Overclassified and Overrepresented: Breaking the Cycle of Trauma and Crime for Indigenous Women in Canadian Federal Prisons (2012-2018)

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Abstract

Despite the Canadian Correctional Service's (CSC) efforts to reduce the overrepresentation of Indigenous women in Canadian federal prisons, Indigenous women continued to receive the 'worst' risk assessment scores between 2012 to 2018. A serious consequence of race impacting an inmate's risk assessment score is that inmates with the 'worst' scores do not have access to reintegration opportunities and programs. Using data from the CSC and expanding on Globe and Mail journalist Tom Cardoso's original study on race and risk assesment scores, I use multiple logistic regression models to explore the relationship between race and receiving low reintegration potential scores. The paper concludes that the CSC risk assessment scores are trapping Indigenous women in a cycle of trauma and crime by limiting their ability to recieve additional privilieges, find employment opportunities, and campaign for early release. The code and data supporting this analysis is available on the project's GitHub repostiory: Interdisciplinary Offenders.

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1 Introduction

On January 21st, 2020, Correctional Investigator of Canada Ivan Zinger revealed that the over-representation of Indigenous peoples in federal custody has reached a historic high and described the trend as "disturbing." Zinger called for bold and urgent actions from corrections and government (Kingsley 2020). Although Indigenous peoples account for roughly 5 percent of the population of Canada, Indigenous peoples account for more than 30 percent of the federal inmate population. In 2020, Indigenous women represented only 4 percent of the total female population of Canada, but accounted for 42 percent of incarcerated women. These numbers mean that about 1 in 100 Indigenous women are currently in a federal or provincial prison (S. Canada 2016).

In this paper, we will use a multiple logistic regression model to analyze the relationship between race and Canadian Correctional Service's (CSC) risk assessment scores for female federal inmates between 2012 to 2018. This study builds upon the Globe and Mail's Tom Cardoso's original article *Bias Behind Bars* (2020) which examines federal risk assessments for Black and Indigenous men in federal custody (Cardoso 2020b). I hypothesize that Indigenous women are not only overrepresented in Canadian federal prisons, but are also overclassified with the "worst" risk assessment scores. These poor scores risk trapping Indigenous women in a cycle of trauma and crime because they are given worst scores for attributes outside their control or cannot change. These poor scores hinder these women from accessing beneficial educational programming and employment opportunities, exacerbates poor mental health and significantly reduces their likelihood of securing early release.

The code and data supporting this analysis is available on the project's GitHub repository: Interdisciplinary Offenders.

The remainder of this paper is structured as follows: Section 2 provides a literature review on the history of Indigenous women in Canada's prison system. Section 3 discusses the datasource, variables, the original's authors work and a descriptive analysis. Section 4 describes the logistic regression models. Section 5 analyzes the logistic regression models' results. Lastly, Section 6 explores the study's finding, weaknesses, and potential future research.

2 Literature Review

There are many layers of historical and contemporary factors at play when it comes to understanding why Indigenous women may be more likely to be criminalized.

Violence against Indigenous women is an ongoing crisis with roots deep in Canada's colonial history. The Canadian nation-state is premised upon the historical and ongoing invasion, settlement, and expropriation of Indigenous lands – the result of which has been the dispossession of Indigenous peoples, communities, and cultures. For instance, Kyllie Cripps' *Media Constructions of Indigenous Women in Sexual Assault Cases: Reflections from Australia and Canada* (2021) argues that Indigenous women are more likely to be victims of violence rather than perpetrators. When Indigenous women do commit violence, its more likely to be in the form of self-defense against a male abuser. However, Cripps' reveals using Canadian and Australian print and online news media from 2011 to 2018 that these women are often depicted as sexual deviants, prostitutes, alcohol and drug abusers, and inept mothers. These negative depictions of Indigenous women contribute to a less sympathetic and indifferent reaction from audiences while perpetuating damaging stereotypes (Cripps 2021). Consequently, Indigenous women are effectively labeled as both "hopeless and helpless" because the media depicts Indigenous women as poor daughters, sisters, wives, and mothers. Therefore, racist stereotypes towards Indigenous women may explain their increased incarceration rate because Indigenous women are perceived as more prone to violent behaviour, deserving of their abuse and unable to integrate into mainstream White society (Cripps 2021).

In colonial stories, Janice Acoose's *Iskwewak Kah' Ki Yaw Ni Wahkomakanak* (1995) suggests that Indigenous women are constrained to two tropes – the *Pocahontas* or the *Squaw*. For example, the *Pocahontas* is a young, chaste, naïve, and extremely beautiful Indigenous women, but is "wise" enough to fall in love with a White man, voluntarily abandon her family and community, and assimilate into Eurocentric cