

# Analyzing Donors Behaviors in Nonprofit Organizations: A Design Science Research Framework

Idrees Alsolbi<sup>1\*</sup>, Renu Agarwal<sup>2</sup>, Bhuvan Narayan<sup>3</sup>, Gnana Bharathy<sup>4</sup>, Mahendra Samarawickrama<sup>5</sup>, Siamak Tafavogh<sup>6</sup> and Mukesh Prasad<sup>1</sup>

<sup>1</sup> Australian Artificial Intelligence Institute, School of Computer Science,  
University of Technology Sydney, Australia

<sup>2</sup> Business School, University of Technology Sydney, Australia

<sup>3</sup> School of Communication, University of Technology Sydney, Australia

<sup>4</sup> Information Systems and Modelling School, University of Technology Sydney, Australia

<sup>5</sup> Australian Red Cross, Sydney, Australia

<sup>6</sup> Department of Finance, Commonwealth Bank Health Society, Sydney, Australia

\*corresponding author: idna1257@gmail.com

**Abstract.** In Nonprofit Organizations (NPOs), analyzing donor behavior remains critical and challenging due to internal and external factors, such as family, political, and environmental issues. Machine Learning (ML) techniques are very promising to provide the solutions to analyze the customer behaviors and churns issues of many different organizations. However, it remains a challenge on how best to build and design an intelligent decision support system for analyzing donor behaviors in NPOs. This paper applies the underlying guidance from Information Systems by utilizing a design science research framework to create an Artificial Intelligence (AI) enabled decision support system to analyze donors behaviors more effectively and efficiently. The framework aims to provide a theoretical foundation for creating generalized design principles and design features for designing an intelligent decision support system. It also presents the capabilities of data analytics and ML techniques to understand donors behaviors by exploring the external factors that affect donors' decision-making.

**Keywords:** Donors behaviors, decision support system, design science, nonprofit organization.

## 1 Introduction

Nonprofit, also known as a non-profit corporation, not-for-profit agency, or nonprofit institution, differs from the businesses and industries as they are private, independent, self-governing institutions and control their practices and goals [1]. Such institutions are museums, schools, universities, research institutions, human services, health organizations, human rights organizations, religious centers and organizations, and charitable foundations [1]. Mahmoud and Yusif [2] describe NPOs in business to meet individuals' and beneficiaries' requirements. NPOs have important social purposes, which contrasts with an entity that operates as a business to generate a profit for its owners in a traditional market [3]. Anheier [1] mentioned that NPO's goals cover individual activities and the values and motivations that drive people to engage in activities to benefit society, the environment, and cultural heritage through charities, philanthropy, volunteering, and giving. NPOs' funding and income sources vary; in Australia, 49.1% of NPOs' income is self-generated, the government contributes 33.5%, and only 9.5% comes from public donations [3]. Notably, Australia's percentage of public donations is greater than Germany, France, and New Zealand but less than the USA [3]. Given this high NPO's funding across different countries, NPOs can significantly influence society by attracting donors (who provide monies/funds) and volunteers (who give their time) and establishing strong relationships with clients to pursue their NPOs' interests.

Donors support the goals of NPOs in different ways, such as giving money, gifts, time for volunteering, and using their experience in various events in many different ways such as playing music, singing, and photography. Private donations represent a significant factor in funding NPOs in the USA, which annually contribute to more than 10% of the Gross Domestic Product [4]. Dietz and Keller [5] reported that individuals donate to NPOs because of their deep passion or beliefs of NPOs' needs which attracted around \$260 billion. It is believed that certain factors impact peoples' intentions towards donating, such as income, educational level, and previous giving history [4]. Today's NPOs focus is not only on gaining donations but also on knowing donors habits, leading NPOs to authentically interact with their donors and how they resonate with them [6]. One of the essential behaviors is the retuning or intention to donate for a second time. Only 19% of donors donate for the second time, which is a major concern for NPOs [6]. However, Sargeant and Jay [7] mentioned that targeting appropriate donors to charities and improving communications remain critical for NPOs.

Given this backdrop, understanding the fundamentals of donors is crucial [8]. Certain behaviors include donors intentions to donate either time or money, donor frequency (returning), donor engagement, donor communications, and volunteering engagement that require a deeper understanding of technologies and capabilities of data science and ML techniques. By analyzing the behaviors using ML techniques, NPOs improve the chances of increasing their current financial support and interaction with outgoing donors for potential opportunities for repeat donation activity [9].

