283	0.422	1.672	0.112	-0.122	1.069