Efficiency Analysis of Partner Organizations: Poverty Stoplight and Analysis of Poverty Stoplight's Organizational Questionnaire and the Relationship between Survey Design and Response Rate

A Major Qualifying Project

Submitted to the Faculty of

Worcester Polytechnic Institute

In partial fulfillment of the requirements of the

Degree of Bachelor of Science in

Industrial Engineering

and

Professional Writing

By

Kayla Brown

Submitted to:

Professors Ryan Madan and Andrew C. Trapp

Abstract

Poverty Stoplight (PS) is a nonprofit organization that works to eliminate poverty in vulnerable communities. PS partner organizations deploy an assessment survey that measures one's poverty level. The Industrial Engineering project analyzed a subset of these partner organizations in relation to the survey to determine which resources and processes partner organizations have that help families move out of poverty more efficiently. We provided recommendations to help improve efficiency between PS and their partner organizations. The Professional Writing project analyzed a PS internal questionnaire's nonresponse through the lenses of theories that connect survey design and response rate. A new survey and best-practice guide were created for PS by applying the theories of survey design.

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Efficiency Analysis of Partner Organizations: Poverty Stoplight

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By
Kayla Brown, Rebecca Noris, Catherine Salvaggio, Hayden Smith

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Abstract

While poverty has a variety of interpretations around the world, almost everyone experiences some aspect of poverty at some point in their lives. Our sponsor, Poverty Stoplight, partners with organizations around the world to reduce poverty through the use of deprivation indicator surveys, which are used to help families progress out of poverty. Our project analyzed a subset of these partner organizations in relation to the Poverty Stoplight survey to determine which resources and processes partner organizations have that help families move out of poverty more efficiently. We provided recommendations based on this analysis to help improve efficiency between Poverty Stoplight and their partner organizations.

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1.0 Introduction

What does poverty mean to you? For some people, poverty is based on their government's absolute definition of poverty. For example, having a lower income than the average person. For others, poverty might be more relative. Not having shoes or not owning a house might be indicators of poverty to different groups of people. To reflect individual and community-based views of poverty, poverty is modernly viewed as being multidimensional and relative (Knight, 2017). What defines someone as poor is not only their economic status, but also their ties with family and their outlook on life. When defining poverty, it is important to consider all aspects of life to understand whether an individual's needs are met, in regards to their environment.

Individuals living in poverty turn to organizations whose mission is to help. These organizations provide communities with the extra services they may need to regain security in their life. Most importantly, these organizations can act as a stepping stone for individuals and alleviate their poverty. Fundación Paraguaya is one of these organizations that is fighting to eliminate poverty in Paraguay and worldwide (Fundación Paraguaya, 2018). This nonprofit organization has developed programs that provide services to people, of which one primary is Poverty Stoplight (PS). PS is a social innovation tool developed by Fundación Paraguaya, combining survey demographic collection with tailored intervention plans to help individuals meet certain goals.

The Stoplight tool is utilized globally by organizations seeking to help communities in need. Fundación Paraguaya partners with over 400 organizations around the world that administer the Poverty Stoplight tool to families and communities (Poverty Stoplight, 2020). Their Poverty Stoplight tool is a self-assessment survey that includes 50 indicators across 6 dimensions. Participants self-evaluate their level of poverty in each area and develop intervention plans in accordance with their specific wants and needs. Fundación Paraguaya communicates with organizations through questionnaires to gather data on results of the surveys, resources, and other information about the organizations.

Our goal was to analyze the partner organizations in relation to the Poverty Stoplight survey datasets to determine which organizations are efficient in helping families improve their situation. To accomplish this goal, we used the Data Science Life Cycle (DSLC) to examine the

PS survey data for each organization and Data Envelopment Analysis (DEA) to analyze the efficiency of the organizations and the resources that they provide.

In total, we developed six different DEA models that analyzed 16 Poverty Stoplight partner organizations in Latin America and South America. These models determined which organizations were operating efficiently and which specific resources aided in this efficiency. After determining these efficient organizations, we interviewed with a Program Manager from Fundacion Paraguaya to gain additional qualitative insights on some of the partner organizations. The results from these DEA models and interviews allowed us to formulate specific recommendations for Poverty Stoplight to increase efficiency in their partner organizations.

The remainder of this report is organized as follows. In Chapter 2, we discuss background research that includes details about our sponsor and brief descriptions of the methods we used. Chapter 3 discusses the methods that we applied to the data for this project. Chapter 4 presents our results from our data analysis, while Chapter 5 presents the applications of our findings and future steps. Finally, Chapter 6 contains conclusions and limitations we have identified throughout this project.

2.0 Background

In this chapter we explore the complexities of poverty, and some of the approaches that have been previously used to alleviate poverty. In addition, we provide a background of Fundación Paraguaya and Poverty Stoplight, the sponsors of our project, as well as an overview of a couple of organizations that are working towards alleviating poverty.

2.1 Poverty and Its Relativity

In this section we review how poverty is defined. We elaborate the two main types of poverty, absolute and relative, as well as the multidimensionality of poverty.

2.1.1 How is Poverty Defined?

Each person, if asked, might define poverty in a different way. This is due to the ambiguous nature of poverty. Even though there is large literature on the topic, there has not been much agreement on its definition (Knight, 2017). However, there are three generic definitions of poverty that cover the majority of viewpoints on what poverty is. These definitions describe poverty as "having less than an objectively defined, absolute minimum", "having less than others in a society", and "a feeling you do not have enough to get along" (Hagenaars & de Vos, 1988). The absolute minimum mentioned in the first definition involves basic needs, a food-income ratio, a fixed cost-income ratio, and a total expenditure-income ratio (Hagenaars & de Vos, 1988). With the many options this absolute minimum could be based on, it can be very difficult to decide which parameter is the most accurate, if any. The second generic definition of poverty takes a different approach to poverty by using relative measurement in regard to deprivation in the society they are living in (Dartanto & Otsubo, 2015). Having a relative definition of poverty shows that poverty is not the same for the masses, since every community is different. The third definition of poverty takes an absolute and a relative approach, by allowing people to define their own minimum income and consumption levels (Hagenaars & de Vos, 1988). This approach combines the first two definitions, but it still does not make the definition of poverty any clearer.

2.1.2 Absolute vs Relative Poverty

Poverty can be measured in the absolute and in the relative. Absolute poverty is a "lack of sufficient resources with which to meet basic needs", which is an outdated way to think about poverty and is no longer accurate as people need more than just their basic needs met (Knight, 2017). Absolute poverty uses a fixed cutoff level that the government makes, which does not change, even with economic growth (Foster, 1998). This rigid view of poverty cannot correctly specify everything that poverty entails. Relative poverty is "low income or resources in relation to the average", which is what expert opinion is now based upon (Knight, 2017). Relative poverty is now used more commonly as a measurement than absolute poverty because of its flexibility. The main distinction between the two thresholds "is not seen in the specific values obtained at a given date, but in how the values change as the distribution changes" (Foster, 1998). Since each community has its own definitions of poverty, it does not make sense to measure poverty the same way for every person.

Relative poverty recognizes that poverty is not the same for each individual. Villagers in Haryana, India believe someone is in poverty when they do not have a house of their own and need to rent housing (Motwani, 2012). This would not be a common belief of poverty in the city, however, where most people rent their housing. People in the middle class may think of poverty as someone not having footwear or wearing dirty clothes (Motwani, 2012). When considering poverty through a relative lens, it is also important to understand the multidimensionality of poverty.

2.1.3 Multidimensionality of Poverty

The multidimensionality of poverty considers the individual characteristics of poverty that each person may have. The basic dimensions of poverty that receive the most focus are "nutrition, shelter, health, education, safe water, and safe sanitation" (Romeshun & Mayadunne, 2011). There are fewer studies that focus on other important aspects such as, "security, self-respect, access to state-provided as well as common property resources, social inclusion, and so forth" (Romeshun & Mayadunne, 2011). Within each dimension, there are indicators that go further into each category to figure out more specifically what someone may be lacking. According to the global multidimensional poverty index, there are ten indicators that span the three dimensions of health, education, and living standards (Alkire et al., 2021). These indicators include nutrition, child mortality, years of schooling, school attendance, cooking fuel, sanitation, drinking water, electricity, housing, and assets (Alkire et al., 2021). Nevertheless, what defines someone as 'poor' is not always their economic status or assets, but "having a positive attitude and family influence were also key determinants of whether a person would be poor or not"

(Burt, 2019). Poverty is difficult to define, but measuring it becomes easier when looking at individuals instead of an entire nation or the world.

2.2 Organizations Focused on Alleviating Poverty

There are many organizations across the globe that are focused on alleviating poverty. These organizations are of all sizes, spanning from global to local. Each of these organizations have a variety of key points of focus including, but not limited to, programming, research, and politics. In the rest of this section, we will provide an overview of two key organizations, the Organization for Poverty Alleviation and Development and the Innovation for Poverty Action. Our sponsor, Fundación Paraguaya is also an organization focused on alleviating poverty. For each of these organizations, we will discuss their overall goals, their key actions, and the specific dimensions of poverty that they are focused on. While we are only discussing these two organizations in the context of this project, there are many other significant organizations that are focused on alleviating poverty, including the Institute for Research on Poverty, the European Anti-Poverty Network, and many more.

2.2.1 Organization for Poverty Alleviation and Development (OPAD)

The Organization for Poverty Alleviation and Development (OPAD) is an international non-governmental organization that was founded in Sweden in 2005. Currently, OPAD operates across over 40 countries with the mission of working "toward poverty eradication and alleviation by promoting human rights, climate change, and sustainable development" (Organization for Poverty Alleviation and Development, 2022). Promotion of human rights, climate change, and sustainable development act as the three pillars to OPAD's overall goal of alleviating poverty. Similarly to Fundación Paraguaya, OPAD wants to empower the people who are impoverished through having people engage with their community through education and resources. This is incorporated in OPAD's eleven current projects which span from Eco-Friendly Livelihood and Education to Health and Humanitarian Aid. All of their current projects are implemented to improve their three main focuses of poverty alleviation.

Out of their eleven currently running projects, two important projects to discuss are the "Blue and White Planet Initiative" and "Humanitarian Aid". In the "Blue and White Planet Initiative" the main focus is increasing clean water access, especially safe drinking water. In order to increase clean water access, OPAD utilizes community partnerships and marketing in order to encourage policies and projects that work to reduce and eliminate water pollution (Organization for Poverty Alleviation and Development, 2022). In their second key project, “Humanitarian Aid”, OPAD’s goal is to work against supply chain obstacles that prevents communities from achieving “increased [agriculture] yields, quality, incomes, and food security” (Organization for Poverty Alleviation and Development, 2022). Supply chain issues have been increasingly prevalent throughout the Covid-19 pandemic, and have had significant impacts on many communities across the globe (West, Juneau, Amarasingam, 2021). These projects are focusing on alleviating poverty in communities in two specific ways, water quality and elimination of supply chain obstacles.

2.2.2 Innovation for Poverty Action

Innovation for Poverty Action (IPA) is a nonprofit organization that was founded in 2002 and has done research and work in 22 countries across the world. IPA’s overall mission is to create stronger evidence about reducing poverty, strategically share that evidence, and to equip decision-makers to use that evidence to improve the lives of those in poverty (Innovation for Poverty Action, 2018). To accomplish their mission, IPA has completed over 900 evaluations of different potential solutions across eight program areas: Agriculture, Education, Entrepreneurship and Private Sector Development, Financial Inclusion, Governance, Health, Peace and Recovery, and Social Protection. These evaluations are a set of randomized control trials that compare the outcome of the program being tested against a control group to determine the effectiveness of said program (Innovation for Poverty Action, 2018). The testing and evaluations allow IPA to determine what works, as well as what does not work, which are valuable insights to share. Throughout their research and projects, IPA has collaborated with over 500 partners across four key types; academic, service providers, funders, and government agencies.

In each of the eight program areas mentioned above, IPA performs evaluations to determine what actions related to these areas can effectively reduce global poverty. While we cannot discuss all of IPA’s evaluations and program areas, we will highlight a few of their important findings that they have released across the years. During one study in the agriculture program area, IPA found that many farmers are risk averse, which was driving underinvestment in their agriculture, rather than any lack of money (Innovation for Poverty Action, 2018). When farmers were provided with weather insurance there was an increase in spending on many resource categories. Additionally, a study in the Education program area found that when uniforms were provided to children and families, children were far less likely to miss days of school. This finding is significant for learning outcomes and literacy rates in communities.

In comparison with OPAD, IPA tests various programs and then provides the outcomes and evidence to key partners and people across the globe. This allows them to make evidence based decisions on how to provide resources to help impoverished communities. However, OPAD partners work with communities directly to help encourage projects for alleviating poverty with both community leaders and affected families.

2.3 Fundación Paraguaya and Poverty Stoplight

This section describes the nonprofit organization, Fundación Paraguaya. We discuss the different ways in which this organization works to help eliminate their poverty, including their organization Poverty Stoplight. Within Poverty Stoplight we discuss the use of their survey tool.

2.3.1 What is Fundación Paraguaya?

Fundación Paraguaya was founded by Dr. Martin Burt in 1985 to address the poverty crisis in Paraguay. The organization provides numerous services to both communities in Paraguay and across the world, focusing on providing families with the education and services they need to eliminate their poverty. Specifically, Fundación Paraguaya is a non-profit and microfinance organization with a mission to "develop and implement practical, innovative, and sustainable solutions that allow activating the entrepreneurial potential of families to eliminate their multidimensional poverty and live with dignity" (Fundación Paraguaya, 2018). To achieve their mission, Fundación Paraguaya partners with organizations around the world to help communities in need by providing education and financial support for new entrepreneurs. For example, in Paraguay, Fundación Paraguaya established a self-sufficient agricultural school for impoverished youth that teaches agricultural and business skills. Fundación Paraguaya also has a global impact through their program Poverty Stoplight.

2.3.2 What is Poverty Stoplight?

Within Fundación Paraguaya is Poverty Stoplight, an organization that provides services to communities to help alleviate poverty. More specifically, PS is on the mission "to activate the potential of families to discover practical and innovative solutions to improve their life in all aspects” (Poverty Stoplight, 2020). Their mission aligns with Fundación Paraguaya's as PS implements the Stoplight survey which is used by other organizations to help their communities. The Stoplight survey is a social innovation tool that gathers data reported by participants to establish a baseline of their current situation and then develop an intervention plan with tailored solutions to address their needs.

The survey conceptualizes poverty through 6 dimensions: Income & Employment, Health & Environment, Housing & Infrastructure, Educations & Culture, Organization & Participation, Interiority & Motivation (Poverty Stoplight, 2020). From these 6 dimensions comes 50 standard indicators that gauge the level of poverty for each participant. One example of these indicators is asking participants to measure their access to clean drinking water. The different levels of poverty for this survey are broken down into three categories: red, yellow, and green. Red indicates extreme poverty, yellow indicates poverty, and green indicates no poverty. The participant self-assesses and selects the level that currently best represents their situation.

Currently, the Poverty Stoplight tool is used in 51 countries by over 400 organizations. These organizations connect to PS through one of their 15 hubs located around the world. The hubs are major organizations that partner with Fundación Paraguaya to expand the Poverty Stoplight tool to local organizations in their country or region. Poverty Stoplight provides their technology to these organizations who then administer the survey in their specific community or region. The surveys are administered by trained field workers who guide participants through the survey. In the initial survey, a participant establishes a baseline of their current strengths and weaknesses. The participant can see the breakdown of their indicators and choose the areas they want to improve, and then an intervention plan is developed. The survey is recommended to be readministered at least six months after the initial survey to see if improvements were made and if any other actions need to be taken.

2.4 Analytics to Alleviate Poverty

This section discusses methods that other organizations have utilized when gathering analytics on communities in poverty. These methods have helped other organizations identify and gather data on areas that are affected by poverty. The examples presented in this section can help Fundación Paraguaya analyze where help is needed and how to optimize resources effectively.

2.4.1 Censuses and National Surveys

There are many organizations similar to Fundación Paraguaya around the world that work to alleviate poverty. One of the ways these organizations receive data is through census and national surveys. The benefit of this method is that these can easily be widely dispersed to allow information to be collected on a larger scale. According to the United States Census Bureau, censuses provide nations with data regarding its economy and the people living there (US Census Bureau, 2022). The downside to conducting these surveys is that they can cost countries anywhere from tens to hundreds of millions of dollars to collect, which many under-developed countries may not be able to afford (Blumenstock, 2016). This results in many less wealthy countries not having access to important demographic data and only being able to provide limited data to anti-poverty organizations.

2.4.2 Satellite Imaging

Researchers have discovered alternative ways of estimating poverty levels that do not have as large of an impact on their budget (Blumenstock, 2016). One method is using satellites to collect images of neighborhoods at night. Blumenstock explains that "Recent studies have shown a strong correlation between nightlight luminosity and traditional measures of economic productivity and growth." These photographs make it possible for researchers to identify regions that may need more assistance from them than others. Therefore, organizations can focus their efforts to areas that emit less light at night since they correlate with less wealthy areas. One major limitation with this method is that it is difficult to differentiate between regions with less light as some may look equally as dark.

2.4.3 Internet Usage and Phone Records

Another method that Blumenstock mentions is mobile phone use which also correlates with the levels of wealth in different areas. Even at an individual level, this correlation holds true and machine learning can be utilized to estimate a person's status of wealth with the same level of accuracy as a 5-year-old household survey (Blumenstock, 2016). Another study was done that examined the results of analyzing call detail records (CDRs) in a region of Guatemala to predict poverty rates. The three models this study investigates are different ways that CDR data can be used in conjunction with other data, such as from censuses. These are spatial infill, time interpolation/extrapolation, and spatial extrapolation. The results of comparing these models showed that “All of the CDR models exhibited a significant degree of predictive value. However, the specifics of different models influenced how well they predicted poverty rates.” (Hernandez et al., 2017). Related to this, mining tweets and internet searches can also provide insight to where areas with higher poverty levels are located. One of the benefits of this is that it can provide more data collection in real time. However, in places where internet use and social media is limited, this alternative is not as reliable.

2.4.4 Plasma Donations

One anti-poverty initiative called Poverty Solutions at the University of Michigan has made use of unique resources to identify areas with more poverty. Poverty Solutions made a connection between plasma donations and people living below the poverty line. They noticed that plasma donations can provide valuable information for anti-poverty organizations as many people who donate tend to be less wealthy. Dr. H. Luke Shaefer, who leads the Poverty Solutions initiative, found that donating plasma “...is a common survival strategy for those without cash who live near one of the nation’s 600 plasma center—which my student Analidis Ochoa has documented tend to locate in or near some of our poorest communities.” (Shaefer, 2019). Depending on the donation center and where you live, individuals can earn some extra money for only an hour and 15 minutes of their time, up to 13 times per year (American Red Cross, n.d.). Donating plasma is a popular way for low-income families to make some extra money legally, while also donating to help people who are in need of plasma.

2.4.5 Which Method is Best?

These are a few of the many examples of what other organizations have done in an attempt to alleviate poverty. There is no single best method for all anti-poverty programs to collect data. Considering the multidimensionality of poverty as well as the many organizations around the world that fight to reduce it, each one will develop the methods that work best given their situation.

2.5 Data Analytics for Poverty Stoplight

Next, we discuss an overview of the methods of data analytics that we used for Poverty Stoplight. These methods include the Data Science Life Cycle, Data Envelopment Analysis, and Cross-Efficiency.

2.5.1 Data Science Life Cycle

The Data Science Life Cycle is an extension of the Data Life Cycle (Stodden, 2020). The DSLC describes the complete process of data science, rather than just the stages a dataset goes through, which was described by the Data Life Cycle (Stodden, 2020). The DSLC includes seven important steps which include: business understanding, data mining, data cleaning, data exploration, feature engineering, predictive modeling, and data visualization (Agarwal, 2018). Table 2.1 below describes what is typically involved in each step of the life cycle. These steps provide a basis for how to conduct data science projects. It focuses on understanding the problem, analyzing cleaned data, and using models to make informed predictions based on the data.

Data Science Life Cycle Step	**Description**
Business Understanding	Ask relevant questions and define objectives for the problem that needs to be tackled
Data Mining	Gather and scrape the data necessary for the project
Data Cleaning	Fix the inconsistencies within the data and handle the missing values
Data Exploration	Form hypotheses about your defined problem by visually analyzing the data
Feature Engineering	Select important features and construct more meaningful ones using the raw data that you have
Predictive Modeling	Train machine learning models, evaluate their performance and use them to make predictions
Data Visualization	Communicate the findings with key stakeholders using plots and interactive visualizations

Table 2.1 Data Science Life Cycle Steps

The steps and descriptions listed above were referenced from an article titled “Understanding the Data Science Lifecycle” by Sudeep Agarwal (2018). Out of the many interpretations of the Data Science Life Cycle, this depiction accurately detailed the process we used when analyzing our data and was the most applicable for our project. The first five steps of the DSLC prepared us to complete the sixth step in which we used Data Envelopment Analysis as our model.

2.5.2 Data Envelopment Analysis

Data Envelopment Analysis is an optimization method used primarily in operations research to determine if a decision making unit (DMU) is operating efficiently based on their specific resources (Cook, Tone, & Zhu, 2014). This method focuses on maximizing the efficiency of each DMU by assigning unit costs to each input and unit prices to each output. For every DMU being analyzed, the DEA model must be run as many times as there are DMUs, with the selected DMU changing each run. With each run, the unit costs and unit prices are specified for the selected DMU to calculate the efficiency with the DMU shown in its best light (Winston & Albright, 2011). Table 2.2 below defines the key terms of a DEA problem. The goal of DEA is to benchmark between DMUs and identify inefficient units and to determine the necessary areas of improvement.

DEA Term	**Definition**
Decision Making Unit (DMU)	A DMU is a process or business that uses a set of resources to produce a set of outputs
Inputs	An input for a DMU is anything that the unit uses to produce the outputs. Common examples are labor and capital
Outputs	An output for a DMU is the end product or outcome of the process that each unit completes
Efficiency	Efficiency calculation = value of output / cost of input, but cannot be greater than 1.0
Unit Cost & Unit Price	The decision variables of the DEA problem, where the model changes the unit costs and unit prices for the inputs and outputs for each DMU

Table 2.2 Data Envelopment Analysis Definitions

2.5.3 Cross-Efficiency for Data Envelopment Analysis Results

Cross-efficiency is a method used on the results from Data Envelopment Analysis. This method allows the DMUs from DEA to be ranked against one another through “peer evaluation” rather than just “self evaluation” from the DEA Model (Zhu, 2014). The unit costs and prices determined for the inputs and outputs of each DEA model can also be used to calculate the efficiency of all other DMUs. After calculating all efficiencies for all DMUs, the efficiencies can be averaged. The average efficiency is used for ranking the DMUs. The goal of cross-efficiency is to gain a deeper understanding of the performance of the DMUs.

3.0 Methods

In this chapter we discuss how we applied the Data Science Life Cycle and Data Envelopment Analysis to the Poverty Stoplight data to reach our project goal of evaluating the efficiency of partner organizations to help families move out of poverty. We discuss the details of the data we have received from the Poverty Stoplight team and then how those datasets will be used for our analysis. We also discuss how our analysis was used to determine recommendations for Poverty Stoplight and the organizations that administer the Poverty Stoplight survey.

3.1 Analyzing Indicator Data from the Stoplight Survey

In what follows we provide greater detail on the data we analyzed from Poverty Stoplight. We also discuss how we applied The Data Science Life Cycle and Data Envelopment Analysis to the Poverty Stoplight data.

3.1.1 Providing Feedback on the Poverty Stoplight Organization Survey

Poverty Stoplight administers the Partner Organization Survey to each of the organizations with whom they partner, which is a form that the partner organizations are requested to complete. This allows Poverty Stoplight to gather information about the organization and how they administer the self-assessment survey to families. We had the opportunity to read through the organization survey prior to the Poverty Stoplight team sending it out in September 2022, and provided Poverty Stoplight some suggestions on other questions to add that would give additional useful data for our analysis. These suggestions would help us and the Poverty Stoplight team gain more insight on topics such as: the organizations' opinions on Life Maps, to whom mentorships are made available and how they are provided, how follow-up surveys are conducted, and more.

Partner organizations were invited to complete the Poverty Stoplight Partner Organization Survey in October 2022. At the initial deadline for the survey, it was reported to us that the survey received less than ten results. Poverty Stoplight communicated instructions to the organizations again to complete the survey, however few additional responses were collected. Without the sufficient survey results, our initial analysis was lacking valuable insights about the partner organizations. This resulted in the direction of the project pivoting slightly so Poverty Stoplight provided an additional dataset with partner organization implementation information.

3.1.2 Overview of Poverty Stoplight Data

We received data from Poverty Stoplight for 70 partner organizations, detailing demographics of families and individuals who have completed the self-assessment survey. This includes information such as the area they live in, income, where they were born, age, and gender. We analyzed the data from these records, as well as the responses from the organizational survey. Some of these indicators, however, were not consistent with one another due to the multidimensionality of poverty and its relativity, which adds another layer of complexity to analyzing this data. The PS stoplight tool contains 50 indicators that are separated across 6 dimensions. Figure 3.1, taken from the Poverty Stoplight Brochure (Poverty Stoplight, 2018), shows these 6 categories and lists the indicators that are in each dimension.

Figure 3.1 PS Indicators and Dimensions

The information from these sources enabled us to analyze the resources that the partner organizations are using to help families. With these differences in indicators, we found similarities and grouped indicators that are similar across multiple partnership surveys. We thoroughly explored this data and its formatting to determine what features of the data would be the most valuable to our analysis and to Poverty Stoplight through the utilization of the Data Science Life Cycle.

3.2 The Data Science Life Cycle

The Data Science Life Cycle includes seven steps that shaped our process of interpreting and working with the dataset received from Poverty Stoplight. These steps include business understanding, data mining, data cleaning, data exploration, feature engineering, predictive modeling, and data visualization. The application of these steps for our project is detailed in the following sections. Figure 3.2 below displays the steps we followed for this project (Agarwal, 2018).

Figure 3.2 Data Science Life Cycle (Agarwal, 2018)

3.2.1 Business Understanding

Step one of the Data Science Life Cycle is business understanding. In this step the goal is to figure out the objectives for the problem that needs to be solved. To understand the problem and how to accomplish it we researched and had several meetings with Poverty Stoplight. From our research, we were able to understand more about PS as well as their goals. Poverty Stoplight utilizes the stoplight tool, which is a self-assessment survey that is administered by partner organizations for families to track their poverty levels. This survey lets families evaluate areas of their life (education, insurance, safety, finances, etc.) that meet their needs or could use more improvement, as well as allow the partner organizations to provide them with resources to alleviate their poverty. Once we were familiar with the PS program, we were able to meet with their team on Zoom and ask further questions. Through this we received more accurate information about the number of partner organizations they have as well as what data-analysis based projects they have previously done.

Based on these insights, we presented them with three project ideas that would be beneficial for the future of the program. With further discussion and input from PS, we decided on one of them, our current project. Our objective for this project became to determine the efficiency of their partner organizations in helping families alleviate poverty, so as to provide recommendations on how to become more efficient and perform future analyses. To accomplish this, we needed to gather and engineer input and output features that are needed for our Data Envelopment Analysis model. We discuss our use of DEA for this project in more detail in Section 3.3.

3.2.2 Data Mining

Step two of the Data Science Life Cycle is data mining. This step encompasses many aspects such as searching for any patterns, trends and anomalies. For this project, however, we only focused on gathering and scraping data to look at everything and determine what would be important to focus on. We received raw survey data from Poverty Stoplight that they have previously collected. These data included information about their partner organizations that administer the surveys, family demographics, and the PS survey results from the families that included any follow-up surveys they had also completed. The data from each of the organizations were presented in their own Excel sheet that helped with categorization.

The organization questionnaire is useful to see what information PS routinely collects about their partner organizations. This can include information such as demographics of the organization, values, objectives, mentoring styles, and PS implementations in different communities. We provided suggestions of other questions to be added to the questionnaire to help in our evaluation of the organizations. Some things that we suggested to add were questions regarding the types of resources provided, what do mentorships involve, and when and how follow-up surveys are conducted. We also received information about the organizations administering the surveys which was beneficial to see how much training the employees administering the surveys receive, the time it takes to complete surveys, and information regarding follow-up surveys. The family demographics and PS survey results that were shared with us were anonymous and unidentifiable, and allowed us to see where different families from different regions ranked themselves regarding the different indicators. Additionally, we identified the number of follow-up surveys that families submitted to see whether they were showing improvement, and in which indicators. Before we began the process of analyzing this data, it was necessary for us to complete the next step in the Data Science Life Cycle.

3.2.3 Data Cleaning

Step three of the Data Science Life Cycle is data cleaning. The purpose of this step is to fix inconsistencies within the data and handle any missing values in preparation for step four: data exploration. From the data we received from Poverty Stoplight, we needed to manually clean the Excel sheets from each partner organization. These Excel sheets showed the collected data from implementations of the Poverty Stoplight survey. After comparing some of the datasets, we realized that the naming of the indicator columns was not standardized. Some indicator names slightly differed from one another, and some of the Excel sheets were in different languages. We made the indicator names consistent with each other by creating a list of names we would use for the indicators and manually changed the column names to ensure consistency. Only by standardizing these names, would we be able to easily compare the partner organizations with the use of Python scripts, which can be found in Appendix C. Once we standardized the indicator names, we found the indicators that were common between each of the partner organizations. We discovered that there were 16 standard indicators that most of the partner organizations shared. Although we could have compared these organizations differently by giving their unique indicators weights, we did not want to assume what indicators were more important than others. Therefore, we chose to compare the partner organizations on only similar indicators. In the next phase of data cleaning, we removed redundancies and missing values in the data.

From observing the data, we realized that some organizations had the same family codes as other partner organizations. Family codes are used to identify the surveys that a specific family has taken. This caused issues when we created a Python script based on the family codes since we assumed that family codes were unique across the organizations. We were unable to properly utilize a new Excel sheet that we created using the script. Therefore, we had to remove the unnecessary data from the newly created Excel file. In addition to this, we handled missing values for the indicators. If the value was blank or zero for an indicator, we changed them into a 1 which represented a red value on the survey. We decided to go with this method instead of deleting the entire row or making missing values a 3, which would equate to green because the missing values were infrequent. We also noticed that sometimes family codes that had a missing value for an indicator would not be missing that same value on the next survey they took. Changing the missing values to 1 enabled the most growth for families.

3.2.4 Data Exploration

Step four of the Data Science Life Cycle is data exploration. The original purpose of this step was to form hypotheses about our problem by visually analyzing the data. However, this description did not fit our project, so we changed the purpose to inform modeling by extracting information from the data. To conduct the Data Envelopment Analysis we have previously mentioned, it was necessary to figure out how many partner organizations had follow-up surveys. To find this number, we created a Python script named getSecondSurveyData.py that pointed out how many families had at least a second completed survey for each partner organization. With this information, we realized that we had enough follow-up survey data to continue with our project plan. We also determined that the minimum amount of second surveys we would accept for any organization to become a Decision Making Unit would be twenty.

We created multiple CSV files from Python scripts. These files are called makeCSVWithFamilies.py, makeCSVWithIndicators.py, and makeCSVWithPriorities.py. These scripts have the same functionality, in which they consolidate all of the data of the family codes that have at least one follow-up survey. However, each script copies specific columns from different sheets within the partner organization Excel workbooks. The makeCSVWithFamilies.py created a CSV with some of the family data from the Families sheet within each workbook. We used this CSV file to consolidate information about all of the family codes that were relevant to our project. Specifically, we used the survey dates from this file to feature engineer an input for our DEA model, which we will discuss in the next section. The makeCSVWithInidicators.py created a CSV with the indicator data we needed from the Indicators sheet within the workbooks. This CSV was tremendously helpful with feature engineering outputs for our DEA model, which will be discussed in the next section as well. Lastly, the makeCSVWithPriorities.py involved the appropriate data from the Priorities sheet. Although we did not use this CSV file in our project, we had thought about using the priorities of each family as a factor in our analysis. However, the amount of priority data available was insufficient for this analysis. Overall, these Python scripts helped prepare us for step five, feature engineering.

3.2.5 Feature Engineering

Step five of the Data Science Life Cycle is feature engineering. In this step, we selected important features from the raw data and then constructed more meaningful features. The important features we were given included the number of days for training and hours to deploy each survey. The number of days for training represents the number of days of training that each partner organization gave their employees before implementing the Poverty Stoplight surveys. The hours to deploy feature represents how long it takes an organization to typically deploy the survey. One of the features we constructed was adaptation, which shows how much the organization adapted the survey in addition to the common indicators. We found the adaptation values by counting the amount of indicators each organization uses from which we subtracted that by sixteen, the number of standard indicators. We believed that more adaptation of the survey would indicate that the partner organizations spent more time curating the survey so they would be more invested to help their families improve. We also feature-engineered a responsiveness input by making a python script called AverageTime.py. In this script, we took the difference in the time between the first and second surveys deployed and then averaged them for each organization. The average responsiveness time tells us how quickly the organizations give their families a follow-up survey. This is important because if the responsiveness is very small, the families may not have had enough time to improve. However, if the responsiveness is too large, then the organizations might lose touch with the families.

In addition to some of the inputs, we feature-engineered four outputs. The sixteen common indicators we discovered previously could be grouped into four dimensions of poverty. These dimensions are income & employment, housing & infrastructure, education & culture, and health & environment. The income & employment dimension consisted of the income, savings, and credit indicators. The housing & infrastructure dimension consisted of enough space, kitchen, bathroom, phone, and electricity indicators. The education & culture dimension was made up of the schooling, literacy, and internet indicators. The last dimension, health & environment, consisted of the garbage, water, health services, safety, and security of property indicators. We created an output out of each of these four dimensions by using Python scripts. These scripts were called IncomeEmployment.py, HousingInfrastructure.py, EducationCulture.py, and HealthEnvironment.py. Each of these scripts calculates the output by subtracting the second survey value from the first survey value for every indicator within the dimension. That score was then averaged by the number of families. These aggregated scores made it possible to have negative values. Negative values show that there was an overall decrease in progress across all of the families for that organization. A positive value shows that there was an increase in progress in moving out of poverty for that organization. We used these inputs and outputs in the next section of the Data Science Life Cycle, predictive modeling.

3.2.6 Predictive Modeling

Step six of the Data Science Life Cycle is predictive modeling. This step involves training machine learning models, evaluating their performance, and using them to make predictions. This description did not exactly apply to our project, so we will be using a slightly different definition. For this step, we used the important inputs and outputs discovered in the previous step, feature engineering, and performed a Data Envelopment Analysis. More detail about our specific DEA process is explained in Section 3.3. The results we found from these analyses allowed us to make informed recommendations for PS to improve efficiency among their organizations. These results and suggestions will be described in more depth in section 3.5.

3.2.7 Data Visualization

Finally, step seven is data visualization. We utilized the information gathered from the steps above as well as our recommendations to create plots, diagrams, charts, and other visualizations to convey our findings to Poverty Stoplight. These visualizations are beneficial to communicate everything we have done in a way that is concise and easy to understand.

3.2.8 Data Science Life Cycle Summary

The Data Science Life Cycle is a helpful tool for approaching a problem like this. We defined our goal to evaluate the partner organizations' efficiency and provide recommendations for future improvement. We met with the PS team and discussed project options as well as what data they could provide us. Then we gathered all of the data and scraped it to examine everything and determine what data would be important to look further into. Cleaning the data allowed us to standardize aspects that were useful to our project so we could perform the next step, data exploration. Exploring involved us looking at the data both visually and using Python scripts to make the process more smooth. In feature engineering we selected important features from the raw data and transformed them into more meaningful features, inputs and outputs, to be used in the next step where we executed DEA. The final step of data visualization is where we took our results from DEA and displayed them in various forms such as charts, tables, and plots to better visualize and understand them.

3.3 Using Data Envelopment Analysis for Poverty Stoplight

Data Envelopment Analysis uses the inputs and outputs of a decision-making unit (DMU) to assess efficiency of relatively similar organizations. We will now discuss our plan to define DMUs, inputs, and outputs to the partner organizations and processes of Poverty Stoplight.

3.3.1 Decision Making Units

Again, the goal of our project is to use data analytics to assess the individual partner organizations that administer the Poverty Stoplight survey for families and provide recommendations for improving efficiency. We will determine the performance of each partner organization through calculating the efficiency of each organization based on their best inputs and outputs. For DEA, each qualifying partner organization will be a decision making unit. These partner organizations must be similar to satisfy homogeneity criteria. We defined the following homogeneity criteria to finalize our set of DMUs:

1. Each DMU must be located in either Latin America or South America
2. Each DMU must utilize group mentoring for their member families
3. Each DMU must have at least 20 follow-up surveys

These homogeneity criteria ensured that we were comparing relatively similar organizations that had sufficient data for the analysis. Homogeneity criteria is important to ensure that all DMUs evaluated are comparable and are operating on a similar level. This allows for the optimal results for DEA.

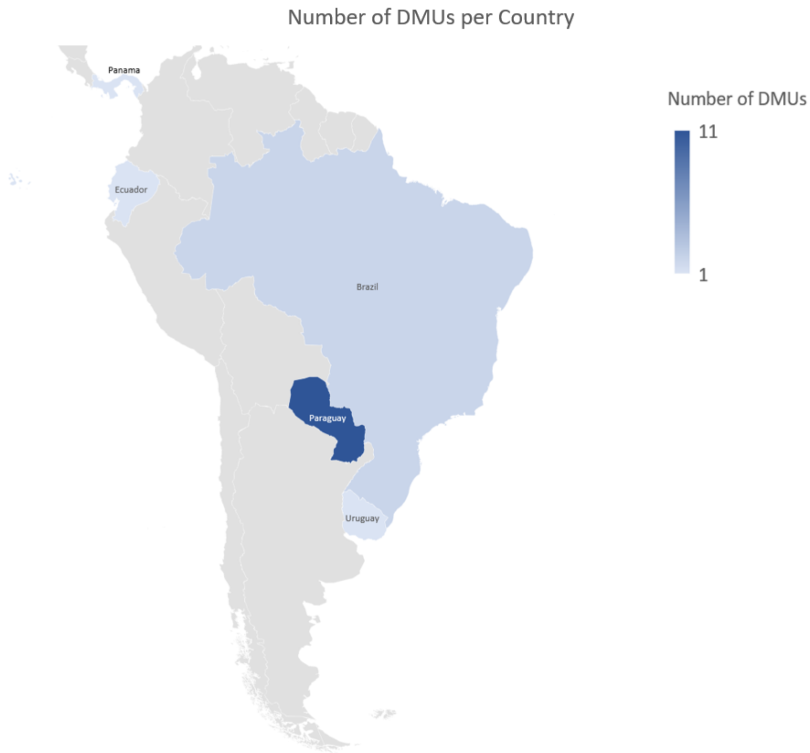

Figure 3.3 The number of DMUs that fulfilled the homogeneity criteria per country

3.3.2 Inputs

All DMUs also had a set of inputs on which they were assessed. These inputs are the resources for their families or data about their survey. For the original DEA model, we defined 4 inputs. As we completed models, we assessed the usefulness of the inputs and removed some as appropriate. The 4 original inputs are defined as the following:

1. *Training*. Each DMU has training for their mentors who administer the Poverty Stoplight survey. This input is defined by the number of days of training for the DMU. It is assumed that more training for mentors is advantageous for families.
2. *Responsiveness.* This input is defined as the average time between the administration of the initial Poverty Stoplight survey and the administration of the follow-up survey where families reassess their indicator levels. Through correspondence with our sponsor, Katharina Hammler, at Poverty Stoplight, we determined that the optimal responsiveness time is 1 year.

3. *Adaptation.* Each DMU is able to adapt the base Poverty Stoplight survey to best suit the needs of their community. This input is defined as the number of indicators present in a DMU's survey. It is assumed that the more indicators in a survey, the better the survey represents a family's specific situation.
4. *Hours to Deploy.* This input is defined as how long a mentor works with a family to complete the Poverty Stoplight survey. It is assumed that more time spent with a family leads to a more thorough analysis and therefore is beneficial for the family.

3.3.3 Outputs

There was also a set of outputs on which all DMUs were assessed. The outputs are the results and improvements of survey responses for the families. For all DEA Models, 4 outputs were defined and used. For the Poverty Stoplight survey there are common indicators that can be grouped into dimensions. The 4 outputs were defined by the following dimensions which included the listed indicators:

1. *Income & Employment.* Income, Savings, Credit
2. *Housing & Infrastructure.* Enough Space, Kitchen, Bathroom, Phone, Electricity
3. *Education & Culture.* Schooling, Literacy, Internet
4. *Health & Environment.* Garbage, Water, Health Services, Safety, Security of Property

The output values represented the improvement in the dimensions between the initial survey and follow-up survey. These values were determined by aggregating the proper indicator data for each dimension of poverty for the first and second survey each family completed and then averaging them by the amount of families. We calculated these output values for each DMU. These output values can be positive or negative. A negative output value for a DMU shows that, overall, the families belonging to the DMU have regressed in their progress of moving out of that dimension of poverty. A positive output value shows that the families of that DMU have progressed with moving out of that dimension of poverty. The absolute value of the output determines the magnitude of the progression or regression.

For DEA, all values for inputs and outputs must be positive (Zhu & Cook, 2007). Since the output value calculation allows for negative values to indicate regressed progress between the initial and follow-up, the values had to be adjusted. To adjust the values to all be positive, we added a value of 1 to every output as the smallest average output for all of our DMUs were between 0 and -1. This allowed the differences between DMUs to still be reflected while having all positive values.

3.3.4 Optimization Model

Now that we have defined the decision making units, inputs, and outputs that we have used, we present the DEA optimization model we used. Figure 3.4 below shows how we defined the DEA optimization used for our analysis. For our analysis we used an output oriented model which allows the DMUs to fix their inputs and then maximize their price-weighted outputs. Since our outputs were defined to be the improvement in survey responses, using an output oriented model allowed for the improvement in poverty indicators to be maximized. Additionally, our model used constant return to scales, as it was assumed that all inputs contributed equally to the outputs. We implemented this model using the Solver add-in in Microsoft Excel, and specifically used the Simplex LP solving method.

<u>*Sets*</u>

D	Set of decision making units
I	Set of inputs
O	Set of outputs

<u>*Parameters*</u>

w_{id}	Amount of input i ∈ I for DMU d ∈ D
v_{od}	Amount of output o ∈ O for DMU d ∈ D

<u>*Decision Variables*</u>

x_i	Weight given to input i ∈ I
y_o	Weight given to output o ∈ O

<u>*Model:*</u>

$$Maximize: \sum_{o \in O} v_{od_0} y_o$$

$$Subject\ to: \sum_{i \in I} w_{id_0} x_i = 1$$

$$\sum_{i \in I} w_{id}\, x_i - \sum_{o \in O} v_{od} y_o \geq 0 \quad \forall\, d \in D$$

$$x_i, y_o \geq 0 \quad \forall\, i \in I,\ \forall\, o \in O$$

Figure 3.4 DEA Optimization Model

As we performed DEA on our original model, we found it necessary to adjust the defined inputs and DMUs to gather the optimal results. Table 3.1 below outlines the differences between each model. The table outlines the number of inputs used, the DMUs evaluated, and whether the data was standardized. In the results section, we discuss how the results led to these decisions being made.

	Inputs	**Outputs**	**DMUs**	**Standardized Data**
Model 1	4	4	16	N
Model 2	4	4	16	Y
Model 3	4	4	15	N
Model 4	3	4	15	N
Model 5	2	4	15	N
Model 6	2	4	13	N

Table 3.1 DEA Models

3.4 Completing Cross-Efficiency on DEA Results

After completing 6 DEA models, we selected 2 models on which to perform cross-efficiency, based on their high variation in the weights placed on each input and output. The details of the model, results, and cross-efficiency results will be discussed in Chapter 4. The higher levels of variation allowed for more differences in the cross-efficiency scores and more insights that are able to be drawn. To complete cross-efficiency on these models, the optimization model was run for each DMU. For each selected DMU, the efficiency for all of the other DMUs was recorded. The values were then aggregated and ranked, with the highest aggregated efficiency having the best rank.

3.5 Developing Recommendations for Poverty Stoplight Partners

Our DEA models determined efficient and inefficient partner organizations. We analyzed and further reflected on these results to determine potential recommendations for Poverty Stoplight and for their partner organizations. Our analysis included both quantitative and qualitative methods. For the quantitative analysis, we analyzed the DEA and cross-efficiency results. For the highest and lowest performing DMUs, we examined their input and output values and the weights associated with those to gain insights. For the qualitative analysis, we organized interviews with two of the project managers that oversee some of the partner organizations. We focused on holding interviews with individuals from both the efficient and the inefficient organizations.

3.5.1 Evaluating DEA and Cross-Efficiency Results

From the results of our DEA and Cross-Efficiency models, we analyzed the highest and lowest performing DMUs. We analyzed the value of their inputs, outputs, and the weights that were used in their efficiency scores. The goal in this analysis was to discover patterns and recurring trends in the efficient and inefficient DMUs. The investigation of whether specific inputs are valued in high performing DMUs guided our recommendations for Poverty Stoplight.

3.5.2 Interviewing Poverty Stoplight Program Managers

Based on the highest and lowest performing DMUs in the DEA and Cross-Efficiency results, Poverty Stoplight connected us with program managers that oversee these partners. To prepare for these interviews, we developed a list of questions, which are in Appendix A. These questions served as a baseline, for further detail we asked specific follow-up questions as needed. Our discussions and questions focused on how partner organization resources are provided to families and how they impact the follow-up survey responses. We discussed their specific implementation methods and the different aspects from their organization that are proving to be successful. This allowed us to gain valuable insights into the processes of Poverty Stoplight and its organizations provided further information beyond only our data analysis. We further shaped our final recommendations based on these interviews and insights.

4.0 Results

In this chapter, we discuss the results and findings from the DEA models, cross-efficiency analysis, and interviews with partner organization representatives. A total of six DEA models were created and the progression from model to model is shown and the reasonings for adaptations to the models is explained. The DEA models with the most variation were supplemented with an additional cross-efficiency analysis to see the comparison of input weights across all DMUs efficiency scores. Along with these quantitative results, the qualitative findings from our discussion with both efficient and inefficient partner organizations is presented below.

4.1 Data Envelopment Analysis Results

Our initial analysis and first DEA Model began with the 4 inputs, 4 outputs, and the 16 DMUs that we defined in our methods. The results of this model showed little overall variation with all but one of the non-zero weights being assigned to the Adaptation input and Income & Employment output. We found that only Partner D was an efficient DMUs as indicated by the green highlighted box in the efficiency column in Figure 4.1 below. Partner D, however, was the only DMU with variation in the weighting with a weight being assigned in the Health & Environment output. For the 15 other DMUs the efficiency scores ranged from a low of .4819 to a high of .8225. With only 1 DMU being deemed efficient and minimal variation in the non-zero weighting, we decided to re-run the DEA model using standardized data in hopes that this would result in more efficient DMUs.

DMU	Efficiency	Training	Responsivness	Adaptation	Hours to Deploy	Income & Employment	Housing & Infrastructure	Education & Culture	Health & Environment
Partner A	0.6351	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000
Partner B	0.6586	0.0000	0.0000	0.0270	0.0000	0.4478	0.0000	0.0000	0.0000
Partner C	0.6977	0.0000	0.0000	0.0270	0.0000	0.4478	0.0000	0.0000	0.0000
Partner D	1.0000	0.0000	0.0000	0.0286	0.0000	0.0000	0.0000	0.0000	0.2380
Partner E	0.5976	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000
Partner F	0.6165	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000
Partner G	0.6040	0.0000	0.0000	0.0345	0.0000	0.5713	0.0000	0.0000	0.0000
Partner H	0.5178	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000
Partner I	0.8225	0.0000	0.0000	0.0385	0.0000	0.6373	0.0000	0.0000	0.0000
Partner J	0.5536	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000
Partner K	0.7811	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000
Partner L	0.5870	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000
Partner M	0.6644	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000
Partner N	0.4819	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000
Partner O	0.7423	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000
Partner P	0.6847	0.0000	0.0000	0.0286	0.0000	0.4734	0.0000	0.0000	0.0000

Figure 4.1 DEA Model 1 Results

The second DEA model was constructed using standardized data, 4 inputs, 4 outputs, and

16 DMUs. When standardizing data in a DEA model, the goal is to have all of the inputs and outputs have a standard format that is easy to understand and use, which is beneficial for when one input or output has values that are significantly different than the others. This standardization is done by taking the mean of the values for each input and output. Then the values are divided by that mean, so that for each input and output, the average has a value of 1.0 and all other values are adjusted accordingly to be on similar scales. Figure 4.2 below shows that, similar to results of Model 1, Partner D was the only DMU found to be efficient and the efficiency scores for the other 15 DMUs were exactly the same. This similarity in results showed that the model was favoring Partner D above the other DMUs. To understand the root of this issue, we examined the data to see if any characteristics of Partner D could be the cause. In the output data, we found that Partner D had almost double the percentage of improvement in survey indicators in comparison to all other DMUs. We analyzed this anomaly further and found that on the input side of the data, Partner D has the shortest responsiveness time between surveys. The average responsiveness time for Partner D was 3 days, while the optimal responsiveness was 1 year and the other DMUs had an average responsiveness of approximately 150 days. With a responsiveness of 3 days, it was hard to understand how the improvement of indicators was so high. We decided to remove this DMU from the model because it was not allowing other DMUs to be assessed properly. Removing Partner left us with 15 DMUs and this was still enough to meet the criteria needed for a DEA model with 4 inputs and 4 outputs.

DMU	***Efficiency***	*Training*	*Responsivness*	*Adaptation*	*Hours to Deploy*	*Income & Employment*	*Housing & Infrastructure*	*Education & Culture*	*Health & Environment*
Partner A	0.6351	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000
Partner B	0.6586	0.0000	0.0000	0.9274	0.0000	0.6153	0.0000	0.0000	0.0000
Partner C	0.6977	0.0000	0.0000	0.9274	0.0000	0.6153	0.0000	0.0000	0.0000
Partner D	1.0000	0.0000	0.0000	0.9804	0.0000	0.0000	0.3890	0.0000	0.0000
Partner E	0.5976	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000
Partner F	0.6165	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000
Partner G	0.6040	0.0000	0.0000	1.1832	0.0000	0.7850	0.0000	0.0000	0.0000
Partner H	0.5178	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000
Partner I	0.8225	0.0000	0.0000	1.3197	0.0000	0.8756	0.0000	0.0000	0.0000
Partner J	0.5536	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000
Partner K	0.7811	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000
Partner L	0.5870	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000
Partner M	0.6644	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000
Partner N	0.4819	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000
Partner O	0.7423	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000
Partner P	0.6847	0.0000	0.0000	0.9804	0.0000	0.6505	0.0000	0.0000	0.0000

Figure 4.2 DEA Model 2 Results

The third DEA model was run using 4 inputs, 4 outputs, and 15 DMUs. The results of this model, as seen in Figure 4.3, showed much more variation in weighting and efficiency, confirming our concern that the high success of Partner D was causing the model to favor it too much. In this model, Partner I, Partner K, and Partner O were found to be efficient. The weighting distribution for the outputs had more variation that the previous models with all 4 outputs being assigned with a weight. The Income & Employment output was the most heavily assigned output. On the input side only 2 of the 4 inputs were assigned weights, Training and Adaptation. The Adaption input was still the most heavily weighted input with a weight being assigned to all of the 15 DMUs. One concern with the Adaptation input was that the values for this input across the DMUs were very similar, which allowed for the DMUs to meet the constraints when a weight was used for the Adaptation input. With the model favoring this input, we decided to remove this input to see if that would allow for more variation in weighting and efficiency.

DMU	***Efficiency***	*Training*	*Responsivness*	*Adaptation*	*Hours to Deploy*	*Income & Employment*	*Housing & Infrastructure*	*Education & Culture*	*Health & Environment*
Partner A	0.8130	0.0313	0.0000	0.0277	0.0000	0.6061	0.0000	0.0000	0.0000
Partner B	0.8202	0.0288	0.0000	0.0255	0.0000	0.5577	0.0000	0.0000	0.0000
Partner C	0.8689	0.0288	0.0000	0.0255	0.0000	0.5577	0.0000	0.0000	0.0000
Partner E	0.7651	0.0313	0.0000	0.0277	0.0000	0.6061	0.0000	0.0000	0.0000
Partner F	0.9449	0.0000	0.0000	0.0286	0.0000	0.0000	0.0000	0.5143	0.0000
Partner G	0.7743	0.0000	0.0000	0.0345	0.0000	0.5432	0.0000	0.1826	0.0000
Partner H	0.6913	0.0000	0.0000	0.0286	0.0000	0.3194	0.0000	0.0000	0.1855
Partner I	1.0000	0.0000	0.0000	0.0385	0.0000	0.6867	0.0000	0.0000	0.0836
Partner J	0.7146	0.0192	0.0000	0.0280	0.0000	0.5534	0.0483	0.0000	0.0000
Partner K	1.0000	0.0000	0.0000	0.0286	0.0000	0.3194	0.0000	0.0000	0.1855
Partner L	0.7515	0.0313	0.0000	0.0277	0.0000	0.6061	0.0000	0.0000	0.0000
Partner M	0.8548	0.0000	0.0000	0.0286	0.0000	0.4503	0.0000	0.1512	0.0000
Partner N	0.6169	0.0313	0.0000	0.0277	0.0000	0.6061	0.0000	0.0000	0.0000
Partner O	1.0000	0.0000	0.0000	0.0286	0.0000	0.0000	0.3649	0.0000	0.0000
Partner P	0.8638	0.0000	0.0000	0.0286	0.0000	0.5171	0.0691	0.0000	0.0000

Figure 4.3 DEA Model 3 Results

The fourth DEA model was constructed using 3 inputs, 4 outputs, and 15 DMUs, with the results displayed in Figure 4.4. This model found that Partner K and Partner O were efficient. The efficiency scores for the other 13 DMUs ranged from .4010 to .9449. With the Adaptation input being removed, the DEA model now was relying heavily on the Hours to Deploy input. This model showed a similar variation in output weighting to Model 3 with all 4 outputs being assigned at least one weight. The most heavily assigned output was again the Income & Employment. Since the Hours to Deploy was being favored in this model, for similar lack of variation between values across DMUs, we decided to remove this input and run the model again. With 2 inputs and 4 outputs, 15 DMUs still meets the standard DEA practice of having at least twice the number of DMUs as inputs and outputs. By removing this input, our goal was that the new DEA model would show more variation in the weight assignments and the determination of DMU efficiency.

DMU	Efficiency	Training	Responsivness	Hours to Deploy	Income & Employment	Housing & Infrastructure	Education & Culture	Health & Environment
Partner A	0.8130	0.0000	0.0000	2.4000	0.6061	0.0000	0.0000	0.0000
Partner B	0.5570	0.0000	0.0000	1.5000	0.3788	0.0000	0.0000	0.0000
Partner C	0.5902	0.0000	0.0000	1.5000	0.3788	0.0000	0.0000	0.0000
Partner E	0.7651	0.0000	0.0000	2.4000	0.6061	0.0000	0.0000	0.0000
Partner F	0.9449	0.0000	0.0000	2.4000	0.0000	0.0000	0.5143	0.0000
Partner G	0.4010	0.0000	0.0000	1.5000	0.2814	0.0000	0.0945	0.0000
Partner H	0.6913	0.0000	0.0000	2.4000	0.3194	0.0000	0.0000	0.1855
Partner I	0.5587	0.0000	0.0000	1.7143	0.4329	0.0000	0.0000	0.0000
Partner J	0.7146	0.0000	0.0000	2.4000	0.5534	0.0483	0.0000	0.0000
Partner K	1.0000	0.0000	0.0000	2.4000	0.6061	0.0000	0.0000	0.0000
Partner L	0.7515	1.0000	0.0000	0.0000	0.6061	0.0000	0.0000	0.0000
Partner M	0.8548	0.0000	0.0000	2.4000	0.4503	0.0000	0.1512	0.0000
Partner N	0.6169	1.0000	0.0000	0.0000	0.6061	0.0000	0.0000	0.0000
Partner O	1.0000	0.0000	0.0000	2.4000	0.5534	0.0483	0.0000	0.0000
Partner P	0.5509	0.0000	0.0000	1.5000	0.3459	0.0302	0.0000	0.0000

Figure 4.4 DEA Model 4 Results

The fifth DEA model was constructed using 2 inputs, 4 outputs and 15 DMUs. With the removal of the Hours to Deploy input, the assigned input weights all shifted to the Training input. The assigned output weights still showed variation with at least one weight being assigned to all 4 outputs. The results of this model showed that again Partners K and O were the only efficient DMUs. Since these partners were the only efficient DMUs found in Model 4, we decided to take a deeper look into the data for these partners to determine if there were any characteristics causing these DMUs to be favored in these models, similar to Partner D in Model 2. We found that these partners stood out amongst the rest of the DMUs in the responsiveness category. Specifically, we found Partner K had an average responsiveness of about 7.5 days and Partner O had an average responsiveness of about 5.5 days. The other 13 DMUs had an average responsiveness ranging from just under 3 months to 1 year. In addition to these short follow-up periods, Partners K and O had high percentages of indicator improvements between baseline surveys and follow-up surveys. The high percentage of improvement was again difficult to understand since the timeframe for progress is so short. These partners were outliers from the rest of the data and decided to remove them and run the model again. We hoped by removing these outliers, it would allow the model to more accurately represent efficiency in the remaining DMUs, and allow more insight to be given into the inputs and outputs.

DMU	Efficiency	Training	Responsivness	Income & Employment	Housing & Infrastructure	Education & Culture	Health & Environment
Partner A	0.8130	1.0000	0.0000	0.6061	0.0000	0.0000	0.0000
Partner B	0.4456	0.5000	0.0000	0.3030	0.0000	0.0000	0.0000
Partner C	0.4721	0.5000	0.0000	0.3030	0.0000	0.0000	0.0000
Partner E	0.7651	1.0000	0.0000	0.6061	0.0000	0.0000	0.0000
Partner F	0.9449	1.0000	0.0000	0.0000	0.0000	0.5143	0.0000
Partner G	0.3208	0.5000	0.0000	0.2251	0.0000	0.0756	0.0000
Partner H	0.6913	1.0000	0.0000	0.3194	0.0000	0.0000	0.1855
Partner I	0.3911	0.5000	0.0000	0.3030	0.0000	0.0000	0.0000
Partner J	0.7146	1.0000	0.0000	0.5534	0.0483	0.0000	0.0000
Partner K	1.0000	1.0000	0.0000	0.3194	0.0000	0.0000	0.1855
Partner L	0.7515	1.0000	0.0000	0.6061	0.0000	0.0000	0.0000
Partner M	0.8548	1.0000	0.0000	0.4503	0.0000	0.1512	0.0000
Partner N	0.6169	1.0000	0.0000	0.6061	0.0000	0.0000	0.0000
Partner O	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.3716
Partner P	0.2938	0.3333	0.0000	0.1845	0.0161	0.0000	0.0000

Figure 4.5 DEA Model 5 Results

The sixth DEA model was constructed using 2 inputs, 4 outputs and 13 DMUs. Of all the models ran, this model showed the most varied and balanced weight distribution as shown in Figure 4.6. The 2 inputs, Training and Responsiveness, were both represented with assigned weights. Although only three of the four outputs were assigned weights, the variation among the DMUs shows that this model did not have any specific DMU being favored. With no singular DMU being favored, all 13 DMUs were able to well represent themselves individually. In this model, we found that Partners C, F, and M are efficient DMUs. The other 10 DMUs have efficiency scores ranging from .4032 to .9766. Overall, this model showed the greatest amount of variance and one of the highest number of efficient DMUs. We found the results of this model to be sufficient and decided to use these results in additional analyses.

DMU	Efficiency	Training	Responsivness	Income & Employment	Housing & Infrastructure	Education & Culture	Health & Environment
Partner A	0.9766	1.0000	0.0000	0.6030	0.0000	0.0000	0.0942
Partner B	0.5643	0.4646	0.0004	0.3837	0.0000	0.0000	0.0000
Partner C	1.0000	0.0000	0.0123	0.5391	0.0000	0.0000	0.1276
Partner E	0.8995	1.0000	0.0000	0.6030	0.0000	0.0000	0.0942
Partner F	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.4388
Partner G	0.4032	0.4618	0.0004	0.3814	0.0000	0.0000	0.0000
Partner H	0.8332	1.0000	0.0000	0.6030	0.0000	0.0000	0.0942
Partner I	0.7165	0.1378	0.0072	0.5551	0.0000	0.0000	0.0000
Partner J	0.8452	1.0000	0.0000	0.6075	0.0966	0.0000	0.0000
Partner L	0.9322	0.9101	0.0009	0.7518	0.0000	0.0000	0.0000
Partner M	1.0000	1.0000	0.0000	0.6030	0.0000	0.0000	0.0942
Partner N	0.7298	1.0000	0.0000	0.6030	0.0000	0.0000	0.0942
Partner P	0.7363	0.0000	0.0090	0.3915	0.1013	0.0000	0.0000

Figure 4.6 DEA Model 6 Results

4.2 Cross-Efficiency Results

After completing the 6 DEA Models, we continued our analysis with determining the cross-efficiency scores. This allowed us to see how each DMU performed when considering the weights of all other DMUs. To gain more insight, we completed cross-efficiency on the Model 3 and Model 6 as they had the most variation in weights in regard to both the magnitude of the weights as well as which inputs and outputs were weighted.

For Model 3, Figure 4.7 below shows the results of cross-efficiency for the DMUs. The figure shows all the DMUs cross-efficiency scores with the best performing Partners at the top and the lowest performing Partners at the bottom. These cross-efficiency scores are the average of their efficiency when using all of other DMU's weights. In Model 3, Partners I, K, and O were efficient in regards to their own inputs and outputs. This remains consistent with the cross-efficiency results as these three partners have the highest cross-efficiency scores.

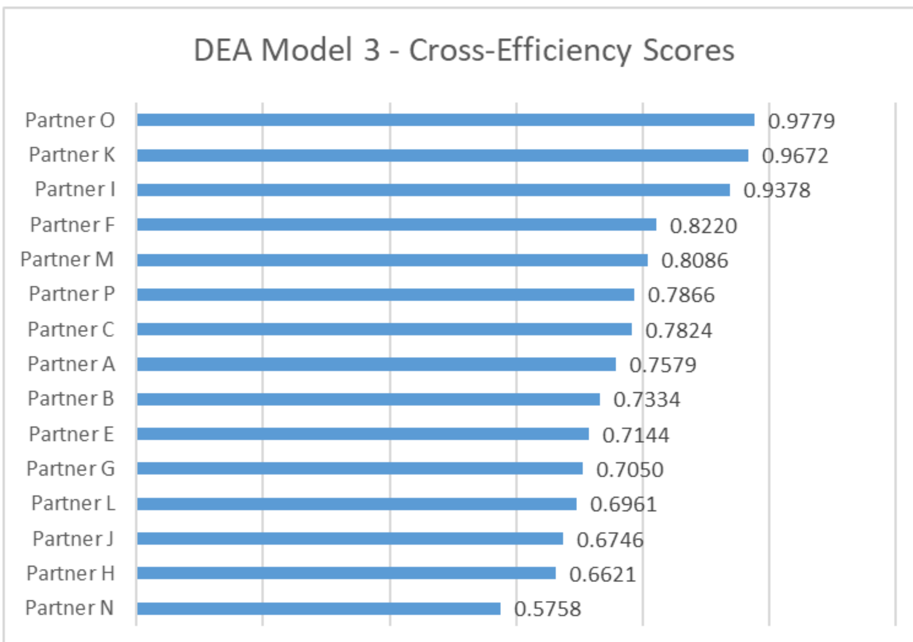

Figure 4.7 DEA Model 3 Cross-Efficiency Scores

The cross-efficiency results for Model 6 revealed more differences to the initial DEA Model 6 results. Figure 4.8 below shows the DMUs ranked by the cross-efficiency scores, with Partners F, and M being the highest performing DMUs, and were two of the three efficient DMUs. However Partner C, the final efficient DMU, has a much lower cross-efficiency score of 0.6393 at rank 8. This reveals that while this DMU is efficient using their own resources, they could increase performance in areas for which other DMUs have found success. For the inefficient DMUs, their rank from the cross-efficiency score is similar to how high their own DEA efficiency is, however the cross efficiency scores are in general a few tenths lower than the efficiency score. Lastly, one key point is that Partner F has a cross-efficiency score of 1, meaning that they are efficient when considering every DMUs' weights.

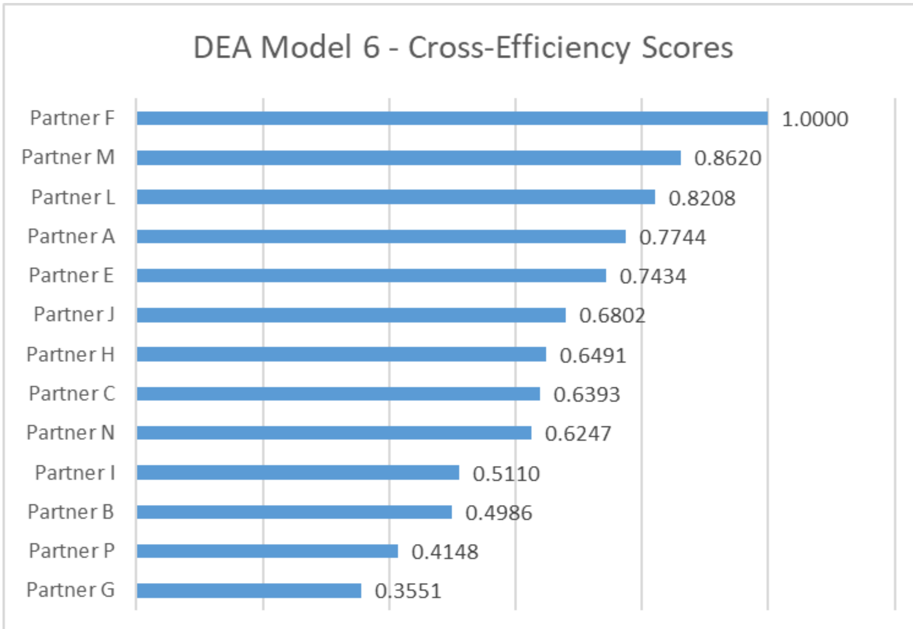

Figure 4.8 DEA Model 6 Cross-Efficiency Scores

4.3 Evaluating Results

After completing the 6 DEA models, we completed quantitative and qualitative analysis. For quantitative analysis, we examined the inputs and outputs to determine patterns in efficient and near-efficient DMUs. For qualitative analysis, we interviewed one of the Poverty Stoplight Program Managers to gain more information about the processes of the DMUs he oversees.

4.3.1 Quantitative Analysis

To start the quantitative analysis. We analyzed the weights on the inputs and outputs for the DMUs in Model 3 and 6. Since the inputs varied in range of values, we calculated their weight by multiplying the unit cost by the value of the input for each respective DMU. Figure 4.9 below shows the percentage that each input contributed for each DMU in Model 3. The DMUs are sorted from highest efficiency on the left to lowest efficiency on the right. For this model, many of the DMUs had only weight on the adaptation input, while the other DMUs had over 90% of their inputs from adaptation and the remaining portion from training. The adaptation input had a limited amount of variation in value, causing the model to favor this input. This figure also highlights the distinct lack of variation between the weights of the DMUs for this model. This enforces our decision to remove this input from future models in an attempt to get more variation.

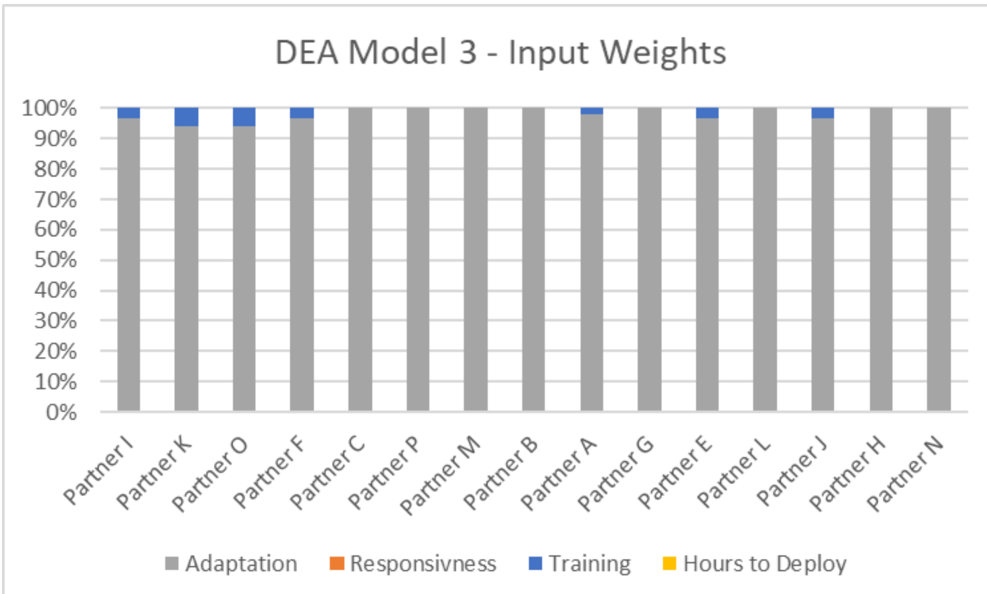

Figure 4.9 Input Weights for DMUs for Model 3

To analyze the outputs, we similarly analyzed the weights used for the values in each dimension of output. Figure 4.10 below shows the percentage of the weights for each DMU to get their efficiency score for Model 3. There is a lot of variation in this model for the weights on the outputs. The Income & Employment output was highly weighted across the majority of the DMUs. For the DMUs with the highest efficiency, there is distinct variation in the 3 efficient DMUs, Partner I, K, and O, as they each have different outputs weighted or the value of the weights on the output. This is further seen in the output weights when extending the view into the DMUs closest to efficiency, as there is a lot of variation in which outputs are valued and weighted by the DMUs where all 4 outputs are seen in the 4 most efficient DMUs. This insight shows that there is no output in which a DMU must be high performing to make them highly efficient, but rather it can come from any combination of the 4 outputs.

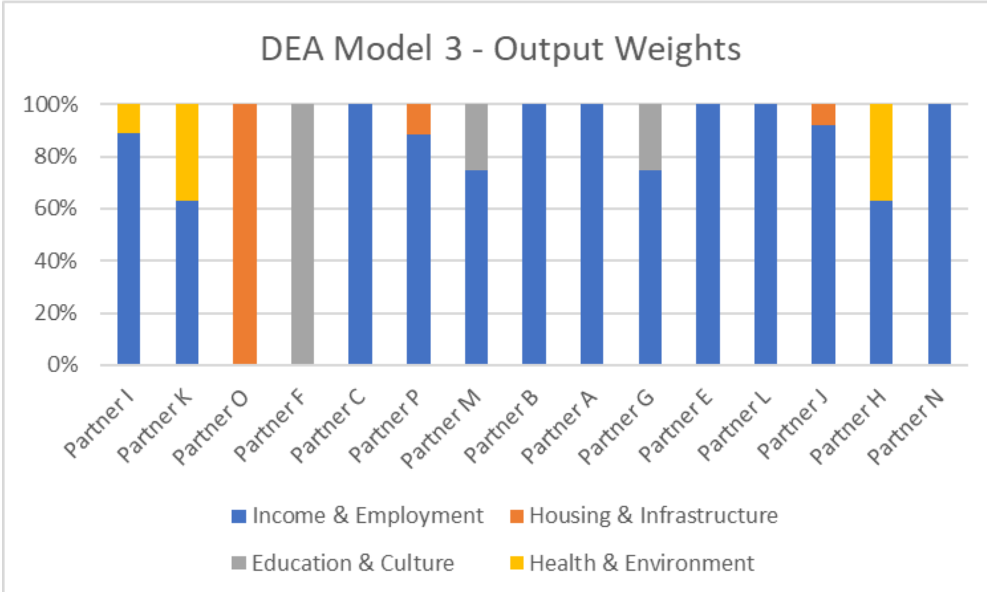

Figure 4.10 Output Weights for Model 3

We completed this analysis again for Model 6. For this model, there are now some DMUs that have weights on responsiveness, as seen in Figure 4.11, which was not the case for Model 3. However, training is still weighted more often and higher than responsiveness. Partners C, F, and M are efficient in this Model, and all three have different weights for their inputs, signifying that a DMU does not need a specific input to have greater efficiency.

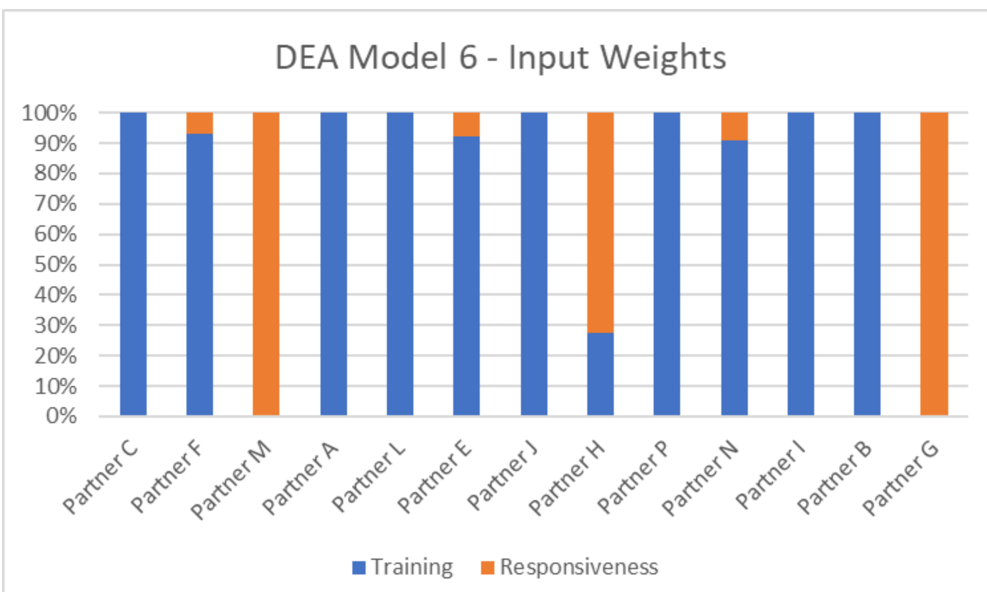

Figure 4.11 Input Weights for Model 6

Lastly, is the analysis of the output weights for Model 6. Figure 4.12 below shows the weights for each DMU, with Income & Employment still being the most frequently weighted output. One pattern of significance is how for many of efficient or close to efficient DMUs, there was also weight for the output of Health & Environment. While there is still some variation between the weights on each dimension, it is less than for Model 3. Additionally, for Model 6 there is no weight on the dimension of Education & Culture.

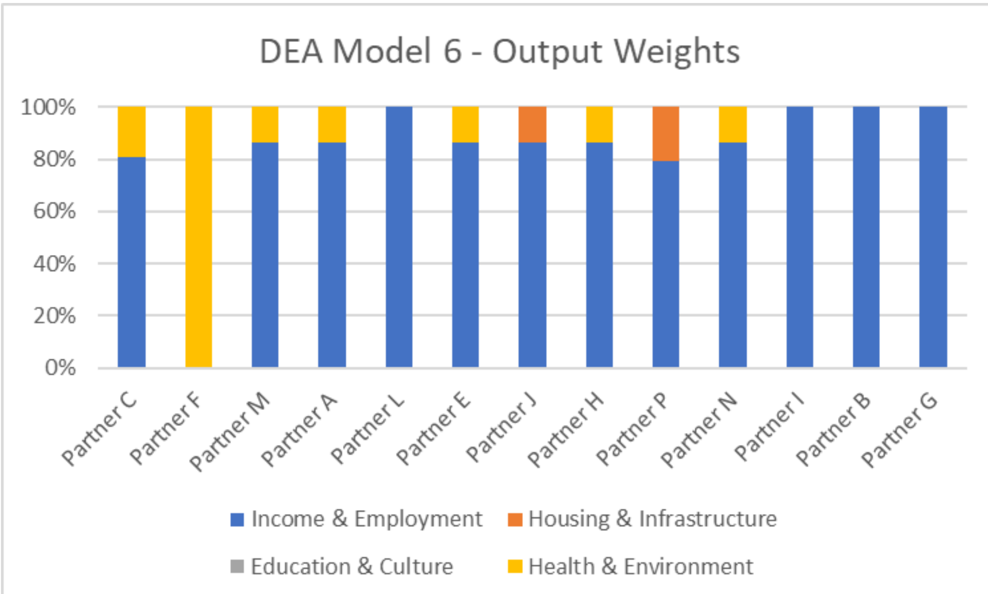

Figure 4.12 Output Weights for Model 6

4.3.2 Qualitative Analysis

Part of our evaluation of results involved interviewing a Poverty Stoplight Program Manager who oversees many of our DMUs, specifically Partners F, H, J, K, M, N, and O. From this discussion we were able to learn about these partners, their partnership with Poverty Stoplight, and their process for working with individuals and families. We learned that there were large differences between the partner's work with Poverty Stoplight and the data that we had for their organization. For example, Partner K had been working with Poverty Stoplight for 10 years, however, we only had data on 20 follow-up surveys. Additionally, Partner O has only recently started working with Poverty Stoplight, and should only have baseline surveys, meaning they should not be considered in our analysis, however, we had just under 150 follow-up surveys. However, despite the discrepancies in the data, these partners had severely low responsiveness values that were skewing the other results, and were then removed before Model 6.

Additionally, we learned about how the training of mentors works, the variation of budgets that partners have for Poverty Stoplight, and the different activities that partners can implement between the initial survey and follow-up survey to help their families improve in their levels of poverty. There were also discussions on some of the major challenges of each organization, such as levels of motivation from the partners and turnover in the program coordinators, who lead the Poverty Stoplight implementation for each partner. This interview and these insights deepened our knowledge of the Poverty Stoplight program for each Partner, which was significant for developing specific and relevant recommendations.

5.0 Recommendations

Throughout this project, we have formed some recommendations for Poverty Stoplight. These were gathered through our own observations working with PS and conducting this analysis.

We suggest the organizations be given minima or benchmarks to meet in certain areas to gain a better understanding of improvement when conducting future analyses. We recommend at least one full day of training for employees because it is important for administering the survey and identifying areas of improvement for the participants. Through previous discussions with PS, we determined a year between the initial survey and follow-up survey to be optimal to show the participants' progress. We advise that PS partner organizations aim to conduct follow-ups with participants about one year after their initial survey. We understand that this may not be feasible, so we recommend the follow-up survey be administered 6 months to a year after the initial survey to increase chances of progress being made and maintaining contact with the families.

We also recommend that Poverty Stoplight use DEA in the future. We believe that this type of data analysis would be very beneficial for them because they can continue to evaluate the efficiency of their organizations. From this, PS can use this information to make any needed changes, and further increase the amount of poverty they can alleviate. We are providing the template for the model we used for this project as well as instructions for how to use it. This instruction sheet can be viewed in Appendix B. For future analyses, we would also suggest standardizing their data collection process as much as possible to simplify the DEA process. One important standardization is to use the same names for each of the indicators across all organizations as well as translate each of their Excel sheets into a common language. Taking these steps will reduce the amount of data cleaning and standardization needed before future analysis can happen. We accomplished the data cleaning by sorting through the Excel sheets manually and changing indicators to have the same name, and then using a Python script to easily pick out the information needed.

We recommend getting as much follow-up data from participants as possible to increase the amount of data used in the analysis, therefore getting more representative results. Currently, the average number of follow-up surveys in the countries we have focused on are relatively low, as shown in Figure 5.1 below. With the organizations we analyzed, some of the average follow-up surveys per country were as few as 56. This is only about 26 percent of the baseline surveys that end up having a follow-up survey. If possible, we suggest that each organization should aim to follow-up with at least 50 percent of the families with baseline surveys. During our data exploration, we noticed that the priorities tab in the datasets, which showed each family's priority to change, contained little to no data for some organizations. Therefore, we also suggest gathering more priority data on each family because it could help focus future analyses and give more useful insights into if families are meeting their specific goals.

Figure 5.1 Average number of follow-up surveys per country for the DMUs

Additionally, we developed specific recommendations for the DMUs based on the DEA Models. For each output, the increase needed to reach efficiency was calculated for each DMU. Each Poverty Stoplight partner organization cannot change the surveys to directly increase the improvement for the families in the specific dimensions and indicators of poverty. However, having these values makes it clear what areas they should focus on in workshops, activities, and other mentoring that they have for their families. These recommendations on the outputs are developed from DEA Model 6.

The output value is the average indicator improvement between the baseline survey and follow-up survey. From this, the necessary improvement is how much the output value, and therefore the improvement in indicator levels, has to increase. While the specific value may be difficult to focus recommendation on, the amount of improvement needed for each DMU allows the partners to prioritize which dimension of indicators to focus on.

The first set of improvements is for the Income & Employment output. Figure 5.2 below shows the improvement needed for each partner to become efficient with their inputs. For DEA Model 6, the Income & Employment output was the most frequently weighted output. Since this output was prioritized for most DMUs, the necessary increase is lower than many other outputs. Partners C, F, and M are already efficient and therefore do not have an additional amount of increase needed. In general, as the efficiency for a DMU decreases, the more improvement is necessary. However, this is not directly related as if Partner 1 is 0.1 closer to efficiency than Partner 2, it does not mean there will be a 0.1 difference in the improvement needed for Partner 1 and 2.

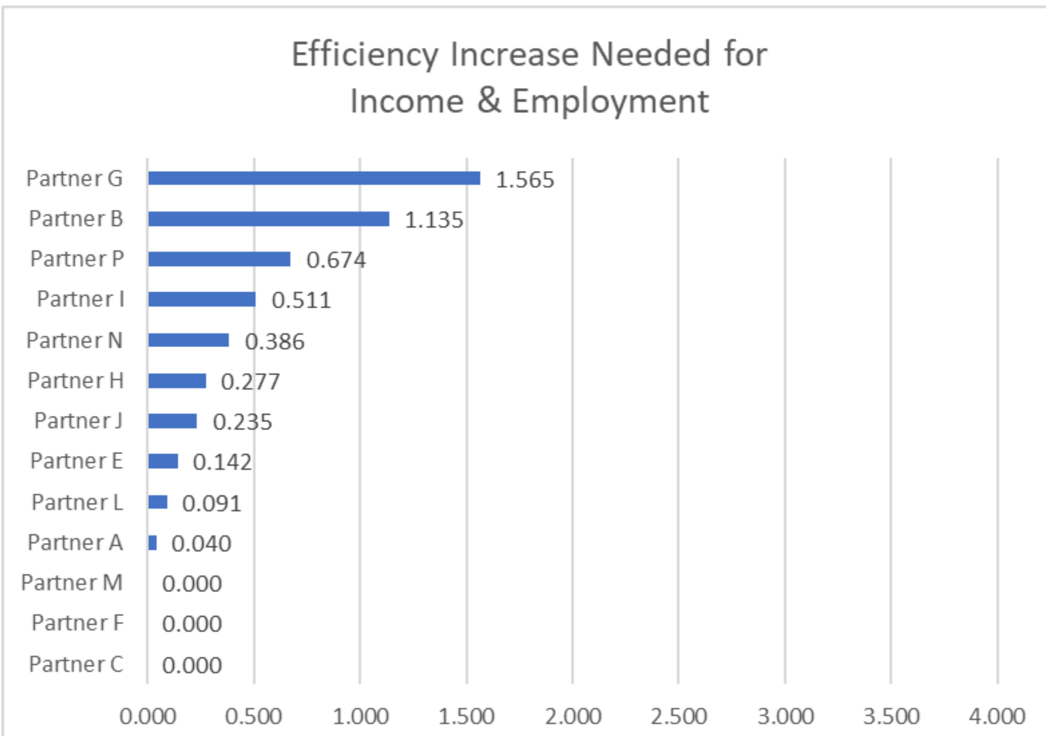

Figure 5.2 Increase Needed for Income & Employment Output

The next output is the Housing & Infrastructure dimension, with the increases necessary being shown in Figure 5.3 below. Unlike the Income & Employment output, the Housing & Infrastructure output is weighted very infrequently, with only two DMUs having a weight for the output, Partner J and Partner P. As this output is not as common to use as a weight, the necessary improvements are much higher, especially for Partner B and Partner G.

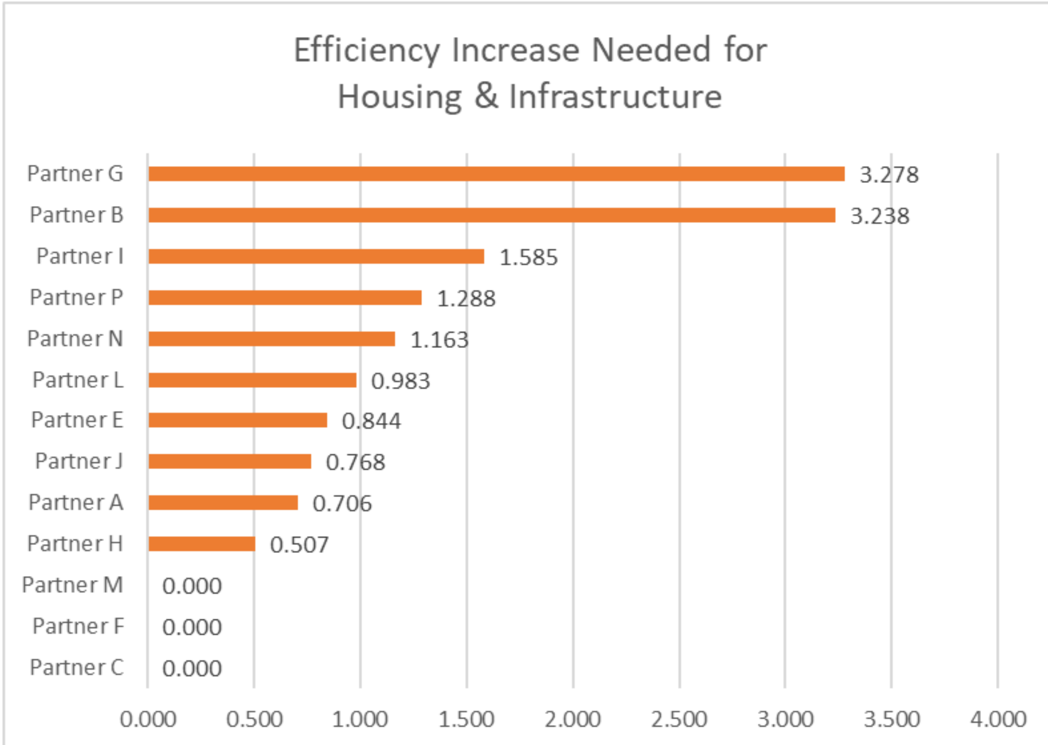

Figure 5.3 Increase Needed for Housing & Infrastructure Output

The third output is the Education & Culture output, which was the only output in DEA Model 6 that none of the DMUs had a weight for. Figure 5.4 reveals that while it was not weighted and thus was not used in any of the efficiency calculations, the increases needed for this output for the DMUs are less than for the Housing & Infrastructure output. This indicates that while not used, likely for many of the DMUs even a small improvement or focus on these indicators could allow for great benefit overall.

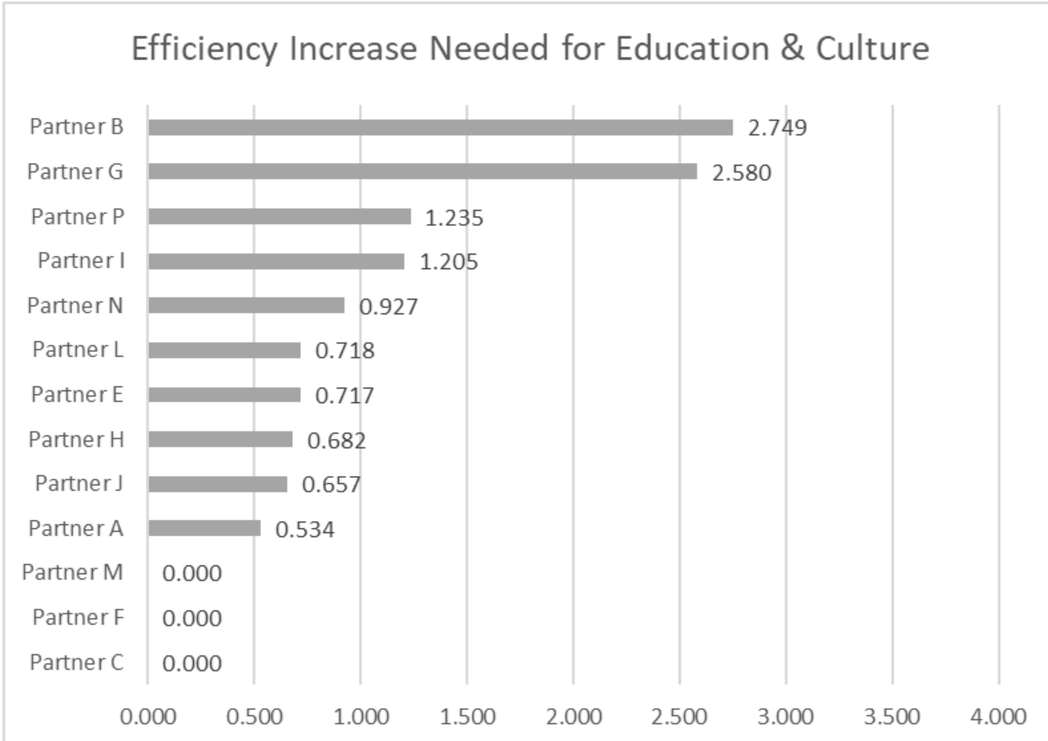

Figure 5.4 Increase Needed for the Education & Culture Output

Lastly, Figure 5.5 shows the increase in outputs needed for efficiency for the Health & Environment dimension. This was the output that had the second most weights, behind the Income & Employment dimension. While this output had a weight for 7 of the DMUs in Model 6, it also had some of the highest increases needed for the DMUs, however, this is not the case for all of the partners. For example, while Partner G has an increase needed of 3.635, Partner A only has an increase needed of 0.249, which is lower than two of the other outputs.

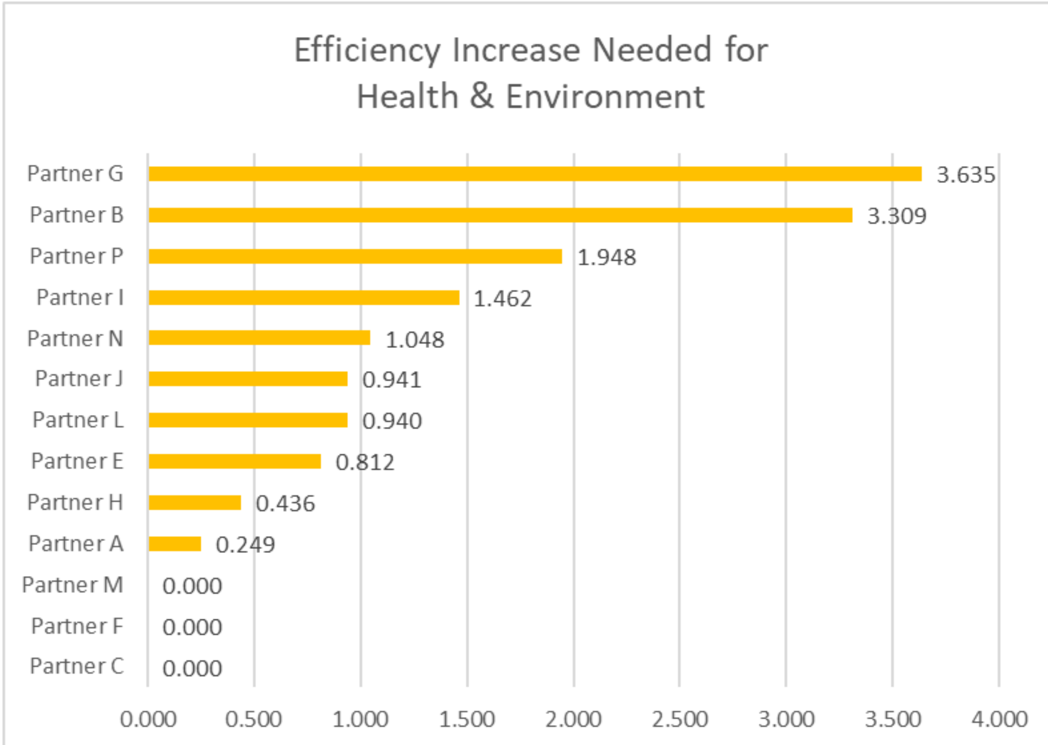

Figure 5.5 Increase Needed for Health & Environment Output

Based on the 4 charts of each individual output, the increase needed for each DMU to reach efficiency was ranked and then prioritized. A higher value of needed increase means there is more improvement necessary for a DMU to reach efficiency. Therefore, that output should be prioritized more than a different output with less increase needed. The results of this are shown in Table 5.1 below, excluding Partners C, F, and M as these are already efficient partner organizations. These prioritizations will allow the DMUs to focus their efforts and activities on helping their individuals and families in these specific areas as a focus. For the DMUs, there was variation in priorities 1, 2, and 3 between the Housing & Infrastructure, Education & Culture, and Health & Environment outputs. However, for all DMUs, the lowest prioritized, or fourth ranked output is the Income & Employment Output.

DMU	Income & Employment	Housing & Infrastructure	Education & Culture	Health & Environment
Partner A	4	1	2	3
Partner B	4	2	3	1
Partner E	4	1	3	2
Partner G	4	2	3	1
Partner H	4	2	1	3
Partner I	4	1	3	2
Partner J	4	2	3	1
Partner L	4	1	3	2
Partner N	4	1	3	2
Partner P	4	2	3	1

Table 5.1 Prioritization for Improvement

6.0 Conclusion

The aim of this project was to analyze a portion of organizations with which Poverty Stoplight partners in relation to the Stoplight survey which they administer. Our goal was to determine what characteristics were efficient to help families that are living in poverty and provide recommendations to PS to help improve efficiency between them and their partner organizations.

To accomplish this, we followed the steps of the Data Science Life Cycle and implemented Data Envelopment Analysis. The DSLC involved steps of understanding our goal, data collection, data cleaning, exploration, analysis, and visualization. Our sponsor, Poverty Stoplight, was very helpful providing us with any information and answers we needed throughout this process. We started by sorting through the data and standardizing names of columns that we would be using as well as translating what we needed into a common language. Then, to determine which organizations would be used for DEA, the use of Python Scripts proved to be extremely useful for deciding the homogeneity criteria. We ended up with 16 organizations that fit this criteria, which ended up being our DMUs. We also defined our 4 inputs and 4 outputs to be used in our initial DEA model. We ran 6 models in total with different combinations of these DMUs, inputs, and outputs to remove any data points that skewed results. Finally, we performed cross-efficiency on two of the models that showed the most variation. Our results showed 3 partners that were efficient, with those being partners C, F, and M.

6.1 Limitations

One of the main limitations we ran into was the amount of data that was available for us to use. The goal of our project was to analyze all of the Poverty Stoplight partners, but had to limit this analysis to only 16 partners that had a comparable amount of data. A factor that contributed to this shortened dataset was a lack of results Poverty Stoplight received from their Organizational Questionnaire. A concurrent MQP was conducted by one member of this group to satisfy a Professional Writing double major requirement. Analysis of Poverty Stoplight's Organizational Questionnaire and the Relationship between Survey Design and Response Rate by Kayla Brown investigates the reasons for nonresponse and best practices used in survey design to assist Poverty Stoplight in their future facilitation of surveys. Since the scope of the project was tightened, we were only able to analyze a select number of partner resource inputs and survey outputs. We understand that Poverty Stoplight partners with many organizations from all around the world and it is difficult to get the needed information, especially given our time constraint for this project. We believe that if PS is able to collect this data and implement DEA on the timeline that works best for them, that this analysis would be very beneficial to achieve their goals of improving efficiency.

We encountered another issue when interviewing a Poverty Stoplight program officer. The program officer mentioned that a couple of the organizations had only baseline surveys and no follow-ups, however on our end the data showed that they did have follow-up surveys listed. We learned this information after our analysis had been completed, and this could have been a problem if those DMUs no longer met the homogeneity criteria. Fortunately, a few of our models already had these DMUs removed for other reasons so we did not have to re-run the DEA. As mentioned in our recommendations to PS, a standardization in the collection and formatting of data can help avoid these occurrences and make data analyses more simple.

6.2 Future Work

Data Envelopment Analysis would be very beneficial for Poverty Stoplight to continue to implement to further evaluate the efficiencies of partner organizations. As we learned more about the organizations and their processes after completing our analysis, we found insights and items that could be implemented into DEA as an input. Additionally, as we focused our analysis on Partners in Latin America, there are many more partners across the globe. As mentioned in the Recommendations Section, for the future use of DEA by Poverty Stoplight, we created an Instructions Sheet to assist in the implementation, which can be seen in Appendix B. This Instruction Sheet details the main sections of the template, the Microsoft Excel Solver Parameters, and general guidelines about DEA and the data to allow for the best possible results.

The inputs and outputs we utilized can still be used for other Partner Organizations, or new/additional inputs and outputs can be implemented. The template in the instruction sheet leaves this option open by having generic titles for all sections. For example, from what we learned through our interview with a Poverty Stoplight Program Manager, different partners will have varying budgets and hold different types of activities throughout the year, and both of these items could be potential inputs for a future DEA model.

Taking our results and what we have learned from this process, we provided recommendations to Poverty Stoplight to take into consideration for the future. These suggestions include giving organizations minimums or benchmarks in certain areas such as amount of training and time between follow-up surveys, getting more follow-ups and priority data, standardizing data collection, and using DEA in future analyses.

7.0 Reflections

We were very fortunate to have such an amazing and responsive sponsor, Poverty Stoplight. They supported us throughout this project with any information we needed. Overall, this project was enjoyable and engaging. We learned new methods and technologies through the use of Data Envelopment Analysis. None of us had used this optimization method before, so it was a great opportunity to research and apply DEA to Poverty Stoplight. We had discussions on how best to define inputs and what the homogeneity criteria should be for the DMUs. It was also a great experience in problem solving as we had to adjust our models throughout the process to gain the most insights. In addition to learning about DEA, we also learned about new methods through the use of Cross-Efficiency to help us gain more insight about our initial results from DEA.

Working in our MQP team for this academic year has also taught us valuable lessons on working in a team for a longer term. We have learned a lot about each other and our own strengths and weaknesses and how we can play towards each other's strengths to support each other and provide the best outcome for the team as a whole. We also learned how important communication is, especially with our advisors and sponsors. Being open about the project and current statuses in our meetings allowed for the most progress to be made as they were able to support us and help us discuss how best to proceed.

However, we did have some challenges along the way. One of which was not being able to get as much data about the partner organizations. This data would have helped us define more homogeneity criteria for our DMUs and make our DEA model stronger. This issue came from a lack of survey responses from partner organizations. If we could do this project over again, we would send that survey out months before our project officially started. This way, the organizations would have more time to respond. It also would have been beneficial for us to speak with the global representatives at Poverty Stoplight earlier to learn more about each of the organizations. We are glad that we did end up meeting towards the end of our project to learn more about the processes as a whole and to figure out why the data analysis of Partner O and Partner K seemed different than the other DMUs. However, this information would have been more beneficial early in our analyses. Additionally, for the data we had challenges with regional differences. Sometimes the indicators used by Partner organizations had slightly different names, so there was an initial challenge of ensuring that everything was properly translated and defined.

Despite these challenges, this project was a valuable experience for us. We are grateful that we had the opportunity to work with Poverty Stoplight and our advisors throughout this process. This project provided us with a better understanding of how to conduct an analysis and work as a team towards a common goal. We will take this experience and the lessons we have learned from it with us into our future endeavors.

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Appendix A: Program Manager Interview Questions

General Questions for All:

- Can you briefly explain the partner organizations' processes of working with families?
    - What resources do you provide to families?
    - How long of a time frame do you aim to have between the initial survey with the families and the second survey with the families?
    - How are these surveys administered? Is the process different between organizations?
- How does each partner train their mentors? How long is this training and what does it entail?
- How long has your organization been working with Poverty Stoplight?
    - Are they still working with PS currently?
- Are there any noticeable differences between organizations?
    - Such as in communication, workflow, and proactiveness?
- What are notable challenges for each partner organization? What are specific areas of success for each partner organization?
- Are there any notable differences between organizations that we should take into account during our analysis?
    - If any of their processes are majorly different to others, factors about how they operate that may explain their performance?

Questions for Specific DMUs:

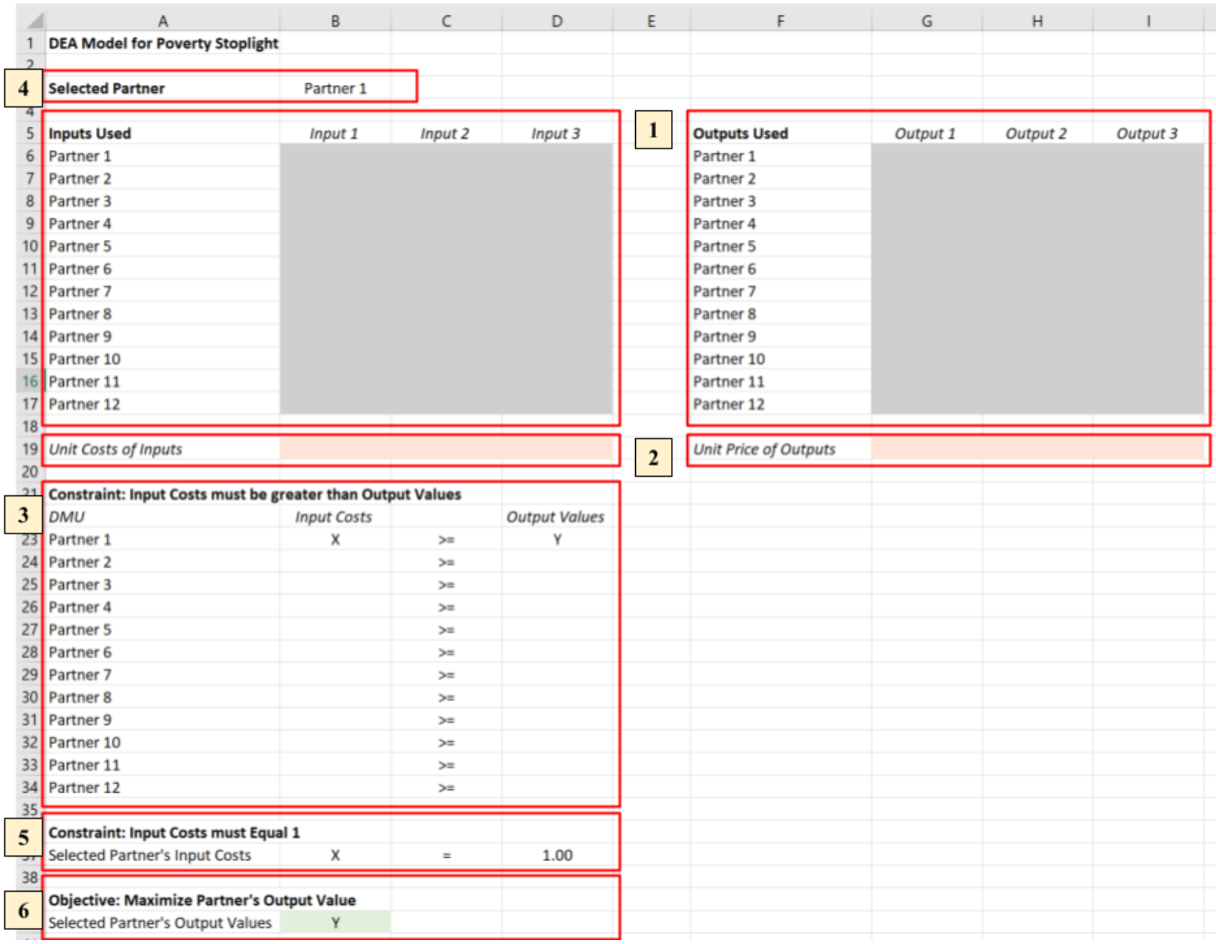
<u>Parner O</u>

- How is this DMU making so much progress given there is an average of about 5 days between survey responses?
- What is this organization doing/what resources do they provide to help families progress?

<u>Partner K</u>

- How is this DMU making so much progress given there is an average of about a week between survey responses?
- What is this organization doing/what resources do they provide to help families progress?

Appendix B: DEA Instruction Sheet for Poverty Stoplight



	A	B	C	D	E	F	G	H	I
1	**DEA Model for Poverty Stoplight**								
2									
3	**Selected Partner**	Partner 1							
4									
5	**Inputs Used**	*Input 1*	*Input 2*	*Input 3*		**Outputs Used**	*Output 1*	*Output 2*	*Output 3*
6	Partner 1					Partner 1			
7	Partner 2					Partner 2			
8	Partner 3					Partner 3			
9	Partner 4					Partner 4			
10	Partner 5					Partner 5			
11	Partner 6					Partner 6			
12	Partner 7					Partner 7			
13	Partner 8					Partner 8			
14	Partner 9					Partner 9			
15	Partner 10					Partner 10			
16	Partner 11					Partner 11			
17	Partner 12					Partner 12			
18									
19	*Unit Costs of Inputs*					*Unit Price of Outputs*			
20									
21	**Constraint: Input Costs must be greater than Output Values**								
22	*DMU*	*Input Costs*		*Output Values*					
23	Partner 1	X	>=	Y					
24	Partner 2		>=						
25	Partner 3		>=						
26	Partner 4		>=						
27	Partner 5		>=						
28	Partner 6		>=						
29	Partner 7		>=						
30	Partner 8		>=						
31	Partner 9		>=						
32	Partner 10		>=						
33	Partner 11		>=						
34	Partner 12		>=						
35									
36	**Constraint: Input Costs must Equal 1**								
37	Selected Partner's Input Costs	X	=	1.00					
38									
39	**Objective: Maximize Partner's Output Value**								
40	Selected Partner's Output Values	Y							

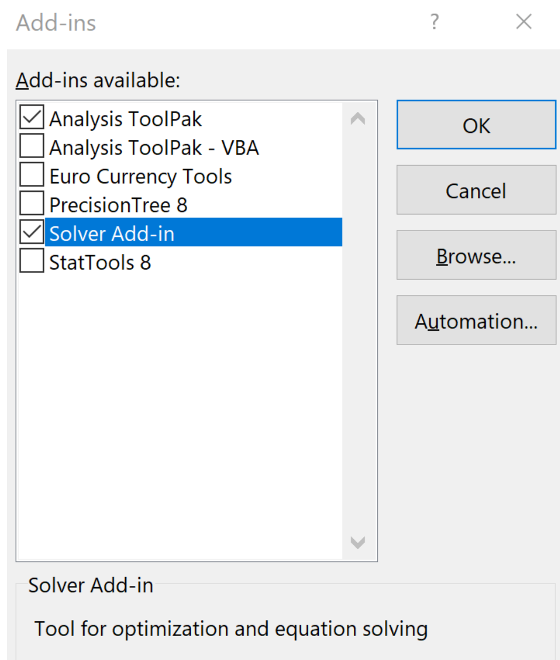
Above is the template for a DEA Model for Poverty Stoplight. We will go step by step for each section to discuss what is required to complete this analysis.

1. **Inputs & Outputs:** This section is the basis of the model. Across the first row list the inputs and outputs you plan to use and down the first column of each section list the Decision Making Units (DMUs). The general guideline is that there should be at least twice the amount of the DMUs than the number of inputs and outputs. For this template example, there are 3 inputs and 3 outputs so there should be at least 12 DMUs. Then, in the gray areas, add the values for the inputs and outputs for each DMU.
2. **Unit Price & Unit Costs:** This section is a part of the optimization model. These cells must be there, but do not need to have data in advance as the model will generate the optimized weights.

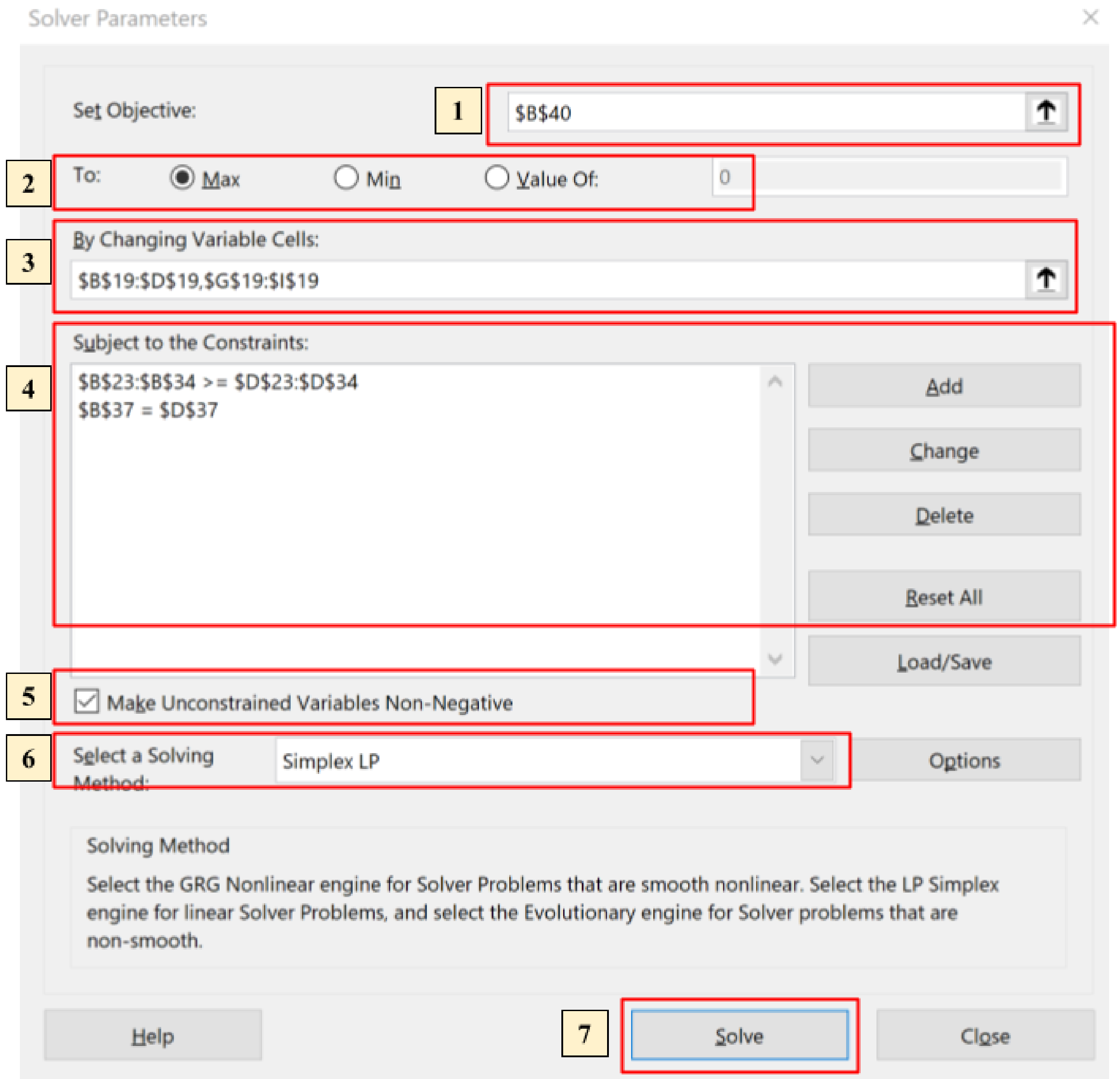
3. **Constraint 1:** For any DMU, the costs of their inputs must be greater than or equal to the value of their outputs, as a DMU cannot have an efficiency greater than 1. In the column under "Input Costs", the formula =SUMPRODUCT(B6:D6,$B$19:$D$19) where B6:B9 is the coordinating value of the inputs from the table in section 1, and $B$19:$D$19 is the unit costs of inputs from Section 2 which stays the same for all Partners. In the column under "Output Values", the formula is similar as =SUMPRODUCT(G6:I6,$G$19:$I$19) where G6:I6 is the coordinating value of outputs from the table in section 1, and $G$19:$I$19 is the unit prices of outputs from Section 2.
4. **Selected Partner:** When the DEA optimization is run, a specified Partner must be selected to determine that Partner's efficiency. This selected partner must be adjusted each run so all DMUs efficiency can be calculated. In this template, to start Partner 1 is selected.
5. **Constraint 2:** For the selected DMU, their input costs must equal 1 in order to then maximize the output value. For Partner 1, their Input Cost is X, which is seen in Section 3 and Section 5. The formula to get the selected partner's input cost from the table to this section is the following: =VLOOKUP(B3,A23:D34,2). In this formula B3 is the cell that contains the selected partner, A23:D24 is the table contained in Section 3, and 2 is the second column in that table, which is the column titled "Input Costs".
6. **Objective:** For this model, the objective is to maximize the outputs. With the constraint that the Input Cost must be greater than or equal to the Output Value, and that the Input Cost must equal 1, for a DMU to be efficient, the Output Value will be 1. For Partner 1, their Output Value is Y, which is seen in Section 3. The formula to get the selected partner's output value from the table to this section is the following: =VLOOKUP(B3, A23:D24,4). In this formula, B3 is the cell that contains the selected partner, A23:D34 is the table contained in Section 3, and 4 is the fourth column in that table, which is the column titled "Output Values."

For the formulas listed above, be sure to edit the cells referenced as inputs, outputs, and DMUs are added or removed. Now that the data and formulas for the models are set up, the optimization model can be run.

This optimization is done through the Solver function in Microsoft Excel. The Solver function can be found under the Data Tab. If the Solver function does not appear, then the Solver add-in must be added. To do this, go to File, Options, Add-Ins, Manage Add-Ins. You should see the following window:



Make sure that the Solver Add-in is selected, then press "OK". Now, the Solver function should be seen in the Data tab. The Solver function allows for optimization parameters to be set, and below shows completed solver parameters for this template with details for each section.



1. **Set Objective:** In Section 6 of the template, the objective formula is set. In the solver parameters, enter this cell into the Set Objective Box.
2. **Set Objective To:** The goal is to maximize the output value, so select "Max".
3. **By Changing Variable Cells:** These are the unit costs and unit prices from Section 2. Be sure to separate these two sets of cells with a comma in between.
4. **Constraints:** The first constraint selects the "Input Costs" column and says that those values must be greater than or equal to the "Output Costs" column, both of which are

from Section 3 of the template. The second constraint selects the Selected Partner's Input Costs from Section 5 and requires that value to be 1. These constraints can be added, changed, or deleted through the buttons on the side.

5. **Make Unconstrained Variables Non-Negative:** Be sure that this checkbox is selected. This will ensure that all variables are non-negative. For example, the unit costs and prices will be either 0 or a positive value.
6. **Solving Method:** The Solving Method for this Optimization Model is "Simplex LP". This is not the default method so be sure to change using the drop down.
7. **Solve:** After all cells and formulas are completed, the objective, constraints, and solving method are set, the model is ready to be solved. This will autofill the decision variables and objectives. The solve button will need to be selected after each Selected Partner is changed, but the other sections of the Solver Parameters will remain the same.

Lastly, below are some general guidelines for DEA and the data to ensure the success of the optimization model.

1. The data for the inputs and outputs for each DMU should be positive.
2. The data must be going in the same "direction." This means that all inputs and outputs should either have the highest value being the best or the lowest value being the best, but it must be consistent between all inputs and outputs. If there is an input or output where the best value is different from the rest, then the data must be transformed.
3. There should be at least twice the number of DMUs than inputs and outputs.
4. The DMUs should be similar and have some homogeneity criteria. This ensures that "like" organizations are being compared.

If there are any further questions, please contact us at gr-PovertyStoplightMQP@wpi.edu.

Appendix C: Python Scripts

All of the Python scripts mentioned in this report can be viewed below or by going to this Github link: https://github.com/hgsmith-wpi/PovertyStoplightMQP

getSecondSurveyData.py

```
import pandas as pd
import os
import glob

#get all excel files under the path
path = os.getcwd()
csv_files = glob.glob(os.path.join(path, "*.xlsx"))

firstSurveys = []
secondSurveys = []

#add up how many second surveys each organization has
def countSecondSurveys(df):
    #get Survey Number and Organization
    organizationDict = {}
    organizations = df['Organization']
    families = df['Family code']
    surveys = df['Survey number']
    for i in range(len(surveys)):
        if surveys[i] == "1º":
            firstSurveys.append(families[i])
        elif surveys[i] == "2º":
            secondSurveys.append(families[i])
        if families[i] in firstSurveys and families[i] in
secondSurveys:
            if organizations[i] in organizationDict:
                organizationDict[organizations[i]] =
organizationDict.get(organizations[i]) + 1
            else:
                organizationDict[organizations[i]] = 1
    return organizationDict
```

```
#print out the organizations with their amount of follow-up surveys
for file in csv_files:
    df = pd.read_excel(file)
    print(file)
    organizationDict = countSecondSurveys(df)
    keys = organizationDict.keys()
    for key in keys:
        print(key + ": " + str(organizationDict.get(key)))
```

AverageTime.py

```
import pandas as pd
from datetime import datetime


df = pd.read_excel("familyCodes-Family.xlsx")

#names of the 16 organizations we are using as DMUs
organizationTotal = {'A' : 0, 'B' : 0, 'C' : 0, 'D': 0,
 'E' : 0, 'F' : 0, 'G':0, 'H':0, 'I':0, 'J':0, 'K':0,
  'L':0, 'M':0, 'N':0, 'O':0, 'P':0}

dates = df['surveyDate']
organizations = df['organizationName']
data = pd.DataFrame()

#get the responsiveness of each organization (time between each
survey)
for i in range(0,len(df),2):
    if organizationTotal.get(organizations[i]) != None:
        date1 = datetime.strptime(str(dates[i]), '%Y-%m-%d %H:%M:%S')
        date2 = datetime.strptime(str(dates[i+1]), '%Y-%m-%d
%H:%M:%S')
        organizationTotal[organizations[i]] +=  (date2-date1).days

#divide the total responsiveness by the amount of follow-up surveys
from the organization
for org in organizationTotal:
    organizationTotal[org] = organizationTotal[org]/(organizations ==
org).sum()

print(organizationTotal)
```

makeCSVWithFamilies.py

```
import pandas as pd
import os
import glob

path = os.getcwd()
csv_files = glob.glob(os.path.join(path, "*.xlsx"))

firstSurveys = []
secondSurveys = []

data = pd.DataFrame()

#get all follow-up surveys
def countSecondSurveys(df):
    #get Survey Number and Organization
    families = df['familyCode']
    surveys = df['surveyNumber']
    firstAndSecondSurveys = []
    for i in range(len(surveys)):
        if surveys[i] == "1º":
            firstSurveys.append(families[i])
        elif surveys[i] == "2º":
            secondSurveys.append(families[i])
        if families[i] in firstSurveys and families[i] in
secondSurveys:
            firstAndSecondSurveys.append(families[i])
    return firstAndSecondSurveys

#get families with follow-up surveys
for file in csv_files:
    df = pd.read_excel(file, sheet_name="Families")
    surveys = countSecondSurveys(df)
    for survey in surveys:
        data = data.append(df[df['familyCode'] == survey])

#make csv with family data
data.to_csv('familyCodes-Family.csv', index=False)
```

makeCSVWithIndicators.py

```
import pandas as pd
import os
import glob

path = os.getcwd()
csv_files = glob.glob(os.path.join(path, "*.xlsx"))

firstSurveys = []
secondSurveys = []

data = pd.DataFrame()

#get all follow-up surveys
def countSecondSurveys(df):
    #get Survey Number and Organization
    families = df['familyCode']
    surveys = df['surveyNumber']
    firstAndSecondSurveys = []
    for i in range(len(surveys)):
        if surveys[i] == "1º":
            firstSurveys.append(families[i])
        elif surveys[i] == "2º":
            secondSurveys.append(families[i])
        if families[i] in firstSurveys and families[i] in
secondSurveys:
            firstAndSecondSurveys.append(families[i])
    return firstAndSecondSurveys

#get indicators with follow-up surveys
for file in csv_files:
    df = pd.read_excel(file, sheet_name="Indicators")
    surveys = countSecondSurveys(df)
    for survey in surveys:
        data = data.append(df[df['familyCode'] == survey])

#make csv with indicator data
data.to_csv('familyCodes.csv', index=False)
```

makeCSVWithPriorities.py

```
import pandas as pd
import os
import glob

path = os.getcwd()
csv_files = glob.glob(os.path.join(path, "*.xlsx"))

firstSurveys = []
secondSurveys = []

data = pd.DataFrame()

#get all follow-up surveys
def countSecondSurveys(df):
    #get Survey Number and Organization
    families = df['familyCode']
    surveys = df['surveyNumber']
    firstAndSecondSurveys = []
    for i in range(len(surveys)):
        if surveys[i] == "1º":
            firstSurveys.append(families[i])
        elif surveys[i] == "2º":
            secondSurveys.append(families[i])
        if families[i] in firstSurveys and families[i] in
secondSurveys:
            firstAndSecondSurveys.append(families[i])
    return firstAndSecondSurveys

#get priorities with follow-up surveys
for file in csv_files:
    df = pd.read_excel(file, sheet_name="Priorities")
    surveys = countSecondSurveys(df)
    for survey in surveys:
        data = data.append(df[df['familyCode'] == survey])

#make csv with priority data
data.to_csv('familyCodes-Priorities.csv', index=False)
```

EducationCulture.py

```
import pandas as pd

df = pd.read_excel("familyCodes-Indicators.xlsx")

#total number of improvements for each organization
organizationTotal = {'A' : 0, 'B' : 0, 'C' : 0, 'D': 0,
 'E' : 0, 'F' : 0, 'G':0, 'H':0, 'I':0, 'J':0, 'K':0,
  'L':0, 'M':0, 'N':0, 'O':0, 'P':0}

#number follow-up surveys from each organization
organizationOccurences = {'A' : 0, 'B' : 0, 'C' : 0, 'D': 0,
 'E' : 0, 'F' : 0, 'G':0, 'H':0, 'I':0, 'J':0, 'K':0,
  'L':0, 'M':0, 'N':0, 'O':0, 'P':0}

#indicators that are in education & culture
schooling = df['Schooling']
literacy = df['Literacy']
internet = df['Internet']
organizations = df['organizationName']

#add up each indicator changes per family
for i in range(0,len(schooling),2):
    if organizationTotal.get(organizations[i]) != None:
        schoolingDifference = schooling[i+1] - schooling[i]
        literacyDifference = literacy[i+1] - literacy[i]
        internetDifference = internet[i+1] - internet[i]
        organizationTotal[organizations[i]] +=
(schoolingDifference+literacyDifference+internetDifference)
        organizationOccurences[organizations[i]] += 1
print(organizationTotal)

#divide by the amount of follow-up surveys
for organization in organizationTotal:
    organizationTotal[organization]  /=
organizationOccurences[organization]
print(organizationTotal)
```

HealthEnvironment.py

```
import pandas as pd

df = pd.read_excel("familyCodes-Indicators.xlsx")

#total number of improvements for each organization
organizationTotal = {'A' : 0, 'B' : 0, 'C' : 0, 'D': 0,
 'E' : 0, 'F' : 0, 'G':0, 'H':0, 'I':0, 'J':0, 'K':0,
  'L':0, 'M':0, 'N':0, 'O':0, 'P':0}

#number follow-up surveys from each organization
organizationOccurences = {'A' : 0, 'B' : 0, 'C' : 0, 'D': 0,
 'E' : 0, 'F' : 0, 'G':0, 'H':0, 'I':0, 'J':0, 'K':0,
  'L':0, 'M':0, 'N':0, 'O':0, 'P':0}

#indicators that are in Health & Environment
garbage = df['Garbage']
water = df['Water']
healthServices = df['Health services']
safety = df['Safety']
security = df['Security of property']
organizations = df['organizationName']

#add up each indicator changes per family
for i in range(0,len(garbage),2):
    if organizationTotal.get(organizations[i]) != None:
        garbageDifference = garbage[i+1] - garbage[i]
        waterDifference = water[i+1] - water[i]
        healthServicesDifference = healthServices[i+1] -
healthServices[i]
        safetyDifference = safety[i+1] - safety[i]
        securityDifference = security[i+1] - security[i]
        organizationTotal[organizations[i]] +=
(garbageDifference+waterDifference+healthServicesDifference+safetyDif
ference+securityDifference)
        organizationOccurences[organizations[i]] += 1
print(organizationTotal)

#divide by the amount of follow-up surveys
```

```
for organization in organizationTotal:
    organizationTotal[organization]  /=
organizationOccurences[organization]
print(organizationTotal)
```

HousingInfrastructure.py

```
import pandas as pd

df = pd.read_excel("familyCodes-Indicators.xlsx")

#total number of improvements for each organization
organizationTotal = {'A' : 0, 'B' : 0, 'C' : 0, 'D': 0,
 'E' : 0, 'F' : 0, 'G':0, 'H':0, 'I':0, 'J':0, 'K':0,
  'L':0, 'M':0, 'N':0, 'O':0, 'P':0}

#number follow-up surveys from each organization
organizationOccurences = {'A' : 0, 'B' : 0, 'C' : 0, 'D': 0,
 'E' : 0, 'F' : 0, 'G':0, 'H':0, 'I':0, 'J':0, 'K':0,
  'L':0, 'M':0, 'N':0, 'O':0, 'P':0}

#indicators that are in Housing & Infrastructure
enoughSpace = df['Enough space']
kitchen = df['Kitchen']
bathroom = df['Bathroom']
phone = df['Phone']
electricity = df['Electricity']
organizations = df['organizationName']

#add up each indicator changes per family
for i in range(0,len(enoughSpace),2):
    if organizationTotal.get(organizations[i]) != None:
        spaceDifference = enoughSpace[i+1] - enoughSpace[i]
        kitchenDifference = kitchen[i+1] - kitchen[i]
        bathroomDifference = bathroom[i+1] - bathroom[i]
        phoneDifference = phone[i+1] - phone[i]
        electricityDifference = electricity[i+1] - electricity[i]
        organizationTotal[organizations[i]] +=
(spaceDifference+kitchenDifference+bathroomDifference+phoneDifference
```

```
+electricityDifference)
        organizationOccurences[organizations[i]] += 1
print(organizationTotal)

#divide by the amount of follow-up surveys
for organization in organizationTotal:
    organizationTotal[organization]  /=
organizationOccurences[organization]
print(organizationTotal)
```

IncomeEmployment.py

```
import pandas as pd

df = pd.read_excel("familyCodes-Indicators.xlsx")

#total number of improvements for each organization
organizationTotal = {'A' : 0, 'B' : 0, 'C' : 0, 'D': 0,
 'E' : 0, 'F' : 0, 'G':0, 'H':0, 'I':0, 'J':0, 'K':0,
  'L':0, 'M':0, 'N':0, 'O':0, 'P':0}

#number follow-up surveys from each organization
organizationOccurences = {'A' : 0, 'B' : 0, 'C' : 0, 'D': 0,
 'E' : 0, 'F' : 0, 'G':0, 'H':0, 'I':0, 'J':0, 'K':0,
  'L':0, 'M':0, 'N':0, 'O':0, 'P':0}

#indicators that are in Income & Employment
income = df['Income']
savings = df['Savings']
credit = df['Credit']
organizations = df['organizationName']

#add up each indicator changes per family
for i in range(0,len(income),2):
    if organizationTotal.get(organizations[i]) != None:
        incomeDifference = income[i+1] - income[i]
        savingsDifference = savings[i+1] - savings[i]
        creditDifference = credit[i+1] - credit[i]
        organizationTotal[organizations[i]] +=
```

```
(incomeDifference+savingsDifference+creditDifference)
        organizationOccurences[organizations[i]] += 1
print(organizationTotal)

#divide by the amount of follow-up surveys
for organization in organizationTotal:
    organizationTotal[organization]  /=
organizationOccurences[organization]
print(organizationTotal)
```

Appendix D: Input-Oriented DEA Model Results

We based our methods and results off of an output-oriented DEA model since this allows each DMU to focus on maximizing their improvement, and therefore focus on the improvement of poverty levels of their families. However, we also completed one input-oriented model for a more complete analysis. An input-oriented DEA model has DMUs vary their inputs, or resources, to allow their outputs to hit a desired level. The optimization model below shows the defined variables and sets, objective, and constraints used.

Sets

D	Set of decision making units
I	Set of inputs
O	Set of outputs

Parameters

w_{id}	Amount of input i ∈ I for DMU d ∈ D
v_{od}	Amount of output o ∈ O for DMU d ∈ D

Decision Variables

x_i	Weight given to input i ∈ I
y_o	Weight given to output o ∈ O

Model:

$$Minimize: \sum_{o \in O} w_{id_0} x_o$$

$$Subject\ to: \sum_{i \in I} v_{od_0} y_i = 1$$

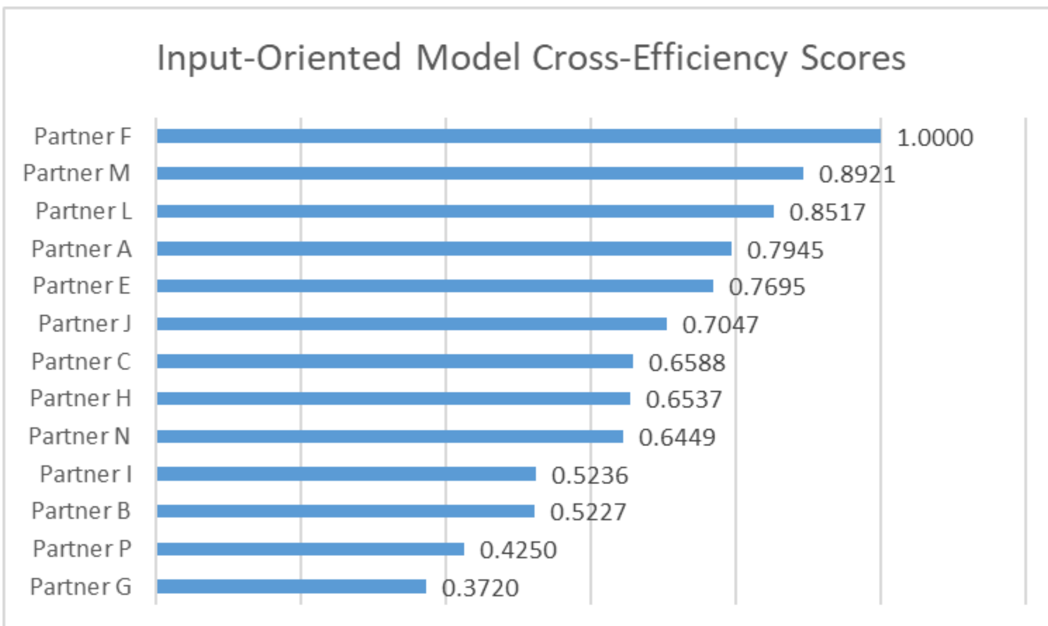
$$\sum_{i \in I} w_{id}\, x_i - \sum_{o \in O} v_{od}\, y_o \geq 0 \quad \forall\, d \in D$$

$$x_i, y_o \geq 0 \quad \forall\, i \in I,\ \forall\, o \in O$$

For our input-oriented DEA model, we based the model after DEA Model 6 in our report. This model had 2 inputs, 4 outputs, and 13 DMUs. The results of this model are shown below:

DMU	Efficiency	Training	Responsivness	Income & Employment	Housing & Infrastructure	Education & Culture	Health & Environment
Partner A	0.9766	1.0239	0.0000	0.6174	0.0000	0.0000	0.0965
Partner B	0.5643	0.8232	0.0008	0.6800	0.0000	0.0000	0.0000
Partner C	1.0000	0.1593	0.0084	0.6418	0.0000	0.0000	0.0000
Partner E	0.8995	1.1117	0.0000	0.6703	0.0000	0.0000	0.1048
Partner F	1.0000	1.0000	0.0000	0.6030	0.0000	0.0000	0.0942
Partner G	0.4032	1.1452	0.0011	0.9459	0.0000	0.0000	0.0000
Partner H	0.8332	1.2002	0.0000	0.7237	0.0000	0.0000	0.1131
Partner I	0.7165	0.1923	0.0101	0.7748	0.0000	0.0000	0.0000
Partner J	0.8452	1.1831	0.0000	0.7187	0.1143	0.0000	0.0000
Partner L	0.9322	0.9763	0.0009	0.8065	0.0000	0.0000	0.0000
Partner M	1.0000	1.0000	0.0000	0.6030	0.0000	0.0000	0.0942
Partner N	0.7298	1.3702	0.0000	0.8262	0.0000	0.0000	0.1291
Partner P	0.7363	0.0000	0.0122	0.5316	0.1376	0.0000	0.0000

In the input-oriented model the efficiency value for all of the partner organizations were the same as for the output-oriented model, DEA Model 6. However, since the output value is fixed to one, and the inputs are varied, the weights are different than in Model 6. Additionally, we completed cross-efficiency for the input-oriented model with the results shown below:



While not identical to the cross-efficiency ranks and values for Model 6, there are very distinct similarities between the results. The ranking of the DMUs is nearly identical, with only slight differences in the order of Partner C and Partner H. Additionally, the cross-efficiency scores are all very similar between the two models, with all of them being only a few hundredths different.

Chapter 2

Analysis of Poverty Stoplight's Organizational Questionnaire and the Relationship between Survey Design and Response Rate

A Major Qualifying Project
Submitted to the Faculty of
Worcester Polytechnic Institute
In partial fulfillment of the requirements of the
Degree of Bachelor of Science in
Industrial Engineering
and
Professional Writing

By Kayla Brown

Submitted to Ryan Madan and Andrew C. Trapp

Abstract

Poverty Stoplight (PS) is a nonprofit organization that works to eliminate poverty in vulnerable communities. PS partner organizations deploy an assessment survey that measures one's poverty level. Gathering metadata from these surveys is crucial to PS's ability to provide adequate resources. PS has tried to collect this metadata through an internal questionnaire that received few responses. This project analyzes the reason for nonresponse through the lenses of theories that connect survey design and response rate. PS's original questionnaire had characteristics that may have contributed to the nonresponse and a new survey was created by applying best practices of survey design literature. A best-practice guide was made for PS that can assist in the design of future surveys.

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Professors Ryan Madan

I'd like to thank my advisor for his motivation and support throughout the course of this project

1.0 Introduction

Poverty is an ever-pressing global issue affecting about 689 million people in 2021 (*Poverty and Shared Prosperity 2022*, n.d.). The term poverty can be defined as “the state of one who lacks a usual or socially acceptable amount of money or material possessions” (*Definition of POVERTY*, n.d.). Poverty was initially understood to be an individual's inability to satisfy their basic needs. This initial understanding puts the focus on an individual’s lack of income as the primary issue affecting their ability to satisfy their basic needs (Costa, 2003). The framing of poverty as solely a “unidimensional” problem has been debated for its applicability to the reality of an individual’s life. Researchers and social scientists have come to the conclusion that a person’s poverty is not just the result of one issue, but of a combination of many issues and social factors. Poverty is a “multidimensional” issue that is the culmination of “multiple disadvantages at the same time” (*What Is Multidimensional Poverty?*, 2016). The redefining of poverty as a multidimensional issue has allowed for new strategies for measuring poverty to emerge. The Oxford Poverty and Human Development Initiative (OPHI) developed the Global Multidimensional Poverty Index (MPI) in 2010 and introduced a new index for measuring poverty on an international scale (*Global Multidimensional Poverty Index | OPHI*, n.d.). This index has fostered new ways of analyzing an individual’s poverty and has become a valuable tool used by humanitarian organizations and governments around the world. One humanitarian organization that has established a name for itself for its work to eliminate poverty through the multidimensional poverty lens is Fundación Paraguaya & Poverty Stoplight.

Fundación Paraguaya is a nonprofit organization focused on providing individuals and families with the help they need to lift themselves out of poverty. As a whole, Fundacion Paraguay provides education and services to at-risk communities around the world. Within Fundación Paraguaya is Poverty Stoplight (PS), an organization that developed a social innovation survey tool called the Stoplight to define an individual's level of poverty and then create an intervention plan outlining steps to remove themselves from poverty. The Stoplight operates on a multidimensional level and measures across six dimensions of poverty. Poverty Stoplight originated in Paraguay in 2010 and has since expanded its reach to help communities worldwide. The Stoplight tool is utilized by outside organizations or “partners” to assist in their efforts to help people work their way out of poverty. Poverty Stoplight has accumulated over 400 partnerships in 47 different countries. These partners communicate with Poverty Stoplight through one of their 15 “global hubs.” Working with their partners, Poverty Stoplight has implemented over 200,000 Stoplights in the world to date and is continuing to provide help to those in need. (*What Is Poverty Stoplight?*, n.d.)

To provide help to communities around the world, Poverty Stoplight relies on its partners' implementation of the Stoplight tool. Therefore, the effectiveness of implementation is dependent upon the partners' understanding of how the tool works and how to interpret the results. Communication between the partner and Poverty Stoplight is extremely important to foster this understanding. However, communication between partners and Poverty Stoplight is not always free-flowing. The partners' primary contact with Poverty Stoplight is through their location-specific Global Hubs. The Global Hubs will then have monthly global meetings with the Poverty Stoplight main office where they can pass along information about the partners. The expanding of partnerships around the world has allowed for wider implementation of the tool but has presented new challenges in maintaining connections with partners. The irregular rate of communication between partners, Global Hubs, and Poverty Stoplight has caused their partner database to become outdated. Without this updated information, Poverty Stoplight can not accurately gauge the implementation techniques of the partners and can not provide these partners with the necessary resources. To address this obstacle, Poverty Stoplight tried reaching out to partners directly through the form of a survey in October of 2023. Poverty Stoplight sent out an organizational questionnaire to all 423 partners to gather this demographic and implementation information. The goal of this questionnaire was to collect information from partners to update the current database and allow for better allocation of resources to these partners. The questionnaire received less than 10% responses from all of the partners. Without the responses from this questionnaire, Poverty Stoplight cannot update its database and the allocation of resources to partners will be delayed.

The nature of being a nonprofit organization and having a finite workforce can present challenges when trying to address issues such as low partner questionnaire responses. Poverty Stoplight is dedicating its time to helping others eradicate their poverty and does not necessarily have the additional time to investigate this issue. The opportunity for added support in examining this issue is the scope of this research project. How to effectively design a survey is a widely debated topic that has garnered the attention of writers and social scientists around the world. Figuring out how to maximize response rates requires insight into how to navigate the different levels of survey design and delivery. Poverty Stoplight's Organizational Questionnaire did not bolster a convincing response rate, meaning there is potential for improvement. The goal of this research project is to understand the levels of survey design and implementation to identify areas of improvement in Poverty Stoplight's current Organizational Questionnaire and to develop a best practice guide for future survey creation

2.0 Literature Review

The root of a survey is to answer a research question and these questions are targeted toward helping the researcher answer this question. Answering the survey research question is dependent upon the success and effectiveness of the survey. This paper looks to investigate the concept of surveys as a form of data collection and the process of survey design to assist Poverty Stoplight in improving the response rate of their Organizational Questionnaire. To achieve this goal, we will first have to examine the quality criteria for surveys. Next, we will turn our attention to the delivery of surveys and ways to engage respondents in participating. Lastly, we will examine the overlap of quality and delivery to determine the best practices for maximizing survey responses and the value of the information collected.

2.1 Survey Quality

To understand quality within surveys, the existing metrics for survey quality must be investigated. In the book, *Introduction to Survey Quality*, Biemer and Lyberg explain essential concepts of quality within survey research. This source introduces quality through the history of continuous improvement and proposes the idea that "a survey organization is no different from any other organization as regards the need for continuous improvement" (Biemer & Lyberg, 2003). The authors claim there is a requirement for quality to be present in not only the output but also the design process. To have continuous improvement in the design process means an organization's survey needs to be able to adapt to changing demands from participants. Aside from needing the continuous improvement mindset in a survey, the authors also determined three dimensions of survey quality: accuracy, timeliness, and accessibility. More specifically, these dimensions define "survey data to be accurate as necessary to achieve their intended purposes, be available at the time it is needed (timely), and be accessible to those for whom the survey was conducted." (Biemer & Lyberg, 2003). Breaking down survey quality into these dimensions allows creators to be conscious of the different factors to consider when designing their survey.

Along with these dimensions of quality, Biemer and Lyberg take this explanation a step further by providing readers with the quality metrics from Eurostat, the statistical office of the European Union. The Eurostat quality dimensions are relevance, accuracy, timeliness and punctuality, accessibility and clarity, comparability, coherence, and completeness (Biemer & Lyberg, 2003). The reference to Eurostat's different dimensions is used to showcase that quality can be broken down into several different dimensions and that paying attention to these dimensions is important for obtaining overall quality. Along with providing these dimensions, the authors also provide some methods for evaluating a survey's quality. The authors break down the different stages of the design process and provide a different evaluation method for each. One example of these evaluation methods is during the design stage of the process, the authors recommend an "expert review of the questionnaire" (Biemer & Lyberg, 2003). The purpose of this review is to "identify problems with the questionnaire layout, format, question-wording, question order, and instructions" (Biemer & Lyberg, 2003). These evaluation methods provide insight into how a person would determine a survey's quality and the quality dimensions listed to provide further guidance for how one would obtain this quality.

However, these three dimensions do not address any guidance for the content of surveys. In the book, *Designing Quality Survey Questions,* Leonard and Robinson, discuss the idea of quality within surveys and guide for creating a quality survey. They claim "at the heart of a quality survey are, of course, quality questions" (Robinson & Leonard, 2019). For a question to be a quality question, the authors claim the writer needs to work to "empathize with and understand respondents" (Robinson & Leonard, 2019). Creating questions that respondents will understand and will engage with is crucial to the quality survey because it is more likely to yield accurate answers. This idea of questionnaire design affecting quality was investigated by Maria Elena Sanchez in her study *Effects of Questionnaire Design on the Quality of Survey Data*. In this study, Sanchez looks at the result of a previous study that tested two formats of a survey to a group and determined the effects the questionnaire design had on the quality of data received. The two surveys contained the same content, but the second survey was an adaptation of the first that utilized a different questionnaire format. Sanchez analyzed the results of these two surveys, paying close attention to the difference in format for each question and the answers provided. From the difference in results in the two survey types, Sanchez determined there is a connection between questionnaire design and the quality of survey data and that "that questionnaire design choices can either help or hurt the quality of data collected" (Sanchez, 1992). Ultimately, the sources discussed place a great emphasis on quality and its importance in surveys.

2.2 Survey Delivery

The delivery of a survey refers to how the survey was shared with the respondent group. Surveys have a wide range of applications across disciplines and in turn, have a wide range of delivery modes as previously discussed. For our analysis, however, we will only be examining the design and delivery of online surveys because Poverty Stoplight utilized this mode originally. Recognizing the advantages and disadvantages of this delivery mode and understanding the factors that influence participant engagement within online surveys is important. Hellen Ball in "Conducting Online Survey" establishes a methodology for online survey research. She presents the advantages and disadvantages of conducting surveys online. Ball claims "the advantages to online surveys include speed and reach, ease, cost, flexibility, and automation" (Ball, 2019). Online surveys can be distributed fast and are relatively low-cost. On the participant side, online surveys allow for added conveniences by the respondent being able to dictate when and where they want to complete it. Another added benefit of online surveys is it allows creators to easily include pictures, diagrams, or video clips in addition to the text (Ball, 2019). On the other hand, Ball discusses the disadvantage of online surveys not having a face-to-face connection to allow the participant to ask for clarity and further explanations if need be.

Another study conducted to investigate the advantages and disadvantages of online surveys is *The Value of Online Surveys* by Joel R Evans and Anil Mathur. This study provided an analysis of the benefits and weaknesses of using online surveys. To conduct this study the authors synthesized existing literature regarding online surveys and developed conclusions. The advantages the study found align with some advantages discussed previously by Ball. Primarily, the study found that online surveys have the advantage of wide-scale distribution to even a global scale because online surveys can be administered to people all around the world. There is an advantage in speed and timeliness because these types of surveys can be administered in a "time-efficient manner," meaning online surveys can be distributed faster and collected responses can be analyzed faster (Evans & Mathur, 2005). Another advantage of online surveys this study found was the advantage of convenience for the respondents. A respondent can answer an online survey at a "convenient time for themselves" (Evans & Mathur, 2005). The study also discusses the advantage of online surveys allowing for easier survey follow-up ability. Because the survey is being administered online, it can be easier for follow-up reminders to be sent out to garner a better response rate, echoing the advantages described by Ball. The similarity in these advantages shows that online survey distribution is a unique form of data collection that can be advantageous to both the creator and the respondent. On the other hand, the disadvantages the study found to point out some communication risks. One risk the study discusses is the possibility of having “unclear answering instructions” (Evans & Mathur, 2005). Without having the option to communicate further instructions, the respondent may not be able to complete the survey to the best of their abilities. This disadvantage to an online format that Evans and Mathur found echoes the same conclusions that Ball had about losing the face-to-face connection.

The customizable nature of online surveys adds another layer of design the creator must be conscious of to maintain respondents' engagement with the survey. In the second chapter of *The Handbook of Online and Social Media Research*, Ray Poynter created a guide for designing online surveys. This guide groups together design aspects that are important for survey creators to know. After defining these functions, Poynter next discusses the “self-completion paradigm.” This paradigm presents the idea that survey creators need to be cautious when designing surveys because the completion of the survey is solely dependent on the respondent’s willingness. Poynter presents a list of steps creators should follow to enhance the respondent’s willingness to complete the survey. One example from this list is “Be polite and friendly. Remember respondents are doing researchers a favor; not vice versa” (Poynter, 2010). Being conscious of how their words are received by the respondents is important to ensuring a willing engagement with the survey. The next design aspect Poynter discusses is structure. Poynter presents structural design aspects that the creator can manipulate. The main structural aspects Poynter discusses are page length, user functions, and first/last pages. In most online survey interfaces, the creator can choose the page length and the number of questions on the screen. The creator also can dictate the user’s navigation of the survey. More specifically, being able to limit the respondent's ability to go back to questions and requires completion of the current question before being able to proceed (Poynter, 2010). Poynter discusses the impact that the first and last pages can have on a respondent's perception of the survey and reminds creators to be welcoming and thankful. Along with these design aspects, Poynter defines all of the standard terms that are used in online surveys: Next/Submit, Back, Browser back, Multi, Checkboxes, Radio buttons, Screen, and Page. The functionality and how respondents will use these functions is described for survey designers understanding.

2.3 Survey Response Rate

When considering quality and design, the response rate should also be considered as an important determinant of the success of a survey. Obtaining survey responses allows the survey creator to get the information they need to determine the answer to their overall research goal. Without these responses, researchers will not be able to draw research conclusions. Surveys are unique cases because the results are dependent upon the respondent's willingness. The increased use of different survey modes has led researchers to wonder if there is a connection between survey mode and response rate. Specifically, researchers have been investigating differences in response rates for online surveys and other modes. One study called "Comparing Response Rates in Email and Paper Surveys: A Meta-Analysis" examined the results of 35 prior studies that compared the response rates of these different survey modes. The meta-analysis of these prior studies found that online email surveys had lower response rates compared to mail surveys. The study "Web and Mail Surveys: An Experimental Comparison of Methods for Nonprofit Research" further investigated this response rate disparity through an experiment with a human services organization. The authors developed two surveys, an online web-based survey, and a paper mail survey. The two surveys were sent out to nonprofit professionals and the responses were analyzed. The study found that the paper mail surveys had a "significantly higher response rate than the web survey" (Lin & Ryzin, 2012). The findings from these studies bring to light a potential issue when utilizing an online survey format and the uphill battle that exists for maximizing responses.

Conducting surveys online allows for increased possibilities for creators to customize their surveys however they please. The way an online survey is designed directly influences the respondent's perception and engagement with it. The effect survey design can have on response rates was researched by Stephane Ganassali in her article called "The Influence of the Design of Web Survey Questionnaires on the Quality of Responses." This article details several design aspects and presents the arguments surrounding these aspects that may affect the quality of responses received and the participant's engagement with the survey. The design aspects discussed in this article that are most relevant to Poverty Stoplight's questionnaire are the general structure and length of the questionnaire, question wording, and response format. Ganassali groups together these design aspects to showcase established arguments surrounding the effect of design on response rate. These design aspects that Ganassali categorized served as starting points for investigating further research on the topic of survey response and nonresponse.

Ganassali presents the argument that the structure and length of the online survey can cause variations in response rates. Ganassali makes the connection that the “length of questionnaire is linked to the required effort perceived by the target audience” (Ganassali, 2008). A respondent’s perception of the effort required to complete a questionnaire can be influenced by the overall questionnaire length. Along with this idea of perceived effort of longer surveys requiring more effort by respondents. Requiring more effort from respondents can lead to respondent fatigue, a result linked to long surveys discusses in the Encyclopedia of Survey Research Method. This fatigue “occurs when survey participants become tired of the survey task and the quality of the data they provide begins to deteriorate” (Lavrakas, 2008). A way to counteract this fatigue is by maintaining the respondent’s motivation throughout the course of the survey.

This connection between questionnaire length and respondent’s effort has been further studied by researchers through the lens of causes for survey nonresponse. One study, Effects of Questionnaire Length on Participation and Indicators of Response Quality in a Web Survey, tested this relationship to see if different lengths of a survey would generate different response rates. This study used a method of showing the total time the survey would take for each respondent on the welcome page of the survey and testing different lengths on respondents. This study found that longer surveys had lower amounts of respondents starting and finishing the survey. The researchers found that stating the survey length “increases the perceived costs of participation and makes it less likely” (Galesic & Bosnjak, 2009). A study done by Takumi Kato and Taro Miura called The Impact of Questionnaire Length on the Accuracy Rate of Online Surveys utilized a similar methodology of deploying different survey lengths to determine the effect length had on response rate. This study found a similar relationship between questionnaire length and response rate. Specifically, the researchers found that the “questionnaire length was found to have a negative effect on response rate but not on the accuracy rate” (Kato & Miura, 2021). The findings from both of these studies agree Ganassali’s claim that longer questionnaires can generate a perception of increased work and this can lead to lower received response rates. Highlighting this relationship allows survey creators to understand the effect design can have on generating responses from respondents.

Ganassali points out that question wording is another design aspect that can affect the response rates of surveys. In *Constructing Questions for Interviews and Questionnaires: Theory and Practice in Social Research* by William Foddy, Foddy develops a theoretical basis on how to effectively construct questions in interviews and questionnaires. Foddy warns survey creators that the wording of questions can affect a respondent's understanding. He discusses how complex and technical wording can lead to higher chances of the respondent misunderstanding the question and this can lead to reduced response rates. Foddy recommends the nature of simplicity when composing questions to lessen the chance of respondent misunderstanding. (Foddy, 1993) The nature of simplicity means being straightforward with the respondent by asking direct questions. In these direct questions, using uncomplicated language that can be easily understood embodies the idea of simplistic nature.

Another design aspect that Ganassali discusses can have an effect on the response rate is the response format. A response format is a visual indication of where the respondent can enter their response. Ganassali considers the findings from previously conducted studies to shed light on this relationship. One source that is mentioned is “Little Things Matter: A sampler of How Differences in Questionnaire Format Can Affect Survey Response” by Tom W. Smith. In this research, Smith considers different visual factors in questionnaires that could affect the survey response. The response format is one of the visual factors that Smith found that affects the generated responses. Specifically, Smith references a survey that was deployed in two formats, and the format that utilized a large space for response format received a greater word count for responses. Smith comes to the conclusion that “allotting more space for answers both facilitates and encourages the recording of longer and more detailed answers” (Smith, 1993). To further investigate this relationship, another study, “The Influence of Graphical and Symbolic Language Manipulations on Responses to Self-Administered Questions,” was conducted in 2004 by Leah Christian and Don A. Dillman which showed that “the amount of space provided in the questionnaire and how it is apportioned among response options can affect the way in which respondents choose answer categories and how much information they provide” (Christian & Dillman, 2004). The finding agreed with the initial claim of Smith and these two works highlight how different design aspects can have an effect on received responses.

The presented discussion of quality provides a ground for determining how the Poverty Stoplight questionnaire matches up with these ideals of survey quality and question quality.

Examining the advantages and disadvantages of online surveys provides important aspects of this delivery mode that can further our understanding of utilizing this mode effectively. The online survey guide discussed serves as an example of the literature available for survey design and how this advice is presented to survey creators. The discussion of how quality and delivery can affect survey response highlights how online survey response rates can vary and survey creators should be conscious of these aspects when making their own. Ultimately, the literature surrounding surveys presents the question of how survey creators can decipher the different aspects of design and implementation to maximize their response rates. For Poverty Stoplight to maximize the effectiveness of their organization questionnaire and future surveys, they need to incorporate the best practices for conducting online surveys.

3.0 Methodology

This section details the methodology used for accomplishing the research goal of identifying areas of improvement in Poverty Stoplight's Organizational Questionnaire and developing a best practice guide for future survey creation. The method section is broken down into two sub-objectives to the research goal: assess the current Organizational Questionnaire and determine key best practices for future survey design and delivery for Poverty Stoplight. The proposed methods to accomplish these sub-objectives are then explained for each.

3.1 Assess the Current Questionnaire

The current Organizational questionnaire employed by Poverty Stoplight to gather background data on their implementation partners needs to be fully assessed in order to determine its specific characteristics that may be contributing to its low response rate. To accomplish this I fully immersed myself in the survey by taking it as if I were a partner completing it. During the process of taking the survey, I recorded a list of its specific characteristics and any other additional information. Using the theories of survey analysis discussed in Section 2, the literature review, I investigated the survey quality, delivery, and characteristics that may be affecting the survey response rate.

The three dimensions of quality, as discussed in the book *Introduction to Survey Quality,* were used to determine if this questionnaire meets these standards. By evaluating the quality of this questionnaire, I was able to compare how this survey stands up to pre-determined survey quality metrics. The importance of question quality, as discussed in *Designing a Quality Online Survey*, was used to shape my analysis of each of the survey questions. This theory showcases the important role that the individual question plays in the entirety of the survey and allows smaller details to be focused on in the analysis. I referenced the online survey handbook by Ray Poynter to guide my determination of the survey's delivery features and how the survey's communication to respondents aligns with Poynter's self-completion paradigm. As discussed in section 2.2, there are both advantages and disadvantages of online surveys and these were used to frame my analysis of the current Organizational Questionnaire to identify areas of improvement. Additionally, I searched for characteristics affecting response rates, such as question wording, response format, and length of the survey, when determining aspects of the survey that may deter respondents from answering.

The theories described in the literature review in section 2.2 guided my analysis of this survey and allowed me to make connections between the survey design and the response rate received. This analysis allowed me to determine areas of the survey that highlight room for further growth. These steps combined will help achieve the overall research goal of identifying areas of improvement in the current Organizational Questionnaire.

3.2 Develop a Best Practice Guide for Poverty Stoplight

The low response rate of the Poverty Stoplight Organizational Questionnaire presents an opportunity for the sharing of information. In order for Poverty Stoplight to address this issue of low response rate, they need relevant information about survey creation and design. The survey analysis will play a role in furthering my understanding of survey design and the best practices across this writing genre. In order to create a best practice guide for Poverty Stoplight, the important information about survey quality, design, delivery, and response rate will be synthesized and compiled into a guide. The changes made to their survey will be supported by reasonings and these reasonings will serve as an additional tool to show Poverty Stoplight the benefit of utilizing this research in their future survey design processes.

4.0 Findings and Revisions

Under the guidance of the quality dimensions defined by Biemer and Lyberg in the *Introduction to Survey Quality*, the Poverty Stoplight Organizational Questionnaire was compared to definitions of accuracy, timeliness, and accessibility. In terms of accuracy, the questionnaire was designed to meet Poverty Stoplight's immediate need for an updated partner organization database for the better allocation of resources. This means the survey can be categorized as accurate because its questions draw relevant information that will assist in achieving this goal.. The timeliness definition explains that the survey must be available at the time it is needed. This questionnaire was created and distributed at the time the goal of updating the database was determined, meaning the timeliness parameter is achieved. The third quality dimension, accessibility, states that the survey must be reachable by those who it is intended to study. The questionnaire should fit this dimension because it was distributed to all partner organizations by email. However, the online format of the questionnaire comes with an increased risk of not reaching the respondents. The sponsor informed me that several reminders were sent to all who had still not completed it, but given the lack of responses received, it cannot be completely verified that all partners received this survey after distribution. Additionally, the communication regarding the distribution of the questionnaire was not able to be analyzed during the course of this project so no specific improvements regarding distribution can be made. Based on these three dimensions, the questionnaire meets the quality criteria for accuracy and timeliness. No revisions were determined for this aspect of the analysis. The next layer of analysis will focus on the quality of the questions.

Designing Quality Survey Questions by Leonard and Robinson discusses the importance of quality questions and Constructing Questions for Interviews and Questionnaires by Foddy discusses the importance of question wording. Specifically, for a question to be quality, the writer needs to "emphasize with and understand the respondents" (Leonard and Robinson, 2019). The Poverty Stoplight Organizational Questionnaire is comprised of 47 total questions. The majority of these questions are simple statements followed by a response field. These statements do not fit the format of a question and lack the blatant asking of information that a respondent would expect in a questionnaire. Most of these statements do not contain any additional direction for the respondent to further understand what Poverty Stoplight is asking them to respond with. One example of this statement format is in the section labeled Organization’s details, the last part with two questions labeled “Mission” and “Vision” and is followed by a response field shown below.

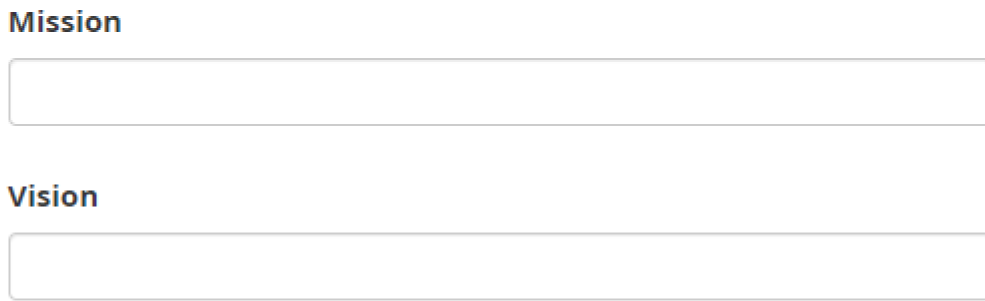

Figure 1: Screenshot from Original Poverty Stoplight Organization Questionnaire

There is no other information presented to further guide the respondents' completion of these questions. The lack of additional guiding information in question statements does not allow the respondent to fully understand what is being asked. To emphasize with the respondents, a survey creator needs to understand “the literacy levels of the respondents” (Leonard and Robinson, 2019). The vague nature of the statement questions and the lack of additional directions for the questions shows an assumption by the survey creators that every respondent will have the same literacy level and the ability to infer beyond what is explicitly written for these questions. For this particular example, the creators believe that all respondents will understand what to respond to simply ‘Mission’ and ‘Vision’ with no further context. The nature of statement questions and limited directional information limits the respondents' ability to understand and fails to meet the empathy quality criteria for survey questions.

Already in the Organizational Questionnaire, there are some instances of this additional guiding information being included. This means the software this questionnaire was created on has the capability to include additional information in the question. A solution to this quality issue would be to include additional guiding information with all the questions that are not completely intuitive. Furthermore, it would be beneficial if some of the statement questions were transitioned into a question format. Adding a guiding description to the questions would allow the respondents to see exactly what is being asked of them and allows all respondents regardless of literacy level to understand. Changing the statement questions to a question format also allows the respondent to respond to understand exactly what is being asked and formulate an accurate response. Rather than an open-ended statement, the respondent now has a clear-cut question in front of them that they can respond to. Since this Organizational Questionnaire is distributed to 423 partners, it can be difficult to fully understand every respondent's literacy level and Poverty Stoplight can emphasize with respondents by creating a survey that is able to be understood by all literacy levels. These changes will allow the Organizational Questionnaire to meet the standards of quality questions and simplistic question wording.

The length of a questionnaire has been discussed as a factor causing variation in response rate (Ganassali, 2008). Specifically, questionnaires of longer lengths have been seen to have lower overall response rates (Galesic & Bosnjak, 2009) (Kato & Mura, 2021). With this theory in mind, the Poverty Stoplight Organizational Questionnaire length was analyzed. The Organizational Questionnaire has 47 total questions and two major sections, "Organization's Details" and "Implementation." All questions are compiled on the same screen, requiring the respondent to scroll down several times to reach the end. It was found that if this online questionnaire was converted to a paper format by utilizing the print function, it would be a total of 14 pages. Long-length questionnaires require more perceived effort for respondents and this perceived effort has been theorized to have negative effects on the completion of the Organizational questionnaire. This long lengthed questionnaire can be perceived as requiring a high amount of effort by the partner organizations and this can be contributing to their reluctance to the survey.

A potential improvement to this issue would be to reduce the number of questions through the use of branching questions. Branching questions or "skip logic" is a tool used to filter out the questions a respondent sees based on their provided results. The respondent would only see the questions that apply directly to them. One example of this opportunity for using the branching tool is shown in Figure 2 below.

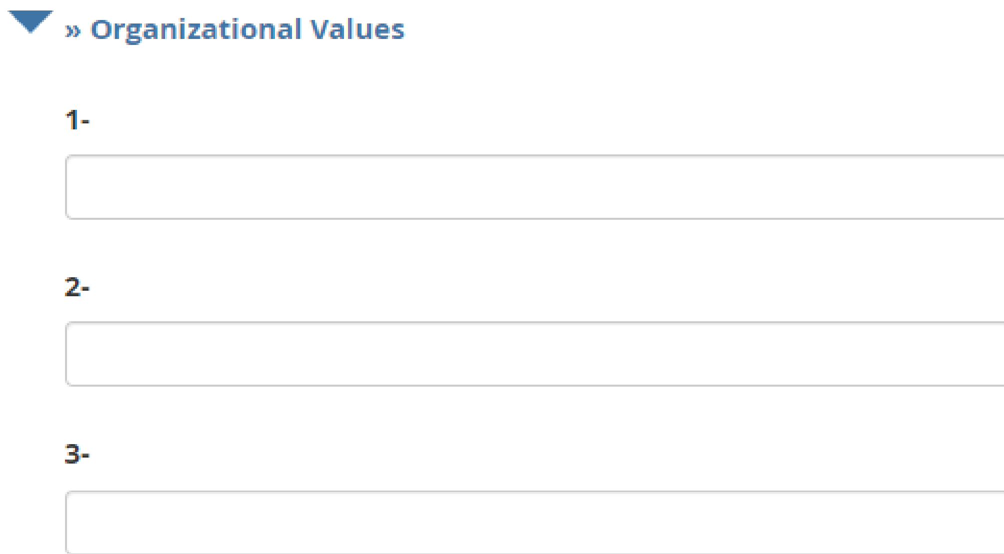

Figure 2: Screenshot from Original Poverty Stoplight Questionnaire

This screenshot shows the original question from the Organizational Questionnaire that requires respondents to provide their organizational values and three open response boxes follow. Three boxes appear regardless if the respondent has that much information to provide. A branching question could direct the respondent to the additional response boxes by asking how many values they want to describe. When the respondent selects the number of values held by their organization, the software would pop up additional response boxes for the respondent to fill out. This way the respondents that only have 1 or 2 values will only see the number of boxes for the number of values they wish to describe. This branching technique can be applied to other questions within this questionnaire to limit the number of questions presented to the respondents. The reduced number of questions presented will reduce the perceived effort by the respondents. Figure 3 below shows the proposed changes for this question using the branching tools. The screenshot shows a respondent that selected they have 2 values that their organization holds and subsequently, 2 additional response boxes appeared.

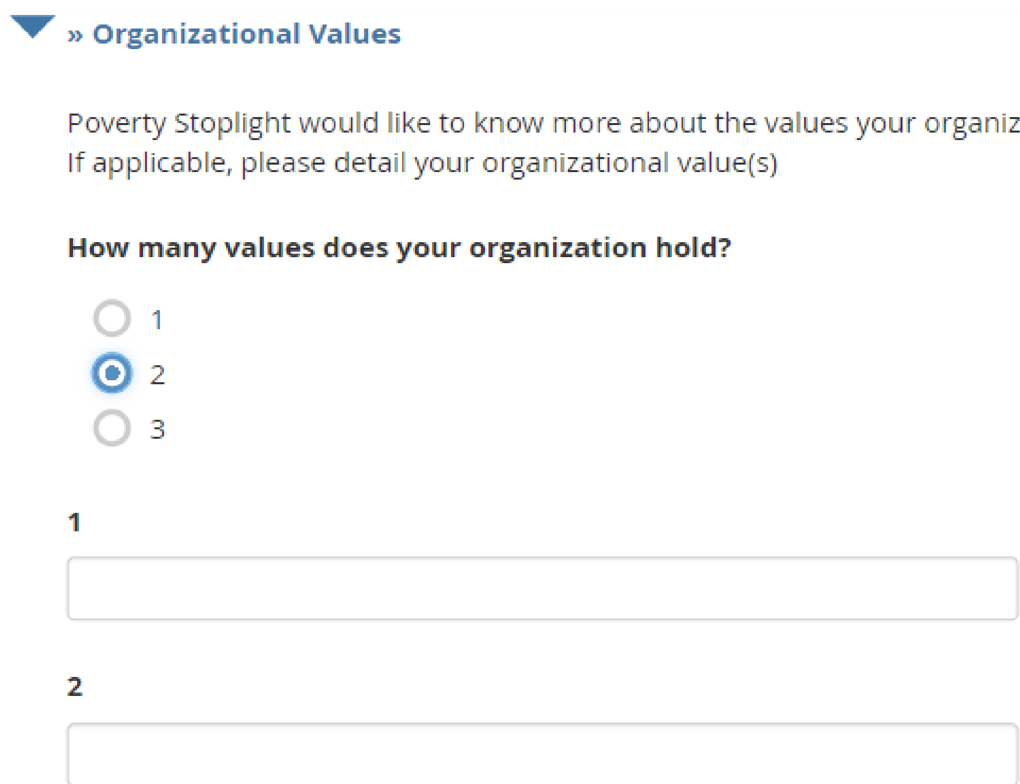

Figure 3: Example of Proposed Change to Branching Questions

In terms of overall length, one potential improvement would be to limit the number of scrolls needed by transitioning to a multiple-screen layout. The Organizational Questionnaire is already broken up into two sections with additional sub-sections and these two sections can be the basis for the multiple-screen breakdown. The survey platform used allows survey designers to create question groups and format the pages by groups. Since the "Implementation" section s comprised of nine subsections, keeping all these groups on one page would still create an issue of increased scrolling. Therefore Implementation subsections should be grouped into five for multiple-screen layout design. By combining all the related questions into pages, the respondent will have to scroll less and will have all questions related to the same topic on the same screen. Poverty Stoplight wants to use this survey to learn more about how the partners are implementing the survey tool for their target population. So, questions in the Implementation section ask the respondent to provide information regarding overall details, the target population, modes used for administering the survey, intervention tools used by the organization, and analysis methods after the completion. Five subsections were created; Implementation Details, Socioeconomic Characteristics of the Target Population, Baseline Survey Characteristics, Intervention Tools, and Post Survey Actions. The subsections were determined by grouping together the type of information the questions were searching for. The Implementation section contained a majority of the questions being asked and separate pages for each subsection were only created in this section. This change will allow respondents to not be overwhelmed with a long page full of questions and the perceived amount of effort needed to complete the survey will be reduced. The reduced amount of perceived effort and time needed to complete the survey lessens the chance of nonresponse occurring.

An additional obstacle in nonresponse is the distribution format of the survey. Online surveys come with advantages and disadvantages and it is important to use these guidelines to determine if an online format is best for this questionnaire. The Poverty Stoplight Organizational Questionnaire was created and distributed on a survey software called Kobo Toolbox. This is a survey platform used by humanitarian organizations across the world and is a free service. The fact that this is a free service and an online format means that there are no additional costs being charged to Poverty Stoplight during the implementation of this survey, which is ideal for a non-profit organization. This is an advantage to this using software and having the survey online. On the other hand, this analysis found that this online survey format does present communication risks. The communication risks stem from the loss of face-to-face connection and the inability for respondents to ask for clarification. Distributing the survey online is the most cost-effective method for Poverty Stoplight because their partners are located worldwide and mailing physical surveys or sending an interviewer to ask these questions is not feasible. The communication risks presented can be mediated by the inclusion of additional question directions as previously discussed.

Along with these advantages and disadvantages, the Poverty Stoplight Organizational Questionnaire was analyzed through the lens of the self-completion paradigm described by Poynter. This paradigm stressed the importance for survey creators to be conscious of the fact that the respondents are completing this survey at their own will and to design the survey in a way that fosters a welcoming environment for the respondent. The survey was analyzed to determine if there were any aspects of the survey that showcased this consciousness in design. This survey did not utilize any of the tools mentioned by Poynter to foster this welcoming environment. Specifically, this questionnaire did not utilize a welcome page and a thank you page. Poynter describes these pages as important tools to engage with the respondent and enhance the survey experience (Poynter, 2010). In Kobo Toolbox there is no specific design function for creating a welcome page or a thank you page, however, it is possible to add notes to the questionnaire. A revision to this questionnaire would be to add personalized communication through a welcome note at the beginning of the questionnaire and a thank you note at the end (Figure 4). The welcome note sets the stage for the questionnaire and the thank you note acknowledges the effort the respondent just put in. Both of these changes will positively affect the user experience and foster a welcoming environment.

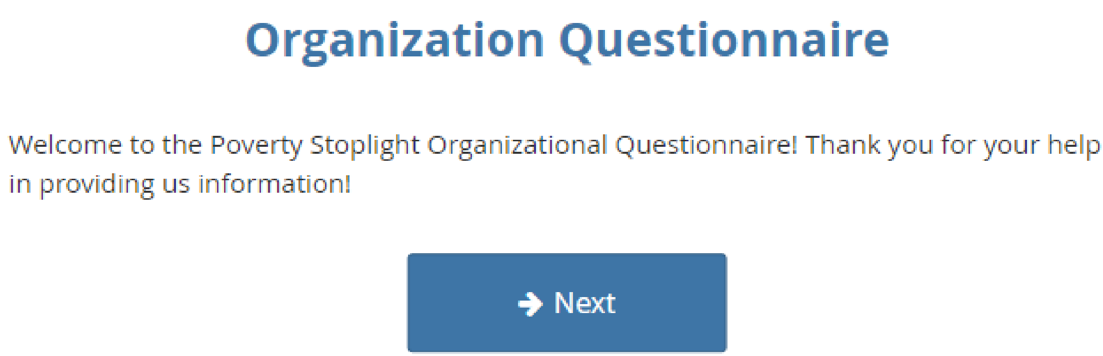

Figure 4: Example of a Welcome Note at the Beginning of the Questionnaire

The last aspect of the Organizational Questionnaire that was analyzed was the response format. The theories discussed in the literature review make the connection that the response format can influence how a respondent will answer. The questionnaire utilizes three different types of response formats: open-ended, single-selection, and multiple selections. The open-ended response field is a single bar that the respondent can enter their information in. It does not expand and if the respondent's answer exceeds the length of the bar, the respondent will not be able to see their answer fully. The limited space for viewing the answer can have effects on how much information the partner organization will provide. An improvement to this potential issue would be to utilize a different format box for open-ended questions. Kobo Toolbox, however, does not have an alternative way to format open-ended responses. The results from the original survey were unable to be shared during this analysis so the exact extent that this response format affected the results is unknown.

5.0 Conclusion

This project helped determine how the Poverty Stoplight Organizational Questionnaire compared to existing research in survey design and practice. The relationship between survey design and the survey response rate was investigated through the analysis of existing research. Limitations and important takeaways from this project are discussed in the following section.

5.1 Limitations

The main focus of this analysis was the Poverty Stoplight Organizational Questionnaire and existing research. The scope of this analysis could have been broadened by including the initial results of the initial survey and wrap-around communication. The initial results would have allowed the analysis to focus more on the response format's effect on responses received. Analyzing the wrap-around communication could have provided better insight into the distribution of this survey. Considering the distribution of this survey and the reminder method used for respondents would have given this analysis another layer to consider and generate improvements for. However, these additional aspects were not able to be included in this analysis. That being said, I am still confident the findings of this analysis will help Poverty Stoplight improve this aspect of their business and will help them in the future construction of business surveys.

5.2 Best Practices Guide

Overall, this Organizational Questionnaire exhibited characteristics that may have contributed to the low amount of responses received. From this analysis, four major categories of best practices for survey design were determined; Quality of Questions, Be Descriptive, Foster a Welcoming Environment, and Be Conscious of the Length. These four major categories serve as the forefront of the best practice guide that was created for Poverty Stoplight which is shown on the next page.

Figure 5: Best Practice Guide Designed for Poverty Stoplight

This best practice guide serves as an important communication tool for relaying the information determined in this analysis to Poverty Stoplight. Poverty Stoplight is a growing organization with new partners being added every year and this Organizational Questionnaire can be used to gain important information from these new partners. To avoid future issues of nonresponse, Poverty Stoplight can use the practices laid out in this best practice guide to generating higher response rates in the redistribution of this questionnaire and future surveys. The work done in this project serves as an initial undertaking of combining the research of survey design and practice into a communicable format. By taking this research and transforming it into an easy-to-read infographic, it can be distributed easily and understood in a short amount of time. Poverty Stoplight is a nonprofit organization that is focused on helping communities around the world through their partners. Making sure their information about these partners is up to date and sufficient is important for Poverty Stoplight to supply these partners with the resources they may need to help more people alleviate their poverty.

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