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Optimization of Port-of-Entry Operation in the U.S.: An Anti-human Trafficking Focus

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OPTIMIZATION OF PORT-OF-ENTRY OPERATION IN THE U.S.:

AN ANTI-HUMAN TRAFFICKING FOCUS

A Thesis

by

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ABSTRACT

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Although decisions at the U.S. port-of-entries take into consideration many factors and stakeholders like government, citizens, travelers, security is their main priority. Officer's decision relies on letting someone into the country or forbids their entrance if they present some threat. They are trained to detect criminals, but little focus is given to identify possible victims. This thesis presents a model that finds an optimal policy regarding how many travelers are going to be conducted to further screening to better detect human trafficking victims. A Bayesian Decision Model was developed and the estimation of costs for the different possible outcomes and scenarios were made and compared. Human trafficking costs and the POE operation were considered. Results showed that decisions were affected by the human trafficking and POE operation costs, as well as the expected number of victims at the border.

DEDICATION

This thesis is dedicated to my mother whose perseverance and hard work have inspired to overcome my fears and finally pursue my dreams. I also would like to dedicate it to my partner, Samuel Pasqualetto, who stayed by myself through many hours of study and pandemic with his support, love, and buckets full of popcorn.

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CHAPTER I

INTRODUCTION

Anyone lawfully entering the United States must go through a Port-of-Entry (POE). It is within the right of a sovereign state to protect its borders and prevent criminal activities through the border or the entrance of unwanted aliens (Miller & Baumeister, 2013). The organization responsible to oversee this operation is the U.S. Customs and Border Protection (CBP), Office of Field Operations (OFO) under the Department of Homeland Security (DHS). They have the responsibility of screening visitors and products that cross the United States border, as well as the American citizens coming back home. Their goal is to detect criminal activities, terrorist threats, and manage migration.

However, the increase in migration flow, due in part to low-cost flights, growth in tourism, and the globalization of the trade of goods and services, have changed the border control landscape in the last decades. Furthermore, the terrorist attack of 9/11 fed the growing concern of policing the border, showing the vulnerabilities of the United States POE to an external attack (U.S. CBP, 2021).

As a result, public attention to border control has been intensified. This attention was focused on the improvements proposed by the United States government that was followed by an impressive growth of the government budget in that area (Haddal, 2010). According to the DHS, the budget destined for the CBP increased 380% in seven years – from 2010 to 2017 (U.S. CBP, 2017). And the budget for the OFO only between 2017 to 2020, has jumped from $ 13.6 million to $ 20.9 million (U.S. CBP, 2021). Moreover, the number of border patrol agents stationed only at the southwest border increased from 3,555 in the fiscal year of 1992, to 16,605 in 2017 (U.S. CBP, 2017). Alternatively, the number of apprehensions along the same border had varied more, without continuous growth, from 479 thousand in 2014 to 288 thousand in 2019. (U.S. CBP, 2021).

To make the operation possible in 2021 there were 328 land, air, and seaports divided into 20 operational sectors in the United States. The OFO employed more than 40 thousand officers and Border Patrol agents and more than 20 thousand employees (U.S. CBP, 2019) to patrol and control around 8 thousand miles of borderline (Figure 1).

Figure 1: Aerial photography of part of the border between U.S. and Mexico (by John Moore/Getty Images)

Transnational crimes as terrorism, drug, plant, and animal trafficking, as well as human smuggling, are in the realm of POE's main concerns. But other criminal activities are also on their radar. One of those activities, commonly associated with transnational borders, is human trafficking. With the large number of apprehensions, it is a crime that affects a very large, but unclear, number of people. In this case, the POEs are virtually the last location the United States DHS to identify possible human trafficking victims and prevent them from being held in slavery condition.

According to CBP data, around 65% of the criminal encounters at the border in the last six years occurred at one of the POEs around the United States border (U.S. CPB, 2021). Table 1 shows the number of encounters per type in each corresponding fiscal year from 2015 to the partial value of 2021 (Sep-Apr). The year 2020 and 2021 were heavily affected by the closure of the borders to foreign due to the COVID-19 pandemic.

Table 1: Number of Criminal encounters at the U.S. Border and POE (CBP, 2021)

U.S. POE						
Fiscal Years	**2016**	**2017**	**2018**	**2019**	**2020**	**2021P**
Criminal Noncitizens Encountered	14,090	10,596	11,623	12,705	7,009	1,983
NCIC Arrests	8,129	7,656	5,929	8,546	7,108	4,704
U.S. Border Patrol						
Criminal Noncitizens Encountered	12,842	8,531	6,698	4,269	2,438	5,861
Criminal Noncitizens with Outstanding Wants or Warrants	3,697	2,675	1,550	4,153	2,054	1,011

Human trafficking is defined as a criminal act that benefits from the exploitation of another human being using force, fraud, or coercion. In the U.S., human trafficking is divided into two legal categories: 1) labor and 2) sex trafficking (U.S. DOS, 2021, TVPA, 2000). Yet, scholars and international legislators consider other types of exploitation too, such as:

- domestic servitude
- trafficking for organs harvesting,
- exploitation for committing crimes, and
- exploitation for begging.

According to the International Labor Organization (ILO), around 20.9 million people were trafficked, and their exploitation generated about 150 billion dollars in profits every year for this global illicit market (ILO, 2014). In 2006, the United States government estimated that 600,000 to 800,000 persons were being trafficked across international borders annually. Nevertheless, The United Nations International Children's Emergency Fund (UNICEF) published that the number is much higher with approximately two million people being trafficked every year worldwide (Boonpala & Kane, 2002). Unfortunately, estimations are at best useful but hardly accurate, because of the shady nature of this crime and the difficult in reaching the victims (Laczko and Gramegna, 2003; Laczko, 2007; Lee, 2011). More recent reports, as the Global Slavery Index (2018), estimated that around 403 thousand people were in forced labor conditions in the United States only, which represents a prevalence of 1.3 victims for every thousand living here.

Even though CBP is already responsible for identifying trafficking victims or perpetrators as they seek to enter the US, their focus is only on the training of border patrol agents. To the best of our knowledge, an automated prescreening procedure that has the focus to identify possible victims of crimes is not used. However, considering the damage this type of criminal activity can bring to a person's life and the cost it inflicts on society, CBP could implement a way to effectively identify potential victims in the border control apparatus, especially when people's freedom is in jeopardy.

The approach used to combat human trafficking to identify and intercepting possible victims before the exploitation happens was called "transit monitoring" (Hudlow, 2015). It is still in its infancy, but there are some other works already considering evaluating the implementation of this approach in Nepal, India (Khalkhali and Bender, 2021). One of the recommendations of the Trafficking in Persons Report 2021 is that the government should "screen all individuals in immigration detention or custody for human trafficking indicators" (U.S. DOS, 2021). A way to achieve it is to improve the system of identification of transnational criminal activities, like human trafficking at the border. According to Miller & Baumeister (2013), it can be the essence of its deterrence. Alongside, Aronowitz, Theuermann, and Tyurykanova (2010) state that taking the opportunity to use the border control operations already in place can be advantageous to identify "the movement of potential victims into a destination country and intervene even before these potential victims are exploited."

Illicit supply chains are resilient and adaptive (Basu, 2014). The use of intelligence systems to combat criminal activities can help to deter them, overcoming their adaptive nature. Being able to detect criminals and possible victims can have a significant effect in disrupting criminal activities.

Nonetheless, an increase in border security procedures can cause delays (Avetisyan et al., 2015; Roberts et al., 2014). Those do not only cause obstacles to trade and tourism, they can also cause environmental costs and personal inconvenience to visitors and citizens (Majeske and

Lauer, 2012). Besides the importance of keeping the security of the population, the role of the border security operation is to preserve the people's right of free movement and the flow of goods between countries. Ideally, during the POE operation, potential threats to United States security would be identified in a way that would bring the least disturbance to the flow of people and goods at the lowest cost possible.

Therefore, the goal of this thesis is to provide a model that optimizes border security regarding human trafficking victims' identification. It offers a systematic approach to examine a societal problem as a border problem. In practice, this tool can help POE officers make more knowledgeable decisions. Its main importance is to shed a light on the issue of transnational human trafficking activities at the United States POEs.

The ancillary objectives of this research are understanding the effects of different human trafficking prevalence scenarios on United States border security. Along with the different costs of human trafficking at the United States POE and the increase in security with a victim's focus. Both models consider inspection costs as well as the non-identification, processing time, and opportunities cost. The results show that implementing some identification of the victim's system at the POE would cost less than the current situation, with no system. The model could also be used as a support for future policy decisions. It is vital to reinforce that early identification of victims can lead to cooperation during investigations, which can lead to higher prosecution rates that would be closer to the real victimization numbers.

The model presented in the next chapters offers a way to optimize the selection of travelers for the screening process at the POEs. It also represents a simplified view of the human trafficking activities at the POEs, so they can provide intuition regarding the issue. In practice, this tool can help POE officers make more knowledgeable decisions. The model can, in theory, be adjusted not only to deter human trafficking but any other illicit activity.

It is not the objective of this thesis to evaluate the security of the current screening procedure. The goal is to evaluate a new security procedure that offers to identify an optimal risk of human trafficking victimization that is acceptable at the POE operation, with consideration of the expected cost for different interested parties, like government, trade stakeholders, NGOs, and citizens. It is also the objective to evaluate how costs of human trafficking can affect decision at the POE and governmental policies regarding border security.

Moreover, this tool will utilize personal traveler's information. It is important to notice that there are a variety of ethical concerns of implementing a scraping tool to analyze this information. Among others, these concerns are data protection, social discrimination, threats to civil liberties, invasive searches and surveillance, lack of transparency and accountability toward the data analysis. Other concerns include the use of irrelevant data that can compromise the effectiveness of the intelligence system. Vulnerability as an identifier can lead to serious profiling or targeting of an already vulnerable population. Aligned with that, the right to migrate and move freely cannot be taken for granted (Konrad et al., 2020; Lee, 2011). Those issues are not addressed in this thesis, but they should be before any implementation.

Furthermore, it is beyond the scope of this thesis to evaluate the effectiveness of the proposed measures. Implementation, and even simulation without real data of daily operations was not possible due to the very sensitive nature of this data. The lack of access to real data, or a specialist opinion to help in the validation, in the end, is at the core of the limitation. This limitation could have been overcome if there were a partnership with CBP or Homeland

Security. Another limitation is that the model can be oversimplified, not portraying all the complexity of the human trafficking problem. The numerical examples do not offer a practical optimal result; yet it provides knowledge regarding the relations between costs. The model offers new knowledge that can better assist decisions at the POE for officers and policy-making specialists.

As Konrad et al (2020) stated, language matters, so choices regarding definitions and terminology need to be explained. The term “potential victim” is being used to indicate the person who has indicators that they were recruited using known human trafficking techniques or by known groups. Since we are dealing with people before their exploitation, the potential victim term is more reasonable than terms like trafficked persons in most of the thesis. The term human trafficking will carry a broad meaning that intersects with forced labor (U.S. DOS, 2021) and modern slavery (Bales, 2007). It was a modeling choice to broaden the meaning of the concept mainly because of the people who are potentially going to be held in a slavery condition upon arrival in the US. This choice will also facilitate the collection of data and could consider a vaster database.

This thesis is divided into six chapters. The first chapter gives an overview of the goal of the research while explaining where it is the intersection between human trafficking and border security. The next chapter offers an overview of the POE operation, with a literature review regarding the optimization models. Chapter III explains the human trafficking problem along with a literature review in the matter. Chapter IV presents the method, the problem formulation, and the model’s assumptions. Chapter V further explains the model using a numerical example to draw relevant conclusions, which are discussed in the final chapter, Chapter VI.

CHAPTER II

OVERVIEW OF THE PORT-OF-ENTRY OPERATION

This section deals with the problem of human trafficking during the transportation of potential victims while they are crossing the border of the United States through some of the many POEs from air, land, or sea. The first section will present the DHS, and POE mission and operation objectives. The importance to the United States security and the economy will also be explained. Afterwards, the operation procedures undertaken at the ports will be described. The last section will present a literature review on optimization models for POE operations.

Port-of-Entry: Definition

The DHS is responsible for POEs in the U.S. The DHS has the mission to offer a "common defense" to counter-terrorism (international and domestic) and enhance security of the borders (U.S. DHS, 2019). They also have the responsibility to secure cyberspace and critical infrastructure, increasing the country's preparedness and resilience. With that, they can defend the United States economy from major distress. DHS comprises of CBP, Coast Guard, Immigration and Customs Enforcement, and the Transportation Security Administration, among other agencies. CBP is, according to DHS (2020), one of the "largest and most complex components" of the Department, corresponding to 24% of the fiscal year 2021 budget (U.S. CBP, 2021). It has the responsibility to manage and control the flow of people and goods between the world and the U.S., keeping terrorists and drugs from entering the country while facilitating the trade of licit goods. Figure 2 shows an aerial photograph of a POE station between the U.S. and Mexico.

Figure 2: Aerial photography of a POE station between the U.S. and Mexico (by Arthur Greenberg/ Shutterstock)

CBP has the mission to “protect the American people, safeguard our borders, and enhance the nation’s economic prosperity” (U.S. CBP, 2021). The OFO is the operational arm within CBP and is responsible for the POE. CBP then, is responsible for the security of the border between POEs. The POE's purposes include to improvement of intelligence risk management at the border, minimize the impact on legitimate traffic, and keep individuals, the economy, and the United States’ infrastructure safe at the same time. In a nutshell, stopping inadmissible people, threats, and illicit goods from entering the country. They also must facilitate the legitimate trade that supports the United States economy besides protecting citizens and businesses “from unsafe products, intellectual property theft, and unfair trade practices" (U.S. CBP, 2019). Besides, they cannot ignore the need to keep traveler's experiences positive, to increase tourism revenue for the US. Nonetheless, security should take precedent, and human trafficking should be one of the focuses because of its enormous social and economic harm caused.

To reach those multi-objective requirements, the OFO controls 328 POEs within 20 field offices and 36 checkpoints (2021). The Figure 3 shows those POE distributed in the U.S. map. The POEs employed around 63 thousand women and men in 2021 from officers to agriculture specialists. It is the largest office in CBP.