This paper has two main contributions: first, to create a new design science theory of designing an artifact for analyzing donor behaviors, and second, to design an artifact (an AI-enabled decision support system) to analyze donors behaviors in NPOs. This

paper's remainder provides a literature review first, then introduces the design science approach, followed by coverage of the research framework, the collection and analysis of data, and finally, the research contribution and expected results.

## **2 Literature Review**

### **2.1 Decision Support System**

Decision Support System (DSS) became a common interest for many researchers since the last few decades in various fields such as Information Systems (IS), mathematics, and economics [10]. Decision Support is the main component of IS research which evolved in improving and managing the decision-making process [11]. DSS is not based on combining all the ongoing alternatives but on choosing the right one based on priorities and goals [10]. DSS has been transformed from being traditional to intelligent-based systems, where AI, ML, Cloud Computing, and Networking are the main reasons for this transformation [10]. These technologies become required when designing a DSS to ensure sustainability, high productivity, and advantages [10]. The intelligent DSS includes knowledge-driven, documents-driven, data-driven, and communication-driven DSS [12]. In addition, an intelligent DSS involves AI techniques to support decision-making, counted as "intelligent" [13].

Moreover, any DSS built based on ML is referred to as intelligent or AI-enabled DSS [14]. The term AI started in the 1950s and led to many AI-enabled systems [15]. ML techniques play a significant role in describing and predicting donations and donor behaviors in this context. ML can help NPOs to handle their current donors more effectively or utilize their existing assets. ML techniques have been used widely in various sciences in different disciplines for organizing the data, extracting helpful information, and recognizing patterns through supervised (i.e., classification) and unsupervised (i.e., clustering) algorithms [16]. For example, classifications can assign benefactions to predefined classes, whereas clusters find any relationships and hidden information without predefined classes [17].

### **2.2 Donors Behaviors**

There are some factors, including behaviors that affect donors' ability to donate funds or volunteer ability to spend their time, such as attitudes, norms, perceived behavioral control, subjective norms, past behaviors, and moral norms [8]. Farrokhvar et al. [4] illustrated some influential factors on donors' behaviors towards donating comprised donors' education level, sex, age, population, household income, and ethnicity. Using these factors, different ML models (Support Vector Regression, Multiple Linear Regression, Artificial Neural Networks) were generated to estimate future charitable giving accurately from donors. The results recommend that educational level, population, and previous giving amount are independent variables and significant. Similarly, a multinomial logistic model in [18] was developed to investigate if multi donations individuals are different from a single donor or non-donors. Shehu et al. [18]

used various predictors: geographical, health-related, psychographics, and sociodemographic variables to generate useful insights of donors behaviors. The results show useful insights into the donor engagement and retention techniques of NPOs along with donor recognized profile characteristics. However, none of the above studies [4, 8, 18] attempted to design a DSS for analyzing donors' behaviors in NPOs. Hence, considering a smart DSS for analyzing donors behaviors remains an essential gap for NPOs.

### **2.3 DSS in NPOs**

Decision-making in NPOs has shown effectiveness in managing decisions [19]. However, decision-making in NPOs faces obstacles due to data growth, which provides more opportunities to manage the data [20]. Most of the data from NPOs are unstructured, which is very challenging to understand the hidden information and find some relationship [21]. Also, it is claimed that managing information in NPOs is a challenging task [21]. There are major challenges for NPOs, such as the lack of technical skills [22] and financial sources [23] for applying data analysis. Hence, if the data is not well collected and organized, NPOs will not benefit from the available data to draw insights and conclusions [19]. Managers may use performance data to gain useful insights into the organization's strengths and weaknesses, providing them the knowledge they need to make informed decisions [24]. Most importantly, developing a DSS for managing NPOs activities is crucial [25].

Nevertheless, the literature shows that no research has focused on designing AI-enabled DSS for analyzing donors behaviors in NPOs. The current literature lacks experimental and theoretical foundations for designing AI-enabled DSS in NPOs to analyse donors' behaviors. Designing an intelligent system is complex, which requires special characteristics such as autonomy, self-learning, and user interactions [16, 17]. All these characteristics distinguish the AI-enabled DSS from the traditional DSS. Moreover, DSS research recently requires more improvements on its relevance and quality [14]. We tackle these issues and research gaps by 1) developing a conceptual AI-enabled DSS design relying on the driven knowledge from theoretical sources, and 2) creating an artifact according to this design to analyze donors behaviors. Thus, we found that Design Science Research (DSR) can overcome the complexity of designing DSS in NPOs. DSR has been an essential approach in DSS research because industry and profession may be involved in intellectually relevant ventures by design-science studies [14]. Moreover, Arnott and Pervan [14] claimed that researchers are searching for assistance with preparing and implementing their DSR projects. In our research project context, DSR proposes a dialogue between abstract theoretical knowledge and practical knowledge.

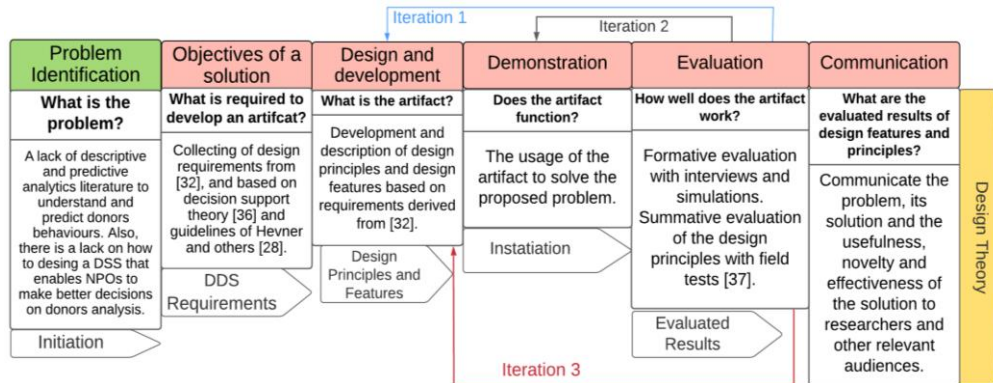
## **3 Design Science Research**

Design Science is creating artifacts and scientific studies to solve a particular problem [26]. DSR is a scientific problem-solving methodology developed specifically for the

IS domain. The DSR has three aims: first, a nominal method model for design research in science, second, a mental model for the presentation, and third, evaluation of design research in IS [27]. The DSR represents a well-established process in the field of IS to create an artifact seeking to expand the barriers and limitations between people and organizations [28]. Artifacts are defined as constructs consisting of software, hardware, systems, or models [28]. The artifact must be creative, more productive, or useful in solving a previously unresolved problem or solving a known problem [28]. In the context of implemented software or algorithms, the artifact may range from simple instantiations to more efforts in the context of final design theories [28]. This research project will construct a design theory for designing an artifact (an AI-enabled DSS) to analyze donors behaviors using ML techniques. This artifact aims to help NPOs' managers make better decisions on future marketing, fundraising management, and other NPOs missions. The design theory will explain the artifact's functions, attributes, and features [29]. The design theory also provides prescriptions on how our AI-enabled DSS is designed and constructed.

### 3.1 Research Framework

DSR seeks to bridge the gap between implementation and theory [30]. One of the advantages of the design science approach is an incremental and iterative process [28], which requires conducting at least three iterations [16, 31]. Thus, we realized that the design science research framework presented by Peffers et al. [27] suits our research project aims. This framework is selected because it has three iterations, a communication stage with scholars via publications and a design theory. Also, the iterative cycles imply constant reflection and abstraction [32], which we assume are necessary foundations for developing a design theory and artifact.



**Fig. 1.** The proposed framework for designing AI-enabled DSS (adapted from Peffers et al. [27])

The framework combines the common stages of DSR approaches presented in the literature [28, 29, 33]. It involves three iterations and consists of six stages/phases, starting from identifying the problem, illustrating the solution's objectives, designing

and developing the artifact, displaying the artifact's viability, assessing the artifact, and reporting the results through communication with scholars and professionals via publications. Each stage produces an output used in the following stage. The proposed framework has six phases, as shown in Fig. 1., and outlined as follows:

### **Phase 1: Problem Identification**

This phase identifies a research problem and the importance of solving the proposed problem. There are attempts to predict donors behaviors using ML techniques such as [4, 34]. However, we found a lack of descriptive and predictive analytics literature to understand and predict donors attitudes towards helping, donating, and giving to the NPOs, especially in the context of donating money and volunteering time. A DSS is developed by Barzanti et al. [25] to rank donors using a fuzzy method to predict the targeted campaign. Although this study is useful for our problem initiation, it lacks in developing guidelines for designing a DSS. The above studies [4, 25, 34] focus on domain-specific explanations that show the capabilities of some ML techniques to analyze donors behaviors. Notably, they are less focused on design knowledge that guides creating an artifact for a better decision-making process in NPOs.

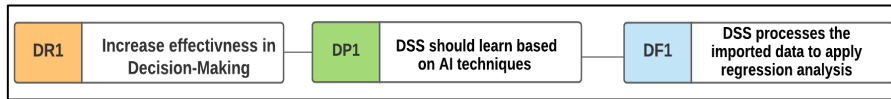
To expand the awareness of the research problem, we conducted two informal interviews with experts from NPOs during this stage. During interviews, we asked the experts (1) to describe the process of donors behaviors analysis, (2) state the challenges they face to design such DSS that helps in describing and predicting donors behaviors, and (3) explicate the potentials of creating a design theory that guides the process of designing AI-enabled DSS. We noted all valuable insights from the interviews. For example, experts mentioned that descriptive and predictive analytics assist NPOs in making better decisions to increase the efficiency and performance of NPOs and understand the influential factors on donations. Furthermore, these analytics can be functioned and generated through a decision support system. At this stage, the interviews helped identifying the problem and increasing the awareness of creating a design theory of an artifact to analyze donors behaviors.

### **Phase 2: Objectives of Solutions**

This stage elicits the intended artifact requirements and determines the main functionalities of the desired DSS. For designing the artifact, the initial requirements for creating an artifact as a product are defined based on the design requirements of Meth et al. [32], the decision support theory [35], and DSR guidelines by Hevner et al. [28]. The approach of Meth et al. [32] is chosen because it applies the fundamentals of developing the decision support theory of Silver [35] and his decisional guidance. Also, the guidelines of creating an artifact suggested by Hevner et al. [28] are followed to ensure that a constructed artifact is scientific in its method and effects. Finally, the collected and generated requirements are evaluated before Iteration 1 through interviews with decision-making and data science experts in NPOs.

### Phase 3: Design and Development

To meet the design requirements (DRs), this framework adopts Meth et al. [32] model to derive a collection of Design Principles (DPs) and Design Features (DFs). DPs can be a statement that tells what the artifact should do [16], and DFs are unique artifact capabilities to fulfill DPs [32]. The DPs will be derived based on the DRs formulated in the model of Meth et al. [32]. Therefore, the DFs will be formulated to satisfy the design principles [32]. The DPs and DFs will be mapped into an conceptualised artifact to present to experts for a formative evaluation in Iteration 1. Each DP can be mapped to one or more relevant DF. The mapping of DPs to design DFs supports evaluating the artifact [32]. Figure 2 shows an example of mapping a DR according to DP and DF.



**Fig. 2.** Preliminary conceptual map of DRs, DPs and DFs

### Phase 4: Demonstration

The artifact aims to support aggregated, high-level data and better understand the donor behaviors data. This demonstration phase builds descriptive and predictive models that predict and describe donations and donor behaviors. The models are generated using ML techniques, which can be supervised or unsupervised methods. Supervised methods make predictions or classifications based on the given labeled input data. Unsupervised methods draw inferences and hidden relationships from unlabeled data. We are applying different techniques of supervised and unsupervised ML techniques. The purpose of this stage is to generate an instantiation to solve the proposed problem. Our intended instantiation is a complete design theory to design an artifact to analyze donors behaviors. Also, the artifact is intended to be an AI-enabled DSS that offers suggestions and presents useful descriptions and predictions of donors behaviors.

### Phase 5: Evaluation

This phase uses evaluation of the framework introduced by Venable et al. [36], which has two types of evaluations, formative and summative. The assessment will be for the AI-enabled DSS and the design theory with relevant DRs, DPs, and DFs. Formative evaluation is involved in creating empirically validated explanations that provide a foundation for effective action to enhance the evaluated features or results [36]. Summative evaluation is used to provide a foundation to produce common meanings of the evaluation in a different context. The evaluation stage will run three iterations:

**Iteration 1:** DRs, DPs, and DFs will be evaluated to ensure their relevance to our research aims and objectives. We will conduct semi-interviews with NPOs decision-makers, data scientists, and managers. Those experts are involved during interviews to

conduct a formative evaluation. The results of this iteration lead to apply any changes or suggestions on DRs, DPs and DFs.

**Iteration 2:** DRs DPs and DFs will be visible and conceptualised before starting this iteration. Then descriptive and predictive models will be completed and fully functioning. For the evaluation, validation techniques associated with ML techniques will be applied, such as K-fold cross-validation, to ensure these models' effectiveness. K-fold cross-validation is a common technique to evaluate the models and estimate errors among practitioners [37].

**Iteration 3:** the evaluation before this iteration aims to ensure the success of DRs, DPs, and DFs. The designed AI-enabled DSS to analyze donors' behaviors will be tested by NPOs decision-makers, data scientists, and managers. We will then interview them for their feedback and apply any final suggestions or changes for this iteration. Following that, we will develop a functional front-end, a back-end, to a web-based DSS for analyzing donors behaviors using ML techniques. Finally, the web-based decision support system will meet all the DRs, DPs, and DFs to analyze donors' behaviors. The output of this iteration is to finalize the design theory by combining evaluation results and results of the developed AI-enabled decision support system.

#### **Phase 6: Communication**

We will create a complete expository instantiation of the design theory to be published in the communication stage. The design theory will be created based on the design theory profile by Gregor and Jones [38]. Thus, the design theory consists of a prescription on how the DSS is developed. Moreover, the results of the evaluation stage will be demonstrated to the researchers and experts in NPOs. The communication stage aims to communicate the effectiveness, usefulness, and novelty of the solution based on the evaluation stage analysis.

## **4 Data Collection and Analysis**

The evaluation stage involves semi-structured interviews with experts (before Iteration 1 and Iteration 3), as illustrated in Fig. 1. The interviews generate data that will be analyzed using MAXQDA. MAXQDA is a software application to analyze qualitative data (such as interviews) and organize the information into categories or groups [39]. The analysis will drop insights for constructing the artifact and expound the design theory's implementation. The data source to feed the analytics models (predictive and descriptive) will be obtained from one or more NPOs. We will focus on certain variables in the data, such as (level of education, income, age, gender, living area, and ethnicity). The created models will be presented to experts during interviews in Iteration 3 to build insights on the accuracy, sufficiency, and visualization of the results.

## 5 Research Contribution and Expected Results

This research intends to design an AI-enabled DSS for analyzing donor behaviors in NPOs. This DSS will create descriptive and predictive models that intensively analyze donors behaviors and provide meaningful information for NPOs. The research contributes to the academic literature practically by implementing ML algorithms on donor behaviors. Therefore, the decision-making process may add value proposals for NPOs missions or improve internal data processing efficiency and effectiveness [24]. We also intend to introduce a design theory to design the smart DSS contributing to the IS literature. The theory of design is intended to collect the theoretical foundations of designing an AI-enabled DSS to analyze donors behaviors in NPOs.

## 6 Conclusion

Data analytics can transform NPOs into data-driven if appropriate analytical models, frameworks, and empirical studies to support and manage resources. One major gap is the lack of literature on designing an intelligent decision support system to analyze donor behaviors towards donating and volunteering. Donor behaviors vary due to various impacts such as income, level of education, sex, etc. Understanding these behaviors and the influencing factors on donors is critical for making decisions in NPOs. Thus, we have presented a design science framework to provide theoretical bases for designing an AI-enabled DSS to analyze donors behaviors. To support the development of the AI-enabled DSS for NPOs, we will (1) derive a theoretical design of a DSS for analyzing donor behaviors and (2) build an artifact (AI-enabled DSS to analyze donors behaviors). This research intends to demonstrate that AI-enabled DSS based on the design science approach can be used and adopted among the global NPOs. The DPs and DFs can also systematically help practitioners deploy the descriptive and predictive models on donor behavior data for further actions.

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