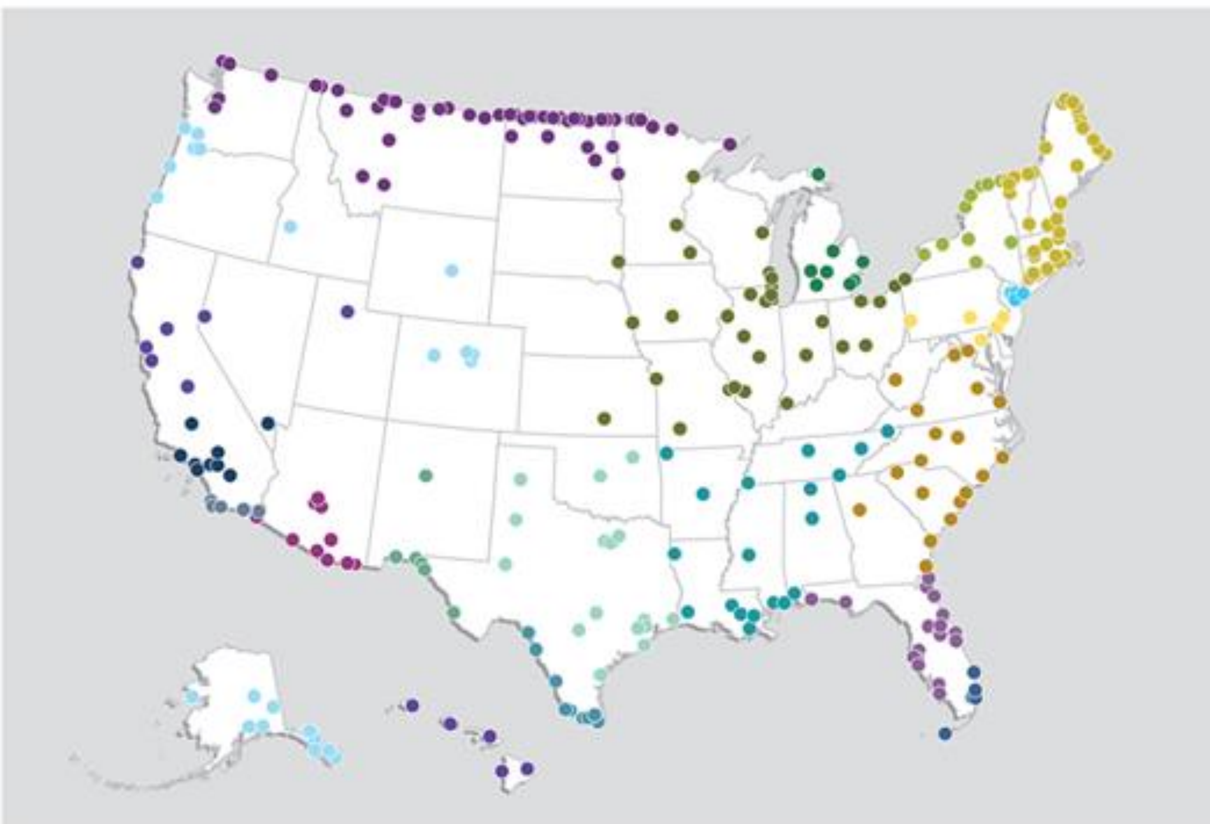

Figure 3: Illustration of most of the POE in the U.S. (Pew Charitable Trusts, 2015)

Along with security, trade is an important part of border management. The United States is the largest importer of commodities in the world holding around 14% of all the world's imports (U.N. Comtrade, 2021). It imported around US$ 2.351 billion in goods from other countries in the last 10 years (U.S. Department of Commerce, 2021). Only with Mexico, the United States imported more than 325 billion dollars from goods and services in 2020 only (Figure 4), which represents 1.98% of all world trade (U.N. Comtrade, 2021). All goods that come from other countries into the U.S. legally, go through a POE. Not interfering with it while securing the country from outside threats is a challenging task the POE faces daily.

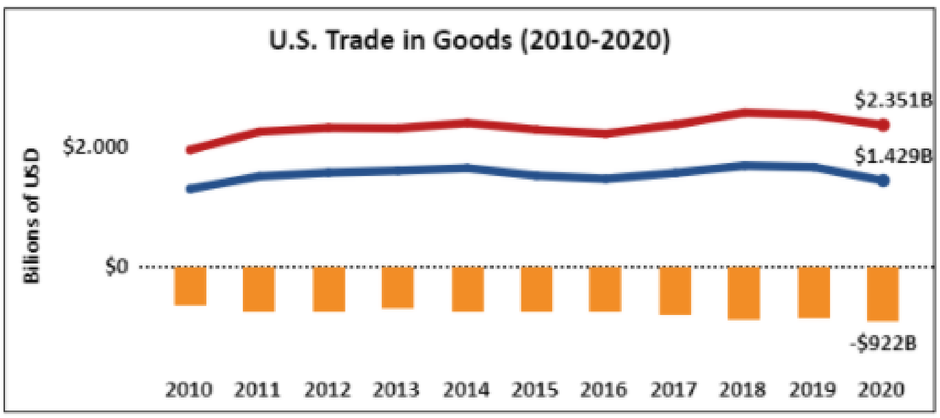

Figure 4: U.S. Trade in goods - 2010-2020 (U.S. Department of Commerce, 2021)

The annual apprehensions made at the POE are published by the CBP in each Fiscal Year (FY) report. Table 2 shows the number of encounters the OFO (U.S. CBP, 2021) made in the years between FY 2015 to partial of FY 2021 (Partial Oct-Apr). The year 2020 and 2021 were atypical years because the COVID-19 pandemic made the U.S. close the border for non-essential travel. Covid-19 put to a halt all non-essential travels around the world. The great fall in the flow of people at the POE can be seen in the numbers in Table 2.

Table 2: Total Encounters of OFO from FY 2016 to FY 2021P (CBP, 2021)

OFO - FY	2016	2017	2018	2019	2020	2021P
Budget (in thousand - USD)	13,565,294	13,941,170	16,387,729	16,690,317	20,850,394	18,209,969
Number of Employees	62,452	61,484	59,726	60,646	61,399	62,697
Total Encounters	274,821	216,370	281,881	288,523	241,786	145,058

Excluding the data from 2020, the number of CBP officers employed since 2015 increased 7% and the number of people crossing the border through some of the POE had the same increase. However, the average number of private vehicles and truck, rail, and sea containers processed more than doubled (Table 3).

In 2020, on any given day, the number of people found inadmissible in all the 328 POEs was around 634, and their operation was able to capture 39 wanted criminals. Most of the travelers come from the land. Almost double the number of passengers and pedestrians processed in air POEs. The risk assessment in Land POEs is more complex than in air and sea POE because the Land POE usually has no access to previous information regarding the travelers, as it happens in Air POE through the airlines and the Sea POE through vessel manifest.

Some of these numbers in Table 3 will be useful to make estimations as inputs for the model regarding cost and number of operations done daily by OFO officers.

Table 3: Data from CBP operation from 2015 to 2020 (CBP, 2021)

On a typical day in the year	2015	2016	2017	2018	2019	2020
Passengers and pedestrians processed:	1,048,632	1,069,266	1,088,300	1,133,914	1,124,075	650,178
- Land travelers	686,162	688,757	691,549	696,555	681,750	444,541
- International air passengers and crew	308,234	326,723	340,444	358,448	371,912	169,842
- Passengers and crew on arriving ship/boat	54,236	53,786	55,709	78,912	70,414	35,795
Incoming private vehicles processed	282,252	282,350	283,664	285,925	273,338	187,049
Truck, Rail, and Sea Containers processed	72,179	74,417	78,137	81,438	78,703	77,895
Apprehensions between U.S. POE	924	1,140	851	1,107	2,354	1,107
Arrests of wanted criminals at U.S. POE	23	22	21	75	23	39
Refusals of inadmissible persons at the U.S. POE	367	752	592	764	790	634
Number of Employees hired:	59,472	59,221	59,178	60,014	61,506	63,685
- CBP officers	22,947	22,910	23,079	23,477	24,511	25,756
- Border Patrol Agents	20,183	19,828	19,437	19,555	19,648	19,740

Port-of-Entry: Operation Procedures

Security is crucial, but screening every person trying to enter the United States would be costly, and maybe impossible with the current flow. Also, the space required to conduct all different screening procedures in all vehicles and travelers would be huge. To better select the ones who will go through a more detailed screening process the POE has an automatic prescreening procedure that flags potential threats (CBP, 2021; U.S. GAO, 2019). The focus is on criminal and terrorist associations, not on victims.

The following detailed operation has the focus on land POE. The land POE was chosen for more detailed analysis because it is considered the worst-case scenario for the modeling we are proposing. The land POE is less likely to receive travelers that have not previously informed the CBP of their arrival. As stated, these are more common in airlines and ships where the information is provided by the airlines or by the vessel manifest directly. Because of that, it is expected that more time would be required to prescreen travelers at the land POE instead of the other types. For simplicity's sake, the explanations, and therefore the modeling efforts are focused on the land POE.

Figure 5 shows the flowchart of what happens to a traveler in a typical land POE with the possible operations and decisions. Upon arrival, the traveler goes through data collection. They collect the data from the travelers by automated License Plate or Radio Frequency Identification (RFID) document readers (Figure 6). The information gathered by the license plate reader and the RFID identification will be analyzed. Also, photography from the traveler can be compared to official document photographs using artificial intelligence (AI) models (U.S. CBP, 2021). The data are compared to law enforcement, intelligence agencies, department of justice, among other databases, to see if that person has some problem with the law or known association with terrorist groups.

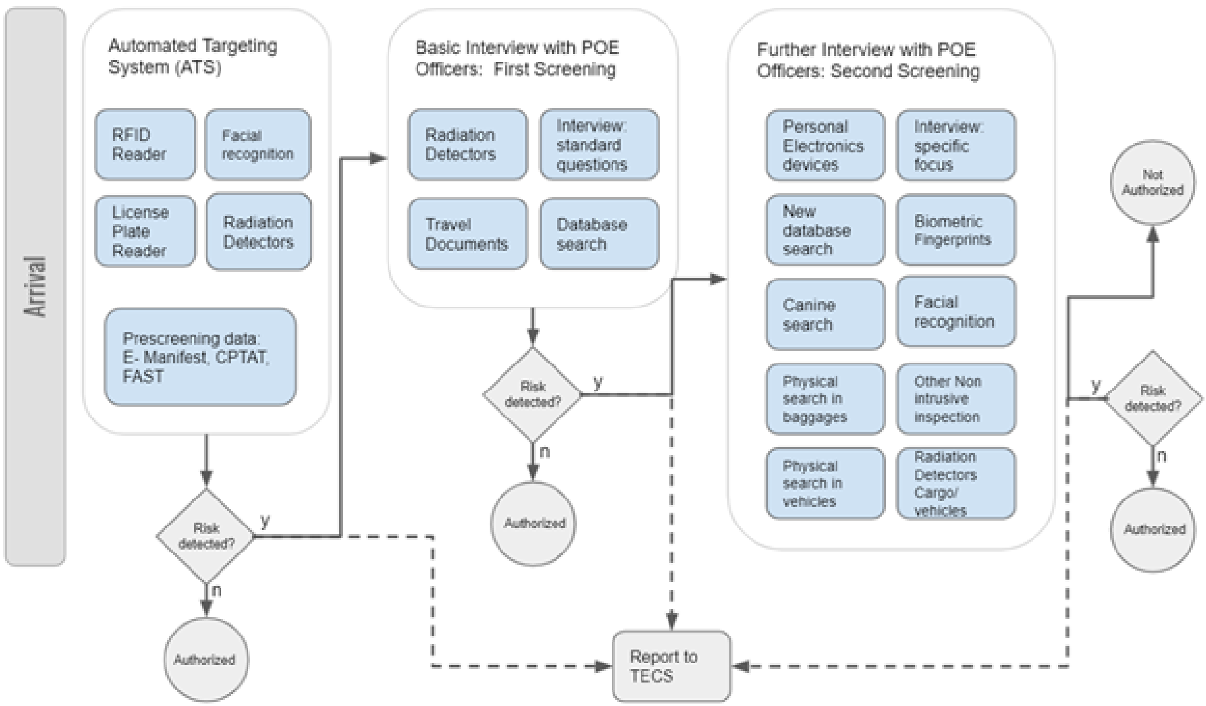

Figure 5: POE operation's flowchart (based on information at U.S. GAO, 2019)

Figure 6: Types of Data Collection for the Prescreening (U.S. GAO, 2019)

Then they proceed to a common screening where an agent goes through the travelers' documentation and interviews them. One step all visitors must go through nowadays is the collection of biometrics, which in the United States is “ten-printed” fingerprints and a digital photograph that runs against the internal and Intelligence databases. This is a standard procedure that, if no risk is found by the agent or the automated system, the person is authorized to enter the US. If something comes up to the attention of the agent, they can forbid entrance or lead the traveler to a second and more detailed screening.

At each POE, CBP officers review the passports, visas, and other supporting documents of every foreign national arriving in the U.S. At the primary inspection station, officers question the border crossers to confirm their identity and nationality. Then, they are asked about the general qualifications they have that support the visa category they are using, and the true purpose of your trip to the U.S. In this step, in case the CBP officer is not satisfied, they can ask for additional supporting documents. They can also send the traveler to a secondary inspection that would have different procedures depending on the reason for the further screening.

The CPB officers must determine if the traveler, passenger, truck, or cargo represents a threat or not. It is assumed that any prescreening procedure implemented will result in a better outcome than if officers would choose travelers randomly to a second screening. And because of that, the procedure would flag, with better accuracy, the threats to enter the US. Otherwise, the DHS would not implement it.

The difference between Sea, Air, and Land POEs is not basically regarding operations hours and procedures before the arrival. For example, international airports usually receive travelers 24 hours a day, every day of the week. Sea POE usually has a smaller hour of operation, between 08 AM to 4 PM. While land POE usually operates from 6 AM to 12 AM every day.

The pre-arrival procedures for the sea POE include the vessel manifest with all the passengers and crew listed with their visa information. A similar procedure would happen with passengers and aircrew from air companies. At the land POE, this is not always the case. Unless the traveler participates in some of the preclearance programs that the United States government offers, there is no way for the land operation to get the information of the traveler before arrival.

Pre-clearance programs

In the case of trucks, the e-manifest. It is an electronic document that companies must submit to the CPB before arrival at the POE. It contains information regarding the cargo, the company, and the driver. They need, usually, to submit it one hour before arrival at the chosen POE.

Free and Secure Trade (FAST) program allows drivers to submit e-manifest only 30 minutes before POE arrival. To be part of this program they need to pay a fee. They also have the right to enter a special line at the LPOE. It allows known low-risk shipments to enter the United States going through only Mexican or Canadian Customs. It is a trusted traveler who expedites processing at the border by pre-assessing travelers through complete background checks and fulfillment of some requirements (U.S. CBP, 2021).

Customs-Trade Partnership Against Terrorism is a program where the companies that agree to participate, agree to help the CBP to safeguard “their supply chain, identify security gaps, and implement specific security measures" to prevent terrorist threats. It is a partnership with companies that usually trade with United States-based companies. They agree to help identify terrorism threats in their supply chain.

Pre-clearance programs for travelers are held in partnership with foreign airports (in time 2021, operating in 16 locations (U.S. CBP, 2021). So that, "travelers then bypass CBP and Transportation Security Administration (TSA) inspections upon U.S. arrival and proceed directly to their connecting flight or destination" (U.S. CBP, 2021).

Similar to the FAST for commercial vehicles, there is the Pre-Check program held by TSA. It is a trusted traveler program that pre-assess usual air passengers. It is not related to the United States POEs but has a prescreening procedure (e.g.: early criminal checks for travelers registered) to reduce security procedures, and consequently lines, at airports. Above those are the Global Enrollment System that unifies the programs that provide a way to expedite inspection and security procedures for those who are considered lower risk travelers (U.S. DHS, 2013).

Prescreening procedures

One of the three groups of CBP main activities is to "identify trends, explore an alternative course of action, and present quality data-driven information for decision making for operational, resource, and policy decisions" (U.S. CBP, 2019, p.19). The proposed model in this thesis explores these key activities, helping CBP officers to make decisions using timely data. It can promote better use of resources and increased safety.

The current prescreening procedures include pre-clearance programs and the conduction of standard procedures. Examples of those procedures are comparing photography taken at the POE with documents using AI, comparing fingerprints with intelligence database (U.S. CBP, 2021), and the search in personal electronics and social media profiles of travelers who authorized search during their visa application.

Screening procedures

Second screening procedures are going to be related to each type of threat present at the POE. The United States government, besides the border searches, is also authorized via the CBP to “inspect and examine all individuals and merchandise entering or departing the United States” including the ones of personal use (U.S. CBP, 2021).

According to the CBP, this type of search has helped detect criminal activities finding evidence of human trafficking among other crimes (child pornography, human smuggling, visa fraud, among others). Other different secondary screening can be other types of biometrics (retina sensors), as well as x-ray, canine search (Figure 7) in look for people, currency, drugs. Also, gamma rays look at nuclear materials. They also can search your luggage or personal devices (such as laptops or mobile phones) for evidence about the true purpose of your trip. In this second screening, there are different procedures for vehicles and people. The canine inspection, for example, uses dogs to look for currency, firearms, narcotics, agriculture products, and humans.

Figure 7: Canine inspection at a Land POE (U.S. GAO, 2019)

They also use agricultural and Drug Enforcement Agents specialists to assess and better decision making at that stage. The use of experienced agents can enhance the capability of detecting illegal materials and intents.

Port-of-Entry: Flow and Crimes

Annually, the number of people that go through the POE is estimated to be more than 13 million. The number of actions held by POE officers to apprehend or expel crossers at the border under Title 8 and 42 (U.S. CBP, 2021) is graphed in Figure 8. Those actions usually vary throughout the different periods of the year, despite the same number of employees, and hours of operation are held. The Title 8 Apprehensions represent the number of people who were found inadmissible by POE officers to enter the country. Many reasons can influence the number of apprehensions.

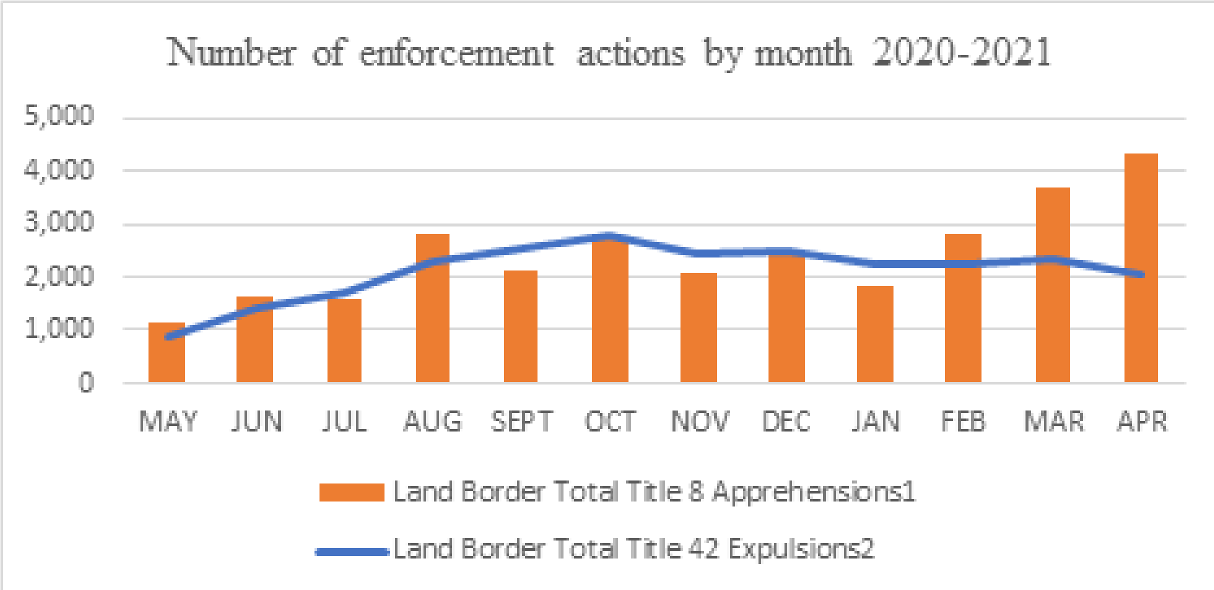

Figure 8: Number of enforcement actions - May 2020 to Apr 2021 (CBP, 2021).

Transnational criminal organizations are involved in different crimes across United States borders. From illicit drug transactions to money laundering and evasion, crimes cross the border daily, and one of the goals of CBP officers is to detect and deter those from happening.

Although, the threats that come through are not a known number. DHS can estimate those numbers by randomly choosing some crossers for a second screening. This procedure would offer an unbiased number of illegal crossing attempts. The procedure is not all free from bias, since the second screening also has a proportion of failure, but it is one of the best ways to gather information in those illegal activities. When considering criminal intentions or possible victims, the detection in a secondary screening is even more flawed since they are only detected with the help of experience and knowledge of the officer, unlike drugs that can be found with the help of detection technology like x-ray.

However, the number of apprehensions by each type of crime is known and collected by the POE. Not all crimes are divulged, just the ones of high concern to the state, like drugs (by type). Transnational crimes interfere with border operations and vice-versa. Regarding human trafficking, few data are collected by the POE officials or publicized. The number of current people crossing the United States border to be trafficked is, as well as other crimes, unknown, but nowadays, poorly estimated (Laczko, 2007).

Table 4: International Travelers Processed with Electronic Device Search (CBP, 2021)

International Travelers Processed with Electronic Device Search			
FY 2018	FY 2019	FY 2020	FY2021P
33,296	40,913	32,038	17,855

Since 2018, the CBP officers are authorized to search electronic devices of travelers. It had a spike in FY 2019, with an expected decrease in FY 2020 since borders partially closed for half of the period due to the Covid-19 pandemic. But the data of the partial FY 2021 seems to indicate an increase in this type of search even with the border remaining partially closed from the totality of the period (Table 4). This could also mean that the discussions regarding the ethical concerns, especially over privacy (Aronowitz, 2017), have not taken enough space to deter the use of this technology.

The extent to which the operation affects the economic situation of the U.S. has been the theme of many studies (Vadali, Kang, and Fierro, 2011; Roberts et al., 2014; Cedillo-Campos and Sánchez-Ramírez, 2014; Avetisyan et al. 2015; Jara Jr. & Moya, 2020). Even though it is a complex problem with different interrelated variables (interfaces with jobs, GDP, Tourism deterrence, etc.), it is agreed that additional security at POE can lead to less trade, which can cause billions of dollars per day.

An increase in security translates into more frequent and time-consuming searches. Those increases can translate into congestion or demand for more officers. The use of technology and information can help reduce this workload while increasing security. The early detection of potential threats from attacking the United States would help to reduce criminal activities and protect its citizens and economy.

Some models are used to improve operations at the United States border. Simulation, game theory, and optimization models can help improve decisions at the POE and fulfill the objectives of this vital organization.

Port-of-Entry: Optimization Models

While security is critical, screening every person trying to enter the U.S. is impossible. The most decisive point in defining screening policies at the POEs is to determine what level of security one expects, which depends on the quantity and types of screening procedures performed.

To verify the POE efficacy is challenging since a lot of information is unknown. Most of the published papers have the goal to prevent terrorist attacks or increase economic efficiency. To the best of our knowledge, no paper was found that dealt exclusively with optimizing POE operations that also considers human trafficking activities. (Majeske and Lauer, 2012) proposed a Bayesian Decision Model to optimize the screening process at airports. They tested two models that consider the cost of security failure from the perspective of passengers and the government.

Their model is going to be used as the basis of the model in this thesis. Another inspiration came from the work of Rueda and Moya (2015) regarding the use of the Rate of False Positives to estimate efficacy in the detection of illicit cargo on border operations. They support the use of the measure to estimate the misclassification of cargo led to further screening procedures at the POE operation.

McLay, Lee, and Jabobson (2010) used statistical models or integer programming to optimize the probability of accurate assessment at the airport screening process for the TSA operation. McLay, Jacobson and Kobza (2008) also have analyzed the trade-off between the use of new technologies and the security in aviation baggage screening. A similar analysis is presented in this thesis but regarding human trafficking screening, costs, and security.

Most of the research in optimal POEs' policies focus on container inspection. The common decision is regarding the type of detection method used (e.g.: radioactive, RX, physical inspections) and on how many containers. Boros et al. (2008) and Elsayed et al. (2009) have shown some optimization approaches to determine optimal threshold levels for automatic sensors of illicit materials or agents while considering misclassification errors, the total cost of the inspection, throughput, and budget constraints. (Zhu et al., 2011) have shown the impact of measurement errors in POEs' operations due to container misclassification depending on those threshold levels. Another method is the one proposed by (Wein et al., 2006). They used a Game Theory model to find an optimal strategy policy to prevent the entrance of nuclear weapons in the U.S. (Romero et al., 2016), for the same purpose, proposed a Multi-Tree Committee algorithm to support decision-making regarding optimal cargo containers inspections. They used a combination of binary decision trees and minimization of Boolean functions. They used real data to validate the efficiency and flexibility of the model. Also relying on binary decision trees, (Madigan et al., 2011) have improved the efficiency of the algorithm to find the thresholds that optimize the POE inspection sequencing task. Along with those, Merrick & McLay (2010) posed an important question that is screening cargo for nuclear threats worth the economic and inconvenience burden. They hypothesize that the cost of delays caused by false detections outweighs the cost posed by the threat. The result would depend on the probability of the threat and the value given by stakeholders to the objective.

For travelers' inspections, most of the models are based on the screening process used at airports with pre-assessment of risk for each passenger. Some use statistical models aligned with integer programming to optimize the probability of accurate assessment at the airport screening process (McLay, Jacobson and Kobza,2008; McLay, Lee, and Jabobson, 2010). Others use multi-objective optimization (Xue & Villalobos, 2012) or dynamic allocation of resources in the airport to improve security and service (Alodhaibi et al., 2020). Albert et al. (2021) presented a systematic literature review on risk-based, multi-level screening model optimizers for airport passenger screening. They consider dynamic programming to consider passengers. Also, they showed how to improve the current TSA PreCheck security system while reducing its costs.

Another type of research uses an economic perspective to evaluate POE`s policies. The economic approach is the one that transforms every considered outcome in monetary value to make some viability or cost analysis of the investment necessary to keep the security at some expected level. In that topic, Moya & Rueda (2019) focused on a Deterministic Equivalent Problem to analyze the cost of outcomes depending on potential threats' assessments by officers at a land POE between the U.S. and Mexico. Some research provided a model that helps to evaluate decisions regarding resource allocation to efficiently accommodate the demand at the POEs (Roberts et al., 2014; Prager et al., 2015; Jara Jr. & Moya, 2020). They simulated the impact on the U.S. economy due to the addition of officers at the POEs using a computable general equilibrium model. They considered U.S. GDP, trade balances, and employment, as well as the opportunity cost of waiting by passengers and truck drivers and used. Another method that considers outcome and opportunity costs was used by Majeske and Lauer (2012). They proposed a Bayesian Decision Model to optimize the screening process at airports considering primary and secondary screening.

To analyze the POE operations, the body of research divided itself into cargo or travelers screening procedures. In both, most of the research is concentrated in queueing models, or integer LP models, and terrorist threat/risk analysis. The last one is the one that CBP currently uses at the POE operation. Since it is classified information, access to how it works is limited. To the best of our knowledge, the focus on human trafficking activities at the POE operations is a gap to be filled in research. Those models have in common the analysis of the security and cost of operation or screening procedure. All of those are dependent on the flow of people and things crossing the border.

At the border, the POE officers are looking for possible indicators of human trafficking activity. However, the current operation focuses only on possible threats, looking for perpetrators, not usually a victim's approach. Having also this victim focus, so the POE can be instrumental to prevent additional harm done to a vulnerable population. According to the Trafficking in Persons Report (U.S. DOS, 2020), only the confluence of human smuggling and human trafficking are looked after with concealments of people or illegal documentation. But the possible victims being transported using legitimate documents are not identified using those methods. An additional issue is that using only the discretion of officers to decide on the entrance or not of those possible victims, without considering a victim's approach, can not only make the identification infeasible but further victimize already vulnerable people (Lee, 2011). An automated prescreening system (ATS) is already in place at the POE, but its focus is on identifying crimes and criminals (U.S. DHS, 2017). The proposed model has the locus on the transportation of those possible human trafficking victims.

Human trafficking is a crime that has also a lot to lose with the outspread use of technology (Birchfield, 2019; Konrad et al. 2017). Identification of the transnational flow of human trafficking victims can be key to disrupt this illicit network.

CHAPTER III

OVERVIEW OF HUMAN TRAFFICKING

Human trafficking is defined as the exploitation of another human being for profit or self-benefit. It can be done by means of coercion, deception, or threats. Human trafficking estimations, as noted before, are a challenge, still some numbers are going to be used as a base for the understanding of the complexity and extent of the human trafficking problem in the World and the US. In this section, the overall characteristics of the crime are explained, the next section explains the different types of exploitation that can occur within the definition of human trafficking, labor trafficking, and sex trafficking being the most common. The last section explains some of the literature already published regarding human trafficking and operations research and analytics research that justifies the use of identifiers to detect human trafficking at the border is also presented.

Human Trafficking: Characteristics

Different types of exploitation come under the umbrella of human trafficking. There are different levels of exploitation that the victim may be subjected to while in this condition. These categories influence the gravity of the victimization, the psychological and physical trauma the survivors would have to face (Reed et al., 2018), and the cost to rescue those victims, among other outcomes.

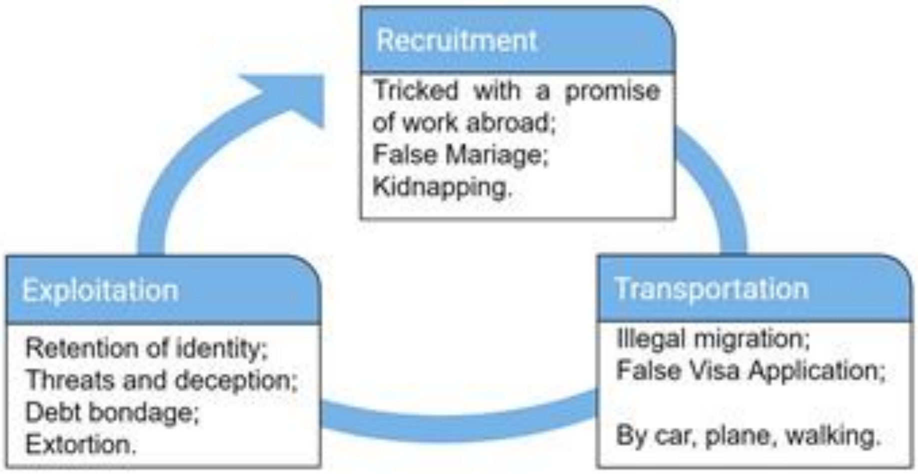

Figure 9: *Modus Operandi* of a typical human trafficking operation

The *modus operandi* of human trafficking activity is illustrated in Figure 9. At first, a human trafficking recruiter contacts a potential victim. They will trick the person with promises of work opportunities. They can be recruited abroad or nationally. There are cases where the recruiter pretends to be romantically attached to the victim and proposes marriage or offers positions to be athletes abroad (Shelley, 2003; Laczko and Gozdziak, 2005, U.S. DOS, 2021).

The second part of the operation is the transportation part. The victim is transported from the place they live to someplace away from their support network (Lee, 2011). To transport the victims, the traffickers can use false documentation, smuggle the victims through the border between POEs, or use legitimate visas to cross through the POE. Polaris Project (2013) interviewed survivors in the United States and found that 70% of the respondents have entered the country using a legitimate visa. Despite not being generalizable, the Polaris findings illustrate a consensus among different specialists (Lee, 2011, Aromaa, 2007, Polaris Project, 2017, Cooper et al., 2017) that many of the foreign victims of human trafficking used port-of-entries to enter the countries they end up exploited.

The third part of the human trafficking operation is the Exploitation phase. In this stage, the traffickers submit their victims to forced labor of different types using threats, coercion, and fraud. The threats are not only directed to the victim but also their family. There are not only physical threats. They also threaten victims with deportation and prison (Farrell and Pfeffer, 2014). Another common way to coax victims to continue working is by retaining their documents upon arrival and reinforcing the barrier language. Debt bondage is also common (U.S. DOS, 2021). The traffickers create a debt, usually regarding living and traveling expenses. The victims do not have any control over that debt, which unsurprisingly keeps growing until it is virtually unpayable. After the exploitation ends by death or escape, the cycle starts again, with the recruitment of new potential victims.

Despite the similar *modus operandi*, the human trafficking term is an umbrella term that refers to different kinds of exploitation systems (ILO, 2017; Bales, 2007; U.S. DOS, 2021; Polaris Project, 2017). From each type of exploitation, there are also different organizational structures of the criminal group that can be found (Kammer-Kerwick, Busch-Armendariz, and Talley, 2018, Busch-Armendariz, Nsonwu, Cook Heffron, 2015, Shelley, 2003). Also, the exploitation in human trafficking is not a binary exploited or not exploited condition. Some scholars have observed and explained that people usually fall into a *continuum* of exploitation (Lee, 2011; Reed et al., 2018; Skrivankova, 2010). It is hard to delimit where the exploitation begins as a bad business practice to ending as a vile criminal act. Sometimes the distinction is blurred between criminal or labor misconduct attitudes, and people can fall into any range of that spectrum.

Another characteristic of human trafficking crime is that it is a crime hard to prosecute. A few of the causes for such a low rate are the lack of data, the hidden nature of its activities, and the victims' fear to report the crimes (Farrell and Reichert, 2017). In 2019, there were 10,164 unique cases received of Human Trafficking in the U.S. and 48,326 contacts to report cases in the national hotline (U.S. National Human Trafficking Hotline, 2020). Figure 10 illustrates the number of cases by state. In 2019, 1,024 investigations were opened but only 343 perpetrators were charged, and 134 were prosecuted (U.S. DOS, 2020). In comparison to other violent crimes, this is a much lower rate of investigation, arrest rate, and prosecution (FBI, 2020).

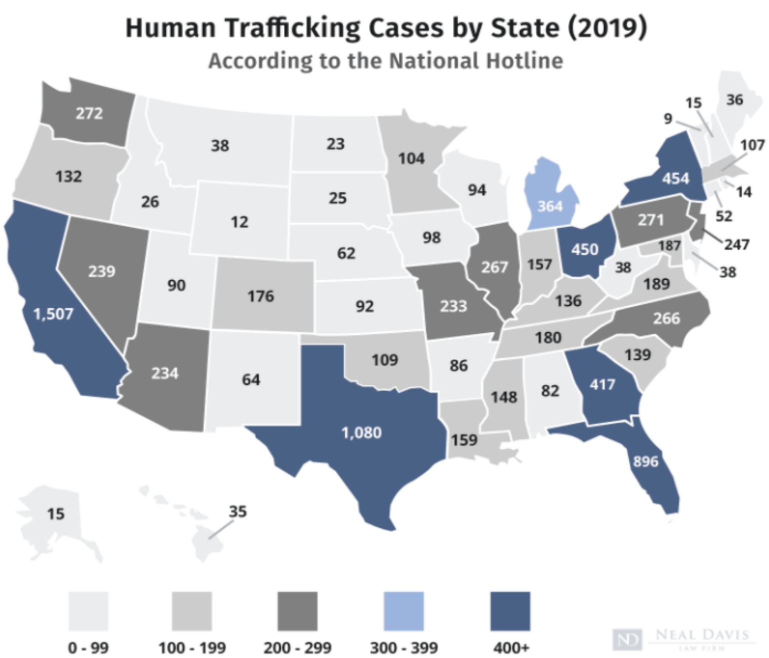

Figure 10: Human trafficking cases by state (2019) - Source: Neal Davis Law Firm using U.S. National Human Trafficking Hotline data.

These characteristics add complexity to human trafficking combat, especially for its identification. When considering the POE operation, where the exploitation part of the operation is yet to come, this identification is especially challenging. This thesis will not dwell on the identification problem but will assume that it is possible, presenting in this chapter a few works to back up this assumption.

Human Trafficking: Types of Exploitation

Different types of exploitation have different types of traffickers and victims' profiles. Cases of domestic servitude and some cases of domestic sexual exploitation are committed by small groups or a single perpetrator, without an organized and hierarchical operation (Kammer-Kerwick, Busch-Armendariz, and Talley, 2018). Therefore, the type of identifiers can vary widely. Some authors argue that the facilitators and victims often share the same vulnerabilities (Voss, 2020; Bales, 2007; Kammer-Kerwick, Busch-Armendariz, and Talley, 2018; Kangaspunta, 2008). Usual vulnerabilities found in both groups are early child neglect; being a runaway teen; having a previous negative interaction with law enforcement; among others. Those intersections can help the identification of possible victims at the border. The classification model will probably infer those perpetrators and victims are in the same group. In the perspective of border security, both identifications could have a positive outcome to prevent further victimization, so this confluence was ignored.

Cross-border human trafficking does not encompass all the types of criminal activities that happen under the definition of human trafficking. For example, most of the sex trafficking happening in the United States happens domestically. It means that they do not transport their victims across borders (U.S. DOS, 2020).

Different authors have proposed typologies to differentiate types of exploitation and organization types of human trafficking (Polaris Project, 2017, Cooper et al., 2017, Busch-Amendariz, Nsonwu, Heffron 2009; Shelley, 2003; Aronowitz et al., 2010). Polaris's research based on the United States (Polaris Project, 2017) proposed 25 types of exploitation divided into three categories: Sex Trafficking, Labor Trafficking, and a mix of both. Even though using only United Kingdom data, the typology proposed by Cooper et al. (2017) is the one used as the foundation in this thesis. There are two reasons for this choice. Firstly, most of the costs of human trafficking we are using in this thesis were estimated based on the work of Reed et al. (2018), and they used the same typology. Secondly, the confluence of sex trafficking and labor trafficking in some categories would bring challenges to the definition of cost per victim, which is already a complex task due to the lack of data. Using the typology proposed by Cooper et al. (2017) estimates a more conservative cost, not considering the convergence of harm done to victims suffering from both categories of exploitation.

They defined the 4 categories of exploitation as Domestic Servitude, Labor Exploitation, Sexual Exploitation, and Criminal Exploitation. The ones Reed et al. (2018) used were only the first three. The typologies can be seen in Table 5.

Table 5: Types of human trafficking exploitations

Category	**What it is and types associated with it**
Domestic Servitude	This form of exploitation happens when a person is held or forced to work as a nanny or a domestic worker for the trafficker. They usually work in the traffickers' homes. Victims are not uncommonly locked in

	rooms, preventing them from escaping. Usually, the exploitation lasts longer than other types of exploitation. The victim can be exploited for more than 20 to 30 years (Reed et al., 2018). Since it usually happens inside homes, where limited people have access, it is seldom for victims to be identified by the law enforcement force or witness.
Labor Exploitation	Labor trafficking is a diverse category. It goes from teenagers trafficked to hunt whales in Asia to seasonal agriculture labor in the US. Public and law officers usually consider the victims of this type of exploitation illegal migrants in the destination country, thus criminals deserving only the heavy hand of the state, not protection. Many are men, and the lack of being a classic victim, women, children, or elders, are usually ignored. (Volodko, Cockbain, and Kleinberg, 2020; Barron and Frost, 2018).
Criminal Exploitation	It is the type of trafficking that occurs to force people to commit some crime or unlawful activity. According to Villacampa and Torres (2017), they are activities "such as begging or prostitution in places where it is illegal, or those that directly constitute crimes". Examples of this type of criminal exploitation are: • forcing someone to grow and sell drugs, • to act as drug mules, or • to commit property-crimes or fraud.

Sexual Exploitation	It is "the recruitment, harboring, transportation, provision, obtaining, patronizing, or soliciting of a person for the purpose of a commercial sex act." (TVPA, 2000). It is considered the most prevalent type of exploitation happening in the United States nowadays. It is also the most researched one (Laczko, 2007; Aromaa, 2007). The confluence between sex workers and prostitution in many U.S. states is one of the reasons for this prevalence. Converging the meaning of those practices is not a consensus among scholars (Lee, 2011).

Another type of exploitation is wage theft, more common in cases of Labor trafficking (Kammer-Kerwick, Busch-Armendariz, and Talley, 2018). In this case, the victim is hired for some job (legal or illegal), and their wage is extorted or not paid using a myriad of excuses as debt to charging some unrequested service. Another type is child exploitation, it is a special case of sex and labor trafficking, and it is considered one of the most perverse types of trafficking. Some authors estimate that children make up to around 25% of the sex trafficking trade (Bales, 2007; U.S. DOS, 2020; ILO, 2017). Child and elderly exploitation for begging, organ Harvesting (Lee, 2011), and child soldiers or athletes (U.S. DOS, 2020) are other types of exploitation too.

Human Trafficking: Literature Review

The identification of human trafficking victims is a challenge. Some authors have tried to compile and test the power of identification of those identifiers (Cockbain and Kleemans, 2019;

UNODC, 2009; Volodko, Cockbain, and Kleinberg, 2020, Bales 2005). A major issue is the stigma of victimization. This stigma affects law enforcement and NGO services (Farrell and Reichert, 2017), heavily distorting the data collected which will eventually skew the classification assignments. The overall idea, however, is that there is a searchable set of possible identifiers for any type of exploitation. Those identifiers would indicate the likelihood that the person is going to suffer from human trafficking crime. Table 6 shows some indicators found in different sources. They were separated by the type of exploitation they are more likely to happen. Those identifiers can be related to the Individual (P), the Recruitment process (R), or both (B).

Table 6: Identifiers of human trafficking

Type of Identifiers	**Type of exploitation**	**References**
Connection with known websites of human trafficking (B)	Sexual Exploitation	Kara, 2017; Rabbany, Bayani, and Dubrawsky, 2018; Tong et al. 2017.
Companies that sponsor visa are in the suspected context (R)	All	Aronowitz et al., 2010; Volodko, Cockbain, and Kleinberg, 2020
Viewed or commented on suspected recruitment or commercial website (B)	Labor Trafficking	Volodko, Cockbain, and Kleinberg, 2020; Andrews, Brewster, and Day, 2018; Rabbany, Bayani, and Dubrawski, 2018.
Demographic characteristics (P)	All	Kara, 2017; Lee, 2011; UNODC 2009; Volodko, Cockbain, and Kleinberg, 2020; Bales, 2007; Cho, 2015; Cockbain and Bowers, 2019.
Country of origin characteristics (B)	All	Bales, 2007; Fry, 2008; Cho, 2015
Social Networks (B)	All	Andrews, Brewster, and Day, 2018

Methods of recruitment (R)	All	Busch-Amendariz, Nsonwu, Heffron, 2009
Behavior patterns or non-verbal languages (I)	Labor Trafficking	Villacampa and Torres, 2017; UNODC, 2009; Hudlow, 2015.
Having someone that hold their documents or are presenting dubious behavior (I)	All	UNODC, 2009

All machine learning models, or AI models found in the literature to identify human trafficking focused on sex trafficking to the best of our knowledge. The existence of advertisement in the sex market, aligned with the convergence in the legislation between sex workers, sex exploitation, and sex traffickers, makes it an easier target to this type of model. Other types of exploitation have more difficult indicators to help the detection (Volodko, Cockbain, and Kleinberg, 2020, Villacampa and Torres, 2017).

Models that use Operations Research or Analytics to evaluate, understand or estimate human trafficking activities can be divided into five main categories: Supply Chain (Kammer-Kerwick, Busch-Armendariz, and Talley, 2018; Flynn, 2019); Decision Support (Konrad et al., 2017); Network Science (Ibanez and Suthers, 2016; Hultgreen et al., 2018); and Machine Learning and AI (Andrews, Brewster, and Day, 2018, Tong et al. 2017, Hultgreen et al. 2018; Burbano e Hernandez-Alvarez, 2017).

The techniques involved were in a range of linear programming models to optimize resource allocation (Konrad et al. 2017) and facility location (Maass, Trapp and Konrad, 2020) to Natural Language Processing (Andrews, Brewster, and Day, 2018; Hultgreen et al., 2018).

Web Crawling and scraping were usually associated with Machine Learning and AI models in websites and social media to identify sex trafficking advertisements online (Tong et al. 2017; Ibanez and Gazan, 2016).

Network and Graph theory was also usually used to identify organized crime in human trafficking rings. The work of Hultgreen et al. (2018) uses a knowledge management approach to identify victims of sex trafficking in online advertisements using network science as the basis of their theoretical framework. Ibanez and Suthers's (2016) work also used a similar approach.

The data used in the papers had diverse origins, and many have just estimations based on professional opinion or rely only on the available online data. The difficulty in researching human trafficking is the access to reliable and accurate data (Laczko, 2007, Aromaa, 2007, Laczko & Gramegna, 2003, Konrad et al. 2017). There is a need for more data to be curated and made available for research to further work in Operation Research and Analytics can improve.

Human Trafficking: Costs

Costs of human trafficking activities will depend on the perspective that you are evaluating. From the government's perspective, we will have the expenditures to sustain the victims' services facilities and the criminal justice system to prosecute human trafficking cases, for example. But from the possible victim perspective, the cost will be perceived very differently. Health issues and the loss of quality of life even for a long period after their release are heavy costs for them to pay. Some are possible to be evaluated financially (Cary et al, 2016; Reed et al., 2018), others, like the cost of freedom and of human life are harder to estimate.

A few scholars have tried to estimate the costs of human trafficking for the government, NGOs, and victims. In research conducted in Texas (Busch-Armendariz et al., 2016), the present value of a lifetime of sexual exploitation for a single minor or youth is $83,125. That cost recognizes health issues, NGOs services, increase in risk associated with the labor in an unhealthy condition, among others. For a labor trafficking victim, the present value of the costs only considering lost wages for the labor would be $ 234,457, which on average would translate to $ 2551,12 for each victim annually. In a European report (Walby et al.,2020) per victim, over their lifetime they estimated that the cost per victim would be € 312,756.

Reed et al. (2018) estimated the cost for each exploitation type and its duration. Until the middle of 2021, similar research was not published with U.S. data. Therefore, their work is the basis of the costs of human trafficking in this thesis. They estimated the cost of modern slavery to the Health and Social work service per victim and found that it goes around $ 430,000, and that will inflict some harm that will depend on the type of exploitation and time exploited.

The costs presented in this section were divided into (1) costs in prevention; (2) cost as consequence; and (3) cost in response to human trafficking. This categorization was the same proposed by Reed et al. (2018). Their breadth includes costs with the criminal justice system, police responses, health-related services, and lost time or cost of opportunity for victims held in a forced labor condition.

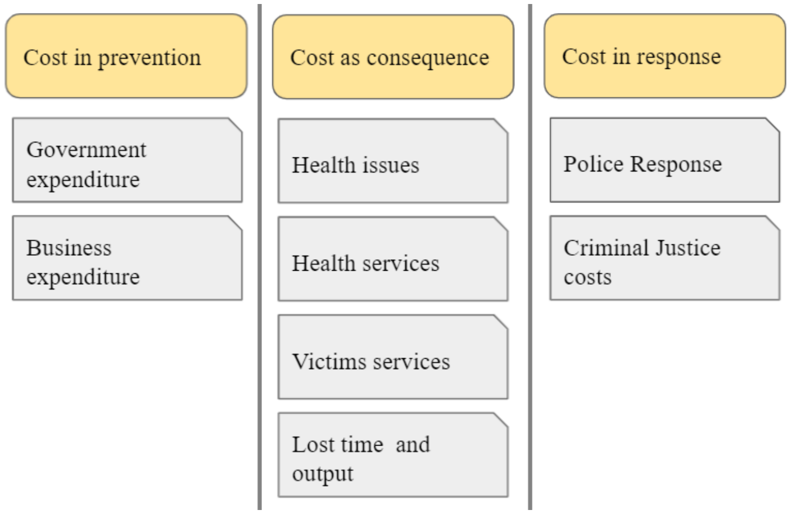

Figure 11: Costs of human trafficking

Figure 11 shows the types of costs under each category that they considered as the cost of modern slavery. This categorization considers the cost of government, health services, criminal justice, and law enforcement responses, as well as economic and business concerns.

Cost in Prevention

Government expenditures are related to the prevention cost, like awareness campaigns, housing for runaway minors, and international partnership efforts. The need for housing is not only to provide for prevention for runaway minors (Maas, Trapp, and Konrad, 2020), the U.S. Department of Housing and Urban Development also provides funding to housing and capacitation to survivors (U.S. DOJ, 2017).

According to Reed et al. (2018), those costs were about £ 210 per victim (in the United Kingdom). Other research conducted by the European Union estimated that the cost per victim was € 2,059. They take into consideration coordination activities within European Union member states (Cooper et al., 2017).

Also, business expenditures are related to the private parties' investments to comply with the Transparency on Supply Chains Act. The impact on business in the United Kingdom was estimated to be £1.4 million (Reed et al., 2018). Those costs are independent of human trafficking deterrence at the border, so they will not be taken into further consideration.

Cost as Consequence

Victims Service. Government and NGOs should provide safety and protection to survivors knowing that not all of them are at the same risk. The cost to rescue a survivor comes from providing physical and psychological support.

Shelters need to be specialized. They must be different from the domestic violence or homeless shelters to attend to the special needs of this population (Bales, Fletcher, Stover, 2004). For that purpose, the Department of Justice alone (U.S. DOJ, 2017) has invested over US$30.5 million in essential social services to survivors.

Besides shelter, food and clothing are also necessities of recently released survivors on top of legal services and advice. The victim's immigration status should be updated so they can provide for themselves legitimately. The T and U-visas (TVPA, 2000; U.S. DOS, 2021) could help with this process offering them economic and legal security. It is an essential step in the process of recovery and reintegration with American society. The cost for a visa will not be taken into account in this thesis because there were only 472 visas type T (for trafficking victims and their dependents) and 708 issued visa type U (for victims of any criminal activities) in 2020 (U.S. DOS - Bureau of Consular Affairs, 2021).

The demand for job placement, through professional training, can help the survivor to not fall victim to another trafficker in the future. Additionally, the Victims of Crime Act assistance is partly used to attend to human trafficking victims. For the fiscal year of 2021, the allocation of funds was over US$ 1 trillion, divided for each state ranging from more than US$126 million to California and around US$350 thousand to American Samoa (U.S. DOJ - OVC, 2021).

Walby et al. (2020) estimated that the cost of victim services per victim was 1 in 2016. Reed et al. (2018) estimated that this cost was around £ 1,630 per victim of labor exploitation; £ 1,650, sexual; and £ 1,710; for victims of domestic servitude.

Health issues and services. Human trafficking is, for some scholars, a matter of public health (Farrell and Fahy 2009; Chisolm-Straker, and Stoklosa, 2017). Different degrees of physical and psychological injuries, which include violent trauma, post-traumatic stress disorder (PTSD), depression, and anxiety disorder are inflicted on victims. There is a pattern in damage that occurs in survivors depending on the type of exploitation they suffered. Also, there is an effect depending on gender and age and how long the abuse occurred. Injures and PSTD are common in all victims, but miscarriages and sexually transmitted diseases are more common among female sex trafficking victims (Cary et al, 2016; U.S. DOS, 2020, Reed et al., 2018). Survivors are at risk of developing health-related problems. Even after getting their freedom, they may suffer from "repetitive stress injury, chronic back pain, visual and respiratory illnesses, sexually transmitted diseases, and depression" (Bales, Fletcher, Stover, 2004; p.5). According to Rothman et al. (2017) “the negative health consequences of human trafficking are well established and include neurologic, gastrointestinal, cardiovascular, musculoskeletal, dermatological, reproductive, sexual, dental, and mental health problems”.

The loss of quality of life, mainly due to those health issues, is the main cost. Walby et al. (2020) estimated that per victim, those costs were around € 127,504. Reed et al. (2018) estimated that it was around £268,450 per victim in case of labor trafficking; £270,890 for sexual exploitation; and £281,150 for domestic servitude.

Another cost will be related to the services provided for the survivors. Walby et al. (2020) estimated that per victim, the cost with health services after their exploitation time and after their release would be around € 20,749. Reed et al. (2018) estimated that the cost was around £ 470 per victim in case of labor exploitation; £ 1,560, sexual exploitation; and £ 390 in case of domestic servitude.

Lost Input and Lost Time. Loss of input represents the lost when the victims are being exploited and unable to participate in the legal economy. It also considers their reduced productivity due to physical and mental health issues after their release.

Walby et al. (2020) estimated that the total cost per victim of lost economic output would be on average € 59,537. Reed et al. (2018) separates the cost in loss of input, that they estimated to be £ 40,330 per person, in case of labor trafficking; £ 98,890 per person, in case of domestic servitude. And loss of time, in case of sex trafficking, that would be £ 37,460 per victim. A better estimation for the U.S. is the one provided in the report conducted by Busch-Armendariz et al. (2016). They estimated that on average it costs $ 2551,12 for each victim annually of labor exploitation and $83,125 per lifetime average of sex trafficking exploitation.

Cost in Response

Criminal Justice. Loss of input represents the loss when the victims are being exploited and unable to participate in the legal economy. It also considers their reduced productivity due to physical and mental health issues after their release.

Walby et al. (2020) estimated that the total cost per victim of lost economic output would be on average € 59,537. Reed et al. (2018) separate the cost in loss of input, which they estimated to be £ 40,330 per person, in case of labor trafficking; £ 98,890 per person, in case of domestic servitude. And the loss of time, in case of sex trafficking, would be £ 37,460 per victim.

Regarding the criminal justice costs in the US, estimations are that they range from 2,000 to 44,000 in violent cases (Hunt, Anderson, and Saunders, 2017). Due to the crime complexity, we estimated the higher cost. Reed et al. (2018) have not estimated the criminal justice costs because they were considered too long and complex procedures to appraise without access to the specified data. Although agreeing with this statement, Hunt, Andersons, and Sanders (2017) will provide a closer approximation of the real costs.

Another work that helped make such an estimation was Busch-Armendariz et al. (2016). They found that in Texas, only in 2014, there were 734 human trafficking-related incidents, with 210 suspects arrested and 85 convicted. It is not only in Texas that prosecution is scarce. Worldwide only 7,000 human trafficking cases were prosecuted, while 40,000 victims were identified in 2012 (U.S. DOS, 2013). Even though it is scarce, its costs are high.

Law Enforcement. The Department of Justice (U.S. DOJ, 2017) has used US$ 10.2 million to fund coordination and collaboration programs of legal services and social workers to support survivors in their legal claims. Also, they invested 4 million dollars in task forces and law enforcement officers' training. Those values indicate that the value considered by Reed et al. (2018) would be more conservative. Considering only the law enforcement response, their estimation the UK would spend around £ 7,730 per victim. Also, Walby et al. (2020) estimated that it costs € 93,293 per victim with Criminal Justice and Law Enforcement expenditures.

Other costs related to the United States Government. Another cost that could be taken into consideration but there was not enough data available was the cost of deportation of unwanted travelers. Others that were not part of the scope of this thesis are the economic impact of human trafficking and the revictimization factor. Trafficking strips the opportunity people have of getting legitimate jobs and contributing to society, which will lead to an economic impact (Wheaton, 2010). Further, fear of the legal and justice system, difficulty integrating into American society, and the stigmatization suffered drive the rate of revictimization (Bales, Fletcher, and Stover, 2004) which would lead to additional costs to society.

CHAPTER IV

METHODS

This thesis uses a Bayesian to gain an overall perspective on how a new security system to identify possible victims of human trafficking affects decisions at the POE. To make it possible, the steps followed were:

- Mapped the current screening process operation and the problem of trafficking in person through archival research.
- Proposed a security screening framework that focuses on the necessity of human trafficking detection at the United States POE.
- Defined the outcomes and costs associated with them to work as parameters of the Bayesian Decision model.
- Designed and test an optimization model to support the decision at the POE screening process regarding its costs and human trafficking detection rate.
- A numerical example including the analysis considering multiple scenarios of human trafficking potential risk of victimization was used to verify the robustness of the model, as well as, to gain insight regarding the trade-offs between security, decision regarding operation, and operational costs.

This thesis presents a Bayesian decision model that has slightly different objectives. The first one has as the output the minimum number of characteristics that should be found in the prescreening procedure so it would flag as a possible victim and send the traveler to a second screening. It is a representation of a proposed POE operation with a trafficking victims' approach. It has the objective to maximize security while minimizing the overall cost. One important assumption is that the system has a specific level of effectiveness in identifying possible victims given by a distribution. It is impossible to know if the crosser is a victim for certain, and the number or distribution of the victim's crossers.

The Bayesian decision model handles better the uncertainty of the estimations regarding human trafficking and its identification at any POE. The model provides the information needed to reach the goal of offering an optimal operation decision in the specific human trafficking contextual constraints. We found how the number of expected victims' level can interfere with the decision at the United States' POEs.

To operate a selective screening procedure at the POE, the CBP officers must decide on a policy regarding who is going to be selected and who is not. The policy will determine which criteria will be used to make that selection. The policy also defines the number of people or the characteristics that would incite the selection of a person for further screening. The goal of that kind of policy is to keep a level of security, with an accurate selection of who is more potentially a victim, while considering the service level of POE operation. For this, the model presented can be used as a decision support tool. Next section the proposed operation is explained and the main characteristics that were modeled in the Bayesian decision model.

Proposed operation

The proposed operation would use the same scheme already in place but implementing anti-human trafficking with a victim's focus. The procedures would help the CBP officers` decision regarding who is a potential victim on sight. Figure 12 shows a simplified flowchart of the proposed new operation with a human trafficking victim focus.

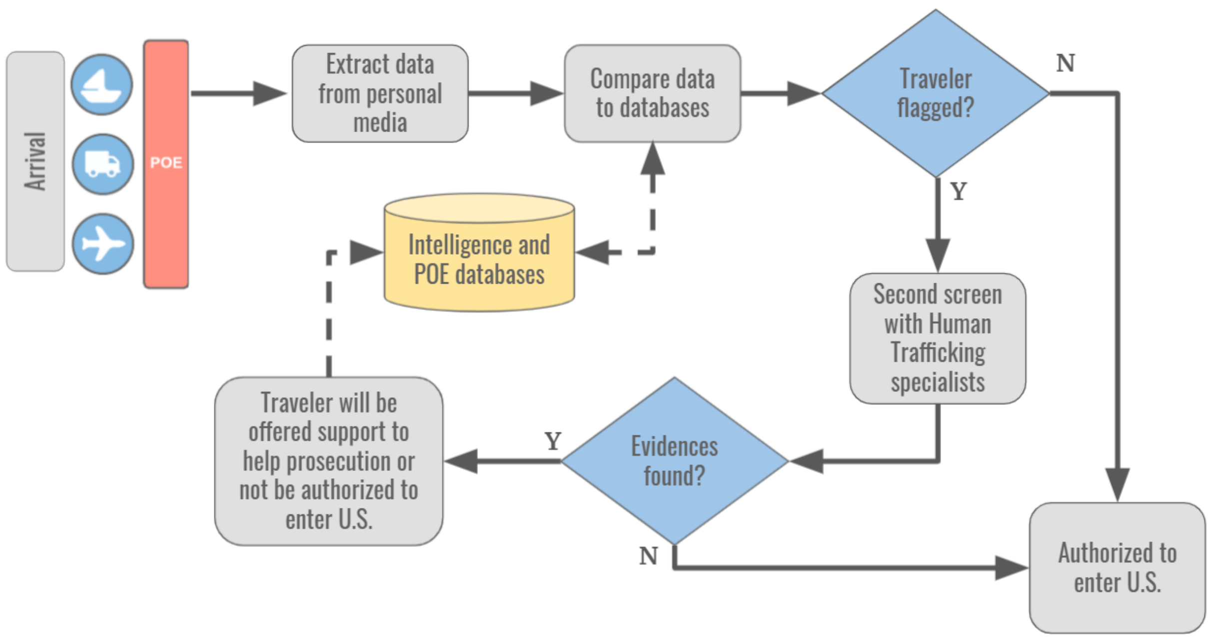

Figure 12: Simplified flowchart of the proposed additional operation

Any method for prescreening border-crossers would give at least two possible responses: (1) the traveler is at risk of becoming a victim of human trafficking, or (2) the traveler is not at risk. The automatic screening system is assumed to determine in each category of risk the traveler would be assigned. Depending on the category of risk, the traveler would be led to a further screening or authorized entrance. In the first case, the traveler would be conducted to a second screening with a human trafficking specialist who would determine if they are really at risk.

The objective of any optimizer of this type of operation is to minimize disruption and cost while guaranteeing a certain level of security. A more refined selection of who is going to be inspected and who is not is crucial. A universal screening, which means screening anyone who crosses the border, would be impossible considering that more than 1 million people enter the United States POEs every day. At least not without a massive investment in hiring and training new officers and new facilities. Therefore, the goal is to determine this optimal, or good enough, number of people who would be extra screened during the operation and the ones that are going to be authorized after the prescreening.

Upon arrival, the passenger or pedestrian would go through an inspection by the United States' Border Patrol agents. If the agents can identify a trafficked victim, then they can prevent the victim from being exploited. Additionally, the government can build a case against the traffickers with the victims' information. If not, nothing can stop the exploitation from happening.

For this proposition, at first, a scraping and classification model would extract all the information and proceed with an automatic generic cleanse and structure. At this stage, if the data exists, the model returns with people and organizations (names), events and dates, and geolocation from the traveler's media. One assumption is that this model would accurately identify victims. Another is that we can use different classification models to represent the level of accuracy and precision of our model, using different databases. These assumptions were made so a baseline value could be designed in the optimization model.

A similar model which could be used for this analogy is the TwilCal (Andrews, Brewster, and Day, 2018) adapted to the border security needs. The new security measure algorithm output is a structured file containing the data found in this first search. Then, using hierarchical rules based on known identifiers, the model classifies the data into human trafficking groups (HTG) of risk.

The number of identifiers found by the model at the prescreening would go from [0, G], in which G is the total number of HTG. This number is constantly changing since the model allows the new information from the traveler and related Intelligence from other agencies to be continually added to the POE Database. The third stage then compares HTGs gathered in a database in the second stage, with a known network of trafficking groups and activities. It looks for all the possible connections between the traveler and the network. The output is going to represent how fused is the relationship between the trafficking network and the traveler. The final output is a number between $[0, \infty]$ that we call the "Risk of traveler is a victim", *r*. The measure *r* is, in practice, the quantifiable connections with events, dates, geolocation, activities, and people already known as human trafficking stakeholders by the United States agencies. Because we understand that not all people who have human trafficking connections and characteristics are victims, r is just a measurement that would need to further inquiries or evaluation.

Utilizing tools that scrape and analyze the social media accounts in real-time, the system aims to assist border patrollers to make their final decision. So, to analyze the best value of *r*, that is the one which would lead to the best cost without great prejudice in the detection rate, we propose a Bayesian decision model. The model used is based on the one proposed by (Majeske and Lauer, 2012) but adapted to fit the thesis' goal. Another way to analyze the system is to identify the best number of people to be led to a second screening so one could minimize the overall costs of all outcomes. The trade-offs between different levels of expected victimization are based on McLay, Jacobson and Kobza (2008). The model will be highly dependable on the assumptions we make regarding the distribution of the input and parameters. For that reason, sensitivity analyses were made with the aid of different scenarios.

Decision Tree

The decision tree that represents the options from the prescreening and second screening proposed to be used with a human trafficking focus is illustrated in Figure 13.

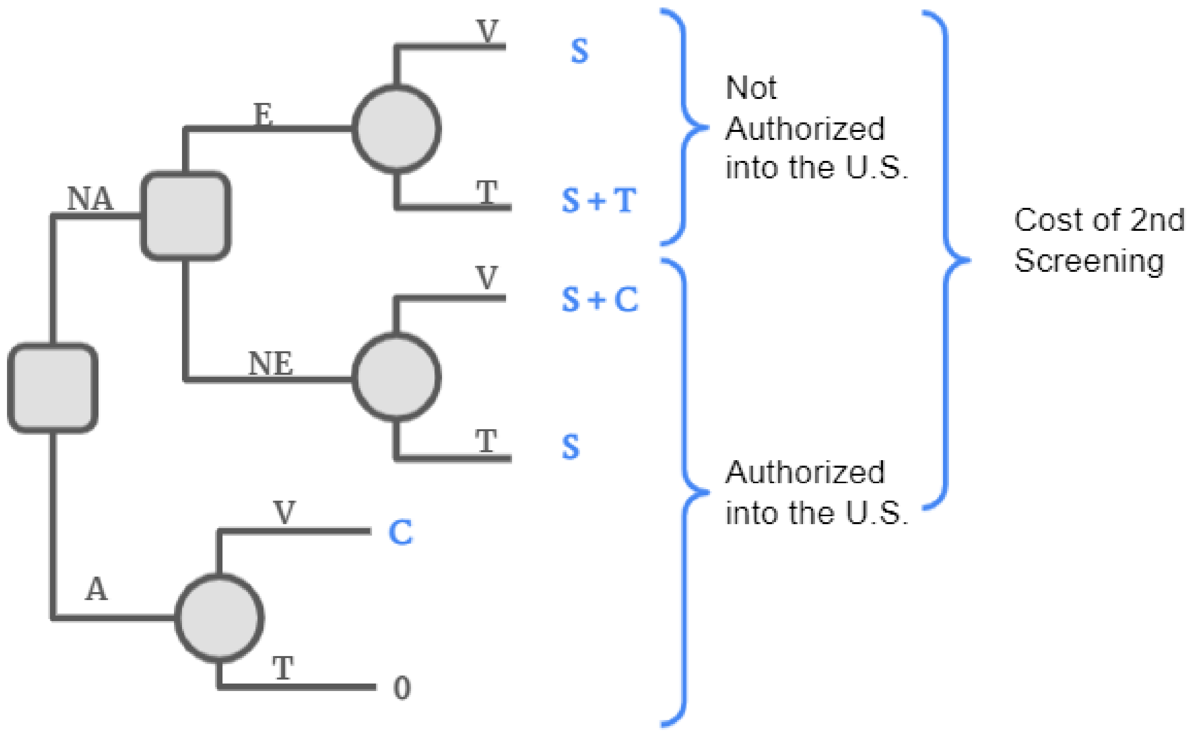

Figure 13: Decision Tree

The traveler (T) or victim (V) will arrive at the POE and go through an initial prescreening procedure as described before. Either way, they will be flagged by the classification model as a possible victim or a common traveler depending on the number of human trafficking indicators found (r). Those who were flagged as possible victims will be conducted to a second screening (NA), and those who were not flagged will be allowed entrance into the country (A). That second screening will be conducted by a human trafficking specialist, to confirm or not that the border-crosser is a common traveler and allow their entrance (NE) or to confirm they are a possible victim, finding new evidence, and deny entrance at that moment (E). The ideal scenario is that the possible victim would be transferred to specialized services that will help them and the judicial system to gain information regarding the traffickers responsible for the recruitment and transportation.

Analyzing the bottom branch first, if the person has arrived at the POE and the prescreening does not flag her/him as a possible victim (A), then the possible outcomes are a victim being allowed entrance into the country with no support and ending up being exploited (A – V). This will result in a cost (L in blue) of the people's liberty, and all the consequences of their exploitation. Another possible outcome is that the person is not a victim, a common traveler (A–T), so there would be no cost for any of the parties involved.

The top branch is the one that occurs when the system flags a possible victim (NA). That person will be screened by a human trafficking specialist that can decide if that person has the characteristics that are more common in human trafficking victims, as discussed in Chapter III. If they find the person is a potential victim, they will not allow entrance to the traveler. Then they will be conducted to an NGO or lawyer to see additional procedures outside of the CBP realm of responsibilities. If they decide that the prescreening system wrongly flagged the person, they will permit entrance in the U.S. In both cases, the traveler can be a traveler or an actual victim. And the costs will be: (S) the additional cost for the traveler of a new operation; (W) the cost of the victims' service; (I) the cost of inconvenience for the common traveler; (T) the opportunity cost for the traveler; and (C) the cost of human trafficking as mentioned before.

Costs and Data Used

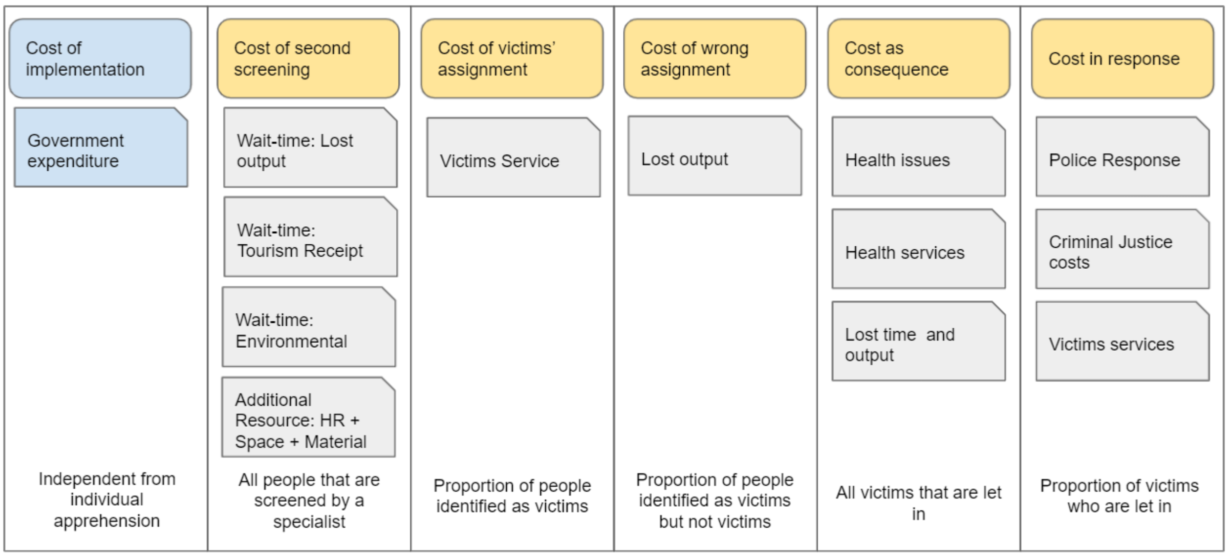

Figure 14: Costs at the POE - Operation and human trafficking

There would be many costs associated with implementing a new screening procedure at the POE. Those costs were divided into two different categories: the cost related to the human trafficking victimization, and the costs related to the POE operation. The costs considered are illustrated in Figure 14. All the costs that are going to be used are in the yellow columns. The one in blue is going to be ignored because it is independent of the individual apprehension of possible victims.

For determining the indirect and direct costs of letting a victim enter the country the considerations made were explained in Chapter III. The final costs used were defined as the range of the lowest and highest value found in the secondary sources adjusted for 2021 (considering inflation) and, when appropriate, currency conversion. The rates used can be seen in Table 7.

Table 7: Rate of conversion and inflation

Inflation	From	Rate	Currency conversion	From	Rate
To 2021	2016	13.2%	EUR TO USD	2016	1.20
To 2021	2017	10.8%	GBP TO USD	2017	1.29

The final values regarding human trafficking can be seen in Table 8. The total cost would range from $242,895.63 to $673,353.86 for each victim.

Table 8: Estimation of the cost of human trafficking

Costs per person		Range in USD$		References
Total Cost of Human Trafficking		$ 242,895.63	$ 673,353.86	Chapter III - Human Trafficking: Costs
Consequence	Health issues	$ 173,201.43	$ 401,853.32	Reed et al., 2018; Walby et al., 2020.
	Health services	$ 557.43	$ 2,229.74	U.S. DOJ, 2017; Reed et al., 2018; Walby et al., 2020.
	Victims' services	$ 2,329.79	$ 2,444.14	U.S. DOJ, 2017; Reed et al., 2018; Walby et al., 2020.
	Lost time or output	$ 53,542.33	$ 141,345.45	Busch-Armendariz et al., 2016; Reed et al., 2018; Walby et al. (2020)
Response	Criminal Justice	$ 2,216.00	$ 48,752.00	Hunt, Anderson & Saunders, 2017
	Police Response	$ 11,048.64	$ 76,729.21	Reed et al., 2018; Walby et al. (2020)

Costs regarding the new operation were estimated using the data from official government and NGO reports. The POE already carries a similar screening system with two levels, so the expected cost only computes the extra cost of a new detection system. For the additional security costs, the estimation was based on current employment and average salary divided by the expected number of people screened (U.S. CBP, 2021). It also included the economic cost of delays in a busy land POE in the United States from a business perspective (Vadali, Kang, and Fierro, 2011) and the effect it has on GDP (Avetisyan et al. 2015; Roberts et al., 2014). All costs have computed the inflation in the period. For the U.S. losses on tourism receipts, the estimation used the total International Tourism Receipt for the U.S. in 2019 (264,6 trillion dollars), divided by the number of international entrances in the U.S. for the same year (79.6 million people). Tourism in the U.S. represented 2.8% of the GDP in 2018 (U.S. DOC, 2020), which would justify its addition.

Other estimations are not related to the costs of outcomes. The first one would be the accuracy on which an officer or human trafficking specialist identifies the possible victims at a second screening. We are using a Bayesian Model to overcome this need. Others are the accuracy of current models used to identify this type of crime and the rate at which possible human trafficking victims would cross the border. Both are challenging estimates to make. The first one was estimated based on the work of Tong et al., 2017; Hundman et al., 2018; Rabbany, Bayani, and Dubrawsky, 2018. The second one, the prevalence of human trafficking, is known to be hard to measure (Laczko & Gramegna, 2003; Aromaa, 2007; Laczko, 2007; Konrad et al. 2017). The specific population that attempts to cross the border every day is even more challenging. Victims sometimes do not even know they are going to be exploited, even more being held captive. Yet, the number of people that cross the border can highly affect the capacity of control of POE operations. To address this issue, the proposed model offers a way to retro-feed the system with specialist information. For privacy issues, the personal data of the traveler is not stored for more than 24 hours (U.S. DHS, 2017), but the combination of characteristics found and specialist decision. With time, the number would increase its accuracy, which would lead to a better decision. For now, compensating for the lack of empirical data, the model ran different scenarios with levels of prevalence of human trafficking transportation through the United States border.

Other costs were identified but will not be translated into the model. Costs of deportation; the environmental cost of an increase in wait-time at the POE; prevention procedures; partnership efforts, and the cost of ICE operations (Roberts et al., 2014; Konrad, 2019; U.S. DOS, 2013).

In Table 9, the range of costs that are going to be considered in the models are described for each type of costs.

Table 9: Range of costs and prevalence of human trafficking in the U.S.

Data		Range in USD$		References
S	Cost of Second Screening	$850.00	$850.00	Explained above
T	Cost of Lost Opportunities for traveler	$2,826.64	$2,826.64	Explained above
C	Cost of Human Trafficking	$242,895.63	$673,353.86	Explained above
Numbers of victims entering U.S. each year		14,500	20,000	U.S. DOS, 2013; U.S. DOS, 2003

CHAPTER V

BAYESIAN DECISION MODEL AND RESULTS

This chapter will bring the basic assumptions and problem formulation for the Bayesian decision model. All the assumptions and parameters used are based on published data or previous research that is not necessarily generalizable. However, they are useful to provide a glimpse of what the model can generate. With the information, the robustness of the model can be tested regarding a change in its parameters.

The main limitation of the model itself is common to most models. It is just a simplified version of reality. It makes assumptions regarding probabilistic distributions of arrivals to the POE and the arrival of possible victims, which are not based on individual data from the operation.

Assumptions and limitations of the model

- The vulnerabilities the perpetrators and victims share can mix them in the identification. This confluence will be ignored.
- One main assumption is that it is possible to identify human trafficking traits at the POE using data from social media and internet access, as well, as personal electronic devices search (that already are allowed in the current operation).
- That the classification model would identify victims better than using random selection.

- The discretion and bias of the POE agent after the prescreening are not directly accounted for. The probability of finding or not evidence would only consider an unbiased operator, which would not always be the case in practice.
- That identifying the victim is beneficial for them.
- The harm of human trafficking is given a monetary value. But not all the costs can be translated to a financial cost, as some people's liberty, and the sense of security were ignored.
- The flow of people is considered to be independent, which is a reasonable assumption (Moya and Rueda, 2019).
- The costs related to the impact on the environment, on jobs, and on productivity as well as in highway safety were also ignored.
- Deterministic value for the proportion of victims in the population, even though they have an unknown stochastic nature.
- Assumption of the costs of human trafficking, an average, as not dependent on the type of exploitation and duration expected of exploitation.
- Lack of primary data and the use of secondary estimations.

The current intelligence behind the security operation at POEs currently investigates people's social media for any undesirable characteristics (U.S. DHS, 2017). They also look for travel history, employment, and address history. The new security measure would make use of this apparatus to further improve the detection of human trafficking victims.

Bayesian Decision Model

The Bayesian Decision model was chosen because of the capacity of handling uncertainty better than deterministic models. As mentioned, data is scarce, and much of the input used was based on rough estimations.

This model outputs the number of characteristics that should be found by the prescreening model so it would classify the person crossing the border as a potential victim. This leads to the number of people expected to be screened for a second time, and of possible victims identified. The probabilities derived from the model can be observed in Figure 15. This model along with the first numerical example were published in the DSI 2020 Conference Proceeding (de A. Drummond & Moya, 2020).

Decision Variable and Parameters

Depending on the *r*, the risk of the travelers has of being trafficked according to the classification model, the model classifies the travelers in two categories, authorized or unauthorized. The unauthorized traveler is submitted for another review which would be conducted by a trained patrol officer or a social worker specialist in human trafficking. They are going to verify if the model is correctly identifying the possible victim and look for new evidence. In case the officer finds new supporting evidence (E or NE), the person is conducted to a victims' service specialist. They would be, at least temporarily, forbidden to enter the US. Some possible indicators that officers can find at the second screening are employment perspectives, employer analysis, psychological signs, distress signs, etc. For those whose entrance is rejected, the ideal scenario would involve assistance and possible corroboration to an ongoing investigation against the possible trafficker. However, these services would not be in the POE's responsibilities. So, the costs associated with these services will not be included in the model.

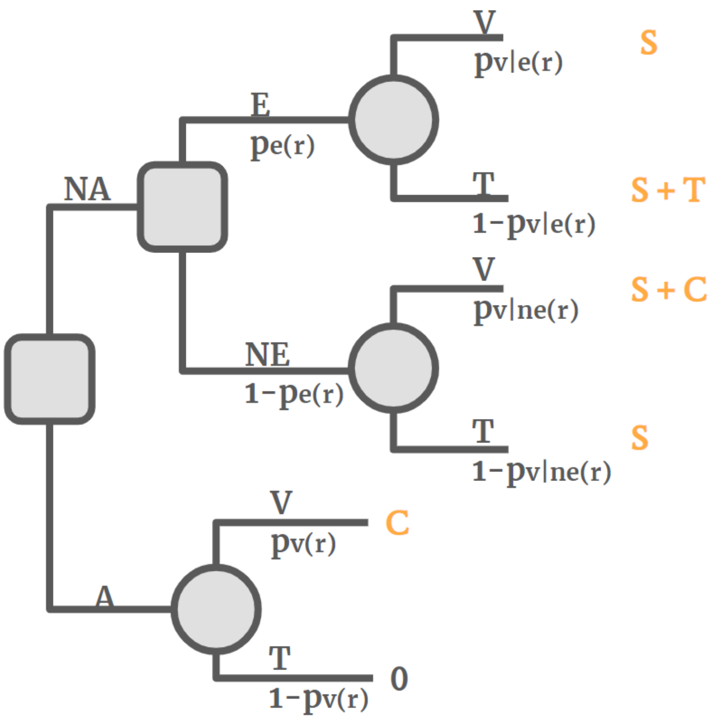

Figure 15: Decision Tree for the Bayesian Decision Model and conditional probabilities

The Model

The $\boldsymbol{pv(r)}$ or $\boldsymbol{p(v|r)}$ is the probability of a traveler, given *r*, is going to be held in the U.S. in slavery conditions. Similarly, $\boldsymbol{pt(r)}$ is the probability of, given *r*, a traveler is not considered connected to human trafficking activities, which is the same as $\boldsymbol{pt(r)=1-pv(r)}$. We assume that, as the screening process is looking for human trafficking indicators, so as *r* increases, $\boldsymbol{pv(r)}$ follows. The errors can be computed as, on one hand, $\boldsymbol{pe|t(r)}$, which represents the probability of finding new evidence in the second screening when the person is a common traveler (Type I error). On the other hand, $\boldsymbol{pne|v(r)}$ is the probability of not finding evidence in the second screening when the person is a victim (Type II error). The first one is easier to estimate by observation, but the second one is difficult since the number of people being trafficked is unknown. The probability of finding new evidence in the second screening with $\boldsymbol{pe(r)}$ is given by the combination of the two errors as can be seen in Equation (1):

$$p_e(r) = p_{e|v}p_v(r) + p_{e|t}p_t(r) = \left[1 - p_{ne|v}\right]p_v(r) + p_{e|t}[1 - p_v(r)] \qquad (1)$$

Finding evidence or not depends on the risk measure (r) the person is assigned. As r increases so should $pe(r)$. When the probability of finding evidence is higher on victims ($[1 - pne|t] > pe|t$), it corroborates with the assumptions of this model. To optimize the model, it is necessary to evaluate the cost of every outcome (see Figure 13). In this scenario, the expected cost is going to be the added security cost (S). **S** is an estimation of the government expenditure for the new security system, considering the possibility of increasing wait times, as well as the cost of hiring and training new employees. New facilities and accommodation are not going to be considered because it is assumed that a different workspace would not be necessary. Also, when this decision is an error, it leads to a cost (T) that can be computed by adding the traveler's cost on non-reimbursed tickets, and the loss of legitimate job opportunities along with the U.S.'s government opportunity costs in tourism receipts.

In another outcome, the victim goes to a second screen, and she/he is accepted, we are going to compute the added security costs (S) too. Although, we added a higher cost since a victim is going to complete their cycle of exploitation. The cost of each trafficked person (C) is computed. The value is going to be an average of the cost associated with law enforcement and prosecution in cases of human trafficking in the U.S.

When a victim is authorized at the first step of the security system, the only cost associated is the cost of human trafficking (C). Then, if a traveler goes to a second screen and they are accepted, the only cost associated with this outcome is the security cost added (S)and the inconvenience cost (I). $\boldsymbol{I}$ would represent the cost for a common traveler that goes through extra procedures (e.g., late for a meeting). This cost was ignored because it revealed itself irrelevant compared to the others.

The best outcomes regarding costs are when a real victim goes to a second screen and is not authorized to have access to the U.S., conducted to a victim's service (W) or when a common traveler is accepted on the first screen (No additional cost). The first one only incurs S + W; and the second, none. In future research, the value related to letting travelers enter the country (GPD) can be evaluated. The cost of the victim's service (W) will be ignored because the value could not be estimated, and it is considered to be small in comparison to the others, as the cost of inconvenience (I).

To evaluate the framework, we have used costs for each outcome as described above. Since we want to optimize it, we need to minimize the Expected Monetary Value (EMV) that is given by the cost and the probability of each outcome. $\boldsymbol{EMVa}$ is the expected monetary value for a person authorized in the first screening (see Equation (2)). The $\boldsymbol{EMVu}$, EMV of the travelers send to a second screening, is going to be given in Equation (3).

$$EMV_a = p_v(r)C \tag{2}$$

$$EMV_{na} = p_e(r)\left[S + T\left(1 - p_{v|e(r)}\right)\right] + (1 - p_e(r))\left[S + C\left(1 - p_{v|e(r)}\right)\right] \tag{3}$$

In that case, to find the optimal policy for the new human trafficking detection process requires that we minimize the total expected cost regarding the value of r. The decision criteria are going to be $\boldsymbol{rf}$ because, as showed, is the value that gives the same cost of screening or not the person with that category of risk. The total expected cost of the optimal screening process regarding r is EC (See Equation (4)).

$$EC(r) = \begin{cases} p_v(r)C & if\ r < r_f \\ S + Tp_{e|t}\left(1 - p_v(r)\right) + Cp_v(r)p_{ne|v}(r) & if\ r \geq r_f \end{cases} \tag{4}$$

When the expected cost from authorizing the traveler at the first screening is equal to the expected value of having a second screening, it is indifferent to if the officer patrol sends the person to further screening or not. That is the optimal state, since we do not want to decrease the cost in expense of diminishing the rate of detention. When $\boldsymbol{EMVu}$= $\boldsymbol{EMVa}$ and the $\boldsymbol{rf}$ values (Equation 5- 6):

$$p_v\left(r_f\right) = C + \mathrm{S} + \mathrm{T}\ \mathrm{p}_{e|t}[1 - \mathrm{p_v}(\mathrm{rf})] + \mathrm{Cp_v}(\mathrm{rf})\mathrm{p_{ne|v}}(\mathrm{rf}) \tag{5}$$

$$p_v\left(r_f\right) = \frac{S + Tp_{e|t}}{C\left(1 - p_{ne|v}\right) + Tp_{e|t}} \tag{6}$$

Numerical Example

A numerical example is provided to demonstrate the described model. All the costs and parameters are going to be estimated. We would like to reiterate that it is just an example, and if tested with more accurate numbers, the result could change considerably.

For this example, first, an adequate distribution to $\boldsymbol{r}$, $\boldsymbol{f}(\boldsymbol{rf})$ was defined. The exponential distribution (with parameter $\boldsymbol{\lambda r}$) is a possible distribution to assume when considering the arrival of potential victims at the POEs having a specific measure of risk. It is expected that just a very low proportion of people are being trafficked in comparison to all the people trying to enter the U.S. The Department of State estimates that around 16,000 people are trafficked into the United States each year, and the U.S. receives around 79.6 million of non-residents visitors annually (U.S. DOS, 2019). The $\boldsymbol{pv}$= 0.0002 and $\boldsymbol{pt}$= 0.9998 were estimated based on that data. Setting the P(r>100) = 0.0002, the same as the probability of victimization, then it is possible to find $\boldsymbol{\lambda r}$ = 0.8517. To find the $\boldsymbol{pv}|\boldsymbol{r}$, the same reflected normal loss function proposed by Majeske and Lauer (2012) based on the work of Spiring, 1993, was used. So, $p_v = \Phi([r - \mu_v]/\sigma_v)$. μ_v is equal to $p_v(r) = 0.5$. Just a small proportion of people will have a $p_v(r) \geq\ 0.5$. It is arbitrarily defined that only 1 in 5 thousand would be that number. So, the value of $\boldsymbol{\mu v}$ is going to be defined as $\mathbf{-ln}\ (\mathbf{0.002})/\boldsymbol{\lambda r}$=100.002 and, an arbitrary value for the standard deviation is given, $\boldsymbol{\sigma r}$=7.

The numbers from the official government and NGOs reports were used to estimate the costs as explained in Chapter IV: Costs and Data Used. The POE already carries a similar screening system with two levels, so the expected cost only considers the increase in costs for the new detection system. For the additional security costs, we estimated based on current employment and average salary (U.S. CBP, 2019). For traveler's costs and U.S. losses on tourism, national data were used. The costs of the person's held in slavery conditions as an estimate were explained in Chapter IV: Costs and Data Used. Future research could use different methodologies or empirical research for more precise estimations. The accuracy of the model proposed to the new security system helped to estimate a value for $\boldsymbol{pne|v}$.

For this analysis, it is going to be ignored by the discretion of the agent after the prescreening. Another simplification to the model is the assumption of deterministic value for victims in the population N, even though they have an unknown stochastic nature.

It is expected that just a very low proportion of people are being trafficked in comparison to all the people trying to enter the U.S. The U.S. Department of State (2003, 2013) estimates that 14,500 to 20,000 people are trafficked into the United States each year and the United States receives around 79.6 million visitors annually (non-residents). The estimated probability of a traveler becoming a victim to be around 0.0002.

In Figure 16, notice that the conditional probability of the victims is dependent on r. Using Equation (5) we find the $\boldsymbol{rf}$=64.5, which means that the number to the risk measure should be around 64.5 to minimize the costs of operation.

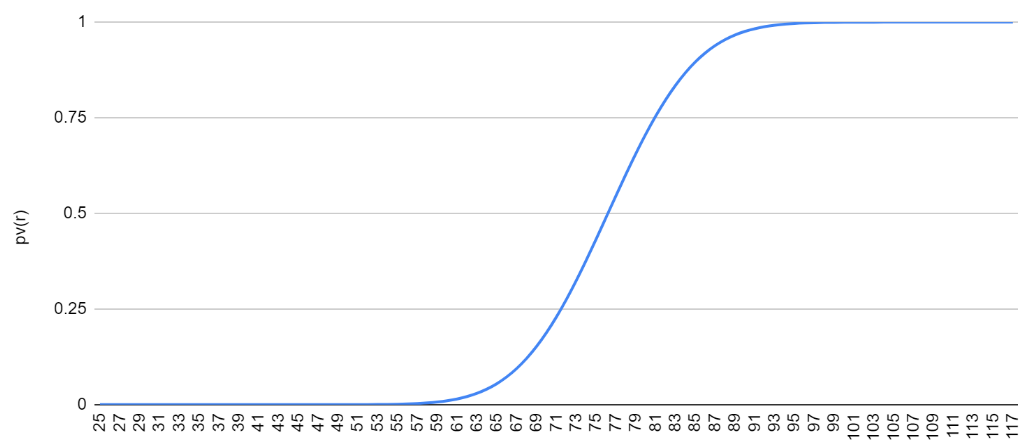

Figure 16: Conditional probability with respect to r characteristics

The results of the outcomes and their given probabilities are presented in Table 10. We can see that the proportion of passengers that are not authorized at the first screening is given by $\int_{rf}^{\infty} f(r)\, dr$, which is 0.997. It is high, indicating that the cost of the second screening is not worth bellow the $\boldsymbol{rf}$. Around 0.26% of the people sent to be screened for the second time are really victims. But in a lower proportion, the victims are being authorized to enter. The probability of finding evidence is given by the integral from 0 to $\boldsymbol{rf}$ multiplied to the probability found in Equation (1) which is 0.010131. This resulted in that about only 1% of the second screening would lead to new information. Results also indicate that almost 99% of the people that go to the second screening and are assigned as possible victims, turn out to be common travelers. From the total that have been granted authorization to enter the U.S, only about 0.0003384 are victims authorized to enter.

Table 10: Results for the Bayesian Decision Model

Outcomes - Probabilities	All	Travelers	Victims
Authorized entrance at first screen	0.9973692	0.9998005	0.0001994
Sent to second screen	0.0026308	0.9973711	0.0026288
Unauthorized entrance (Found new evidence)	0.0101305	0.9862297	0.0137702
Authorized entrance	0.9886950	0.9996616	0.0003384

Different scenarios: Level of victimization

The estimated probability of a traveler becoming a victim will be 0.00018 to 0.00025 based on the estimations made by the U.S. Department of State (2003; 2013) of human trafficking victims crossing the border of the U.S. every year.

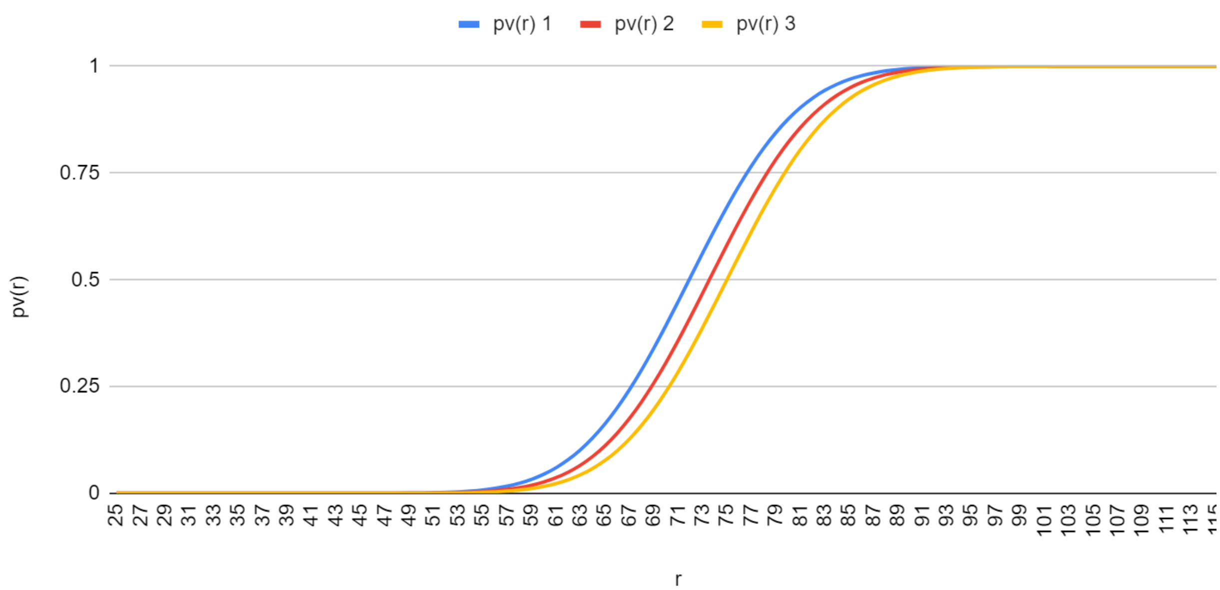

Figure 17: *Pv(r)* x *r* for each level of victimization

The *pv(r) 1* corresponds to the lower level of victimization, with only 14,000 victims crossing the U.S. border. The *pv(r) 2* corresponds to the middle, with 17,000; and the *pv(r) 3* to the higher level, 20,000 victims. Those *pv(r)* in relation to *r* were graphed and they are illustrated in Figure 17. In those conditions, using the lower costs, the rf for each level of victimization is compiled in Table 11.

Table 11: *rf, pv(rf), p(a),* and *p(na)* for each victimization level.

	Victimization level		
	Low	Average	High
pv(rf)=	0.005165	0.005165	0.005165
rf=	53.928375	55.579845	57.021385
p(a)=	0.989515	0.990881	0.991927
p(na)=	0.010485	0.009119	0.008073

One can see that the difference between the optimal value of r does not vary much to the level of victimization (less than 6% from the low to the high). However, if the scenario cannot be accurately estimated, as expected in human trafficking situations, this error will carry out people to a second screening to a number far from the optimal.

In the case of the posterior probabilities, they will be the same for all the levels because the *pv(rf)* has not change, nor the *p(e|t)(rf)* and *p(ne|v)(rf)*. Table 12 shows the posterior probabilities for all three scenarios.

Table 12: Posterior probabilities for the different victimization level

Posterior Probabilities		
	Traveler (t)	Victim (v)
Evidence (e)	0.996415	0.003585
No Evidence (ne)	0.998429	0.001571

Different scenarios: Costs of human trafficking

In Table 13, the results for three levels of estimated costs of human trafficking. The low level is the one that represents the smaller estimation based on the literature in Chapter IV: Costs and Data Used. The other levels have an increase of 15% and 177.22%, the last representing the maximum cost found in the literature presented in the same Chapter IV.

The number of risk factors necessary (*rf*) to identify possible victims decreases, which means fewer characteristics would be required to be found to send someone to a second screening with a human trafficking specialist. The variation of *rf* with the increase of 15% and 177.22% is -0.52% and -4.36%, respectively. The cost of human trafficking affects the number of people who are or not authorized, *p(a)* e *p(na)*, which represents the number of people that will be sent to a second screening changes.

Table 13: *rf*, *pv(rf)*, number of people in a second screening for each cost level (1)

	Human Trafficking Cost Estimations levels		
Cost	Low	+15%	+177.22% - Max cost
pv(rf)=	0.00516	0.00449	0.00186
rf=	53.92838	53.59150	51.57756
Variation: *rf*		-0.62%	-4.36%
p(a)=	0.98943	0.98913	0.98711
p(na)=	0.01057	0.01087	0.01289
Number people - Second Screen	841,222	865,474	1,025,763
Variation: Number people - Second Screen		+2.88%	+21.94%

The difference was expected since the only cost that varies was the cost of human trafficking. There was an almost 22% increase in the number of people conducted to a second screening, but a very small decrease in risk identifiers. This indicates that the model is robust to some variation of the cost of human trafficking. Considering that variation is expected when dealing with this type of uncertain estimation, the robustness of the model is greatly desirable.

Different scenarios: Costs of POE operation

Table 14 shows the results for different costs of operation at the POE scenarios. The first one "Low" will consider the value presented in Chapter IV: Cost and Data Used, the 'Average' is 15% greater than the Low, and the 'High', is 15% greater than the 'Average'. The values of an optimal risk factor to identify possible victims are 53.93, 54.26, and 54.60, and the number of people who will be sent to a second screen are 841,222; 818,001; and 794,988, respectively. These results show that the model is behaving as expected, having a severer sense of the probability of victimization given the risk factors (*rf*), and decreasing the number of people who will be further screened. So, the cost of the POE operation will negatively affect the decision of how many people are conducted to a second screening.

Table 14: *rf, pv(rf)*, number of people in a second screening for each cost level (2)

	POE Operation costs estimations levels		
Costs	Low	Average + 15%	High +32.25%
pv(rf)=	0.00516	0.00591	0.00678
rf=	53.92838	54.26015	54.59839
Variation: *rf*		+0.62%	+1.24%
p(a)=	0.98943	0.98972	0.99001
p(na)=	0.01057	0.01028	0.00999

Number people - Second Screen	841,222	818,001	794,988
Variation: Number people - Second Screen		-2.76%	-5.5%

The same difference in the variation of costs and *rt* or number of people conducted to a second screen is observable when running different scenarios of low, average, and high operational costs. This again shows that the model is robust to some extent of error in the cost's estimations.

In all scenarios, new evidence is found in a great number of travelers, which is expected for the way the model was built, with little cost for this type of error. Considering the cost of inconvenience from the traveler's perspective could change this evaluation. And that could be something to be considered in future research.

CHAPTER VI

CONCLUSION

The main conclusion is that the costs of human trafficking and the POE operation affect Agents' decisions at the POEs. These decisions affect the ability to detect and intercept human trafficking activity. The estimated prevalence of human trafficking also affects the decision of how many people would be sent to secondary inspection with a human trafficking specialist. Another conclusion is that the costs of human trafficking are great, even when not considering more intangible and indirect costs, such as the loss of an individual's freedom, human rights, and the impact of unpaid labor in the economy.

In the numerical example, the model was tested in different scenarios considering different estimated costs of human trafficking and POE operation. It also compared different levels of expected prevalence of human trafficking at the border. The goal in running the numerical example was not only to verify if the model was performing as expected but also to gain insight on how decisions regarding optimality would change when considering different parameters' estimations.

In the first run of the model with initial parameters, some considerations could already be made. Firstly, the optimal value of risk factor (rf) found was 64.5. This value means that the automated system that could identify human trafficking victims would have to find the measure of 64.5 in the expected value of 100 to consider someone at risk of being a victim. It showed that the model favors sending someone to a second screen with a human trafficking specialist to be sure that the person is not a victim. Further, increasing the cost of POE operation increases the number of risk factors (r) needed to consider someone a possible victim while reducing the number of people sent to a second screening procedure. Secondly, the first run showed that the number of human trafficking identifiers quantified by the risk factor *r* is high. This would be good since it could englobe the many factors that could be a risk of victimization as one of a normal employment agreement instead of an exploitative relationship, as similarly seen with Volodko, Cockbain, and Kleinberg (2020). The numbers also show that the second screening leads to a better proportion of victims not authorized entrance after the second screening.

The results of the numerical example when changing the prevalence of human trafficking parameters showed that it would affect the decision, so a better estimation of this number is crucial for making better policies. Investments in improving this type of estimations are advocated by many scholars in the area (Laczko & Gramegna, 2003; Farrell & Reichert, 2017; Aromaa, 2007, Laczko, 2007).

Additionally, the result of the example when considering different human trafficking costs within the range found in the literature was that it would affect the decision but to a smaller degree. It would allow some range in the estimates, which is a good thing considering that estimations of those costs are challenging to be accurate. The robustness of the model regarding this measure is an important contribution.

Likewise, when considering POE costs, we found that the rate in the decrease in the number of people sent to a second screening is not as great as the rate in increase in the cost. Even though, it is smaller robustness when compared to the human trafficking costs. But since this parameter is expected to be a more accurate estimation because it is in the domain of the

POE, this is not considered to be a problem. Therefore, the smaller difference in the rate would not be a problem to the capacity of the model to give an appropriate optimal value.

The increase in the cost of the POE operation will affect the decision regarding the probability of victimization and the number of people further screened, but the decision regarding the number of optimal *rf* would allow some variation in the estimation of the cost. All the model runs showed that the optimal decision change depending on the human trafficking, and POE operational costs, as well as the estimated prevalence of the crime at the U.S. border. But it would not be affected by smaller and expected changes in the estimation of those parameters, providing a good model to be used as a support for decisions at the U.S. POEs.

Contributions

The main contribution of this master's thesis is the application of a Bayesian decision model to support the decisions of CBP Agents at the U.S. POEs when considering human trafficking victims. Another contribution is the presentation of a model that can provide insights into POE cost considerations and misclassifications.

Ancillary contributions include:

- A published peer-reviewed article in the proceedings of the Decisions Science Institute (de A. Drummond; Moya, 2020) that contributed to the body of knowledge of human trafficking and POE cost considerations.
- A robust POE decision support model for policy evaluation with a human trafficking focus.

- Insights about how the human trafficking's costs can affect decision at the U.S. POEs.
- Light shed on the importance of analyzing human trafficking through an Operation Research and Analytics perspective.

Limitations and Future Research

Limitations of this research were the lack of access to real data, which was mitigated by using published reports and empirical research. Also, the decision to use a narrow approach to human trafficking, addressing it as a homogeneous problem was based on the idea that a simplified model would provide more insightful capabilities.

Future research could use better methodologies for the estimation of cost of life considering the United States-based costs of Health and Criminal Justice systems. Also, there is the option of testing different models to optimize costs of border security. This could be used using the same estimations as done in this thesis to investigate results. Furthermore, some comparison regarding their ability to provide a better solution to the decision-maker and the robustness of the models could also be done.

Moreover, designing and testing an automated classification model for other types of human trafficking other than sex trafficking is much needed. The value related to letting travelers enter the country (GPD) should be evaluated and taken into consideration.

Future research could also deal with the cost of human trafficking in the United States and maybe account for the 17 different types of exploitation (Reed et al., 2018). Moreover, considering the United States typology proposed by Polaris Project (2017), estimating the costs for the 25 types of exploitations, and their overlapping when appropriate, could also be a future research focus. Significantly, the *continuum of exploitation* characteristic of human trafficking could be explored using a stochastic model based on this work.

Finally, the inspection of cargos from companies that are suspected of forced labor (U.S. DOS, 2021) could also be targeted at the POE using a similar model. The inspection process to identify inadmissible cargo can incorporate risk factors of human trafficking to identify the risk and save victims from being transported through the supply chains of large companies, or the logistics operations of independent contractors.

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BIOGRAPHICAL SKETCH

The student Priscila de Azevedo Drummond completed her bachelor's degree in Industrial Design in Brazil. After years in industry, mostly working as a Financial Analyst, she decided to continue her education pursuing a Master of Science in Business – Operations Research that she was granted in 2019. In 2021, she was granted the degree of Master of Science in Engineering Management at University of Texas Rio Grande Valley.

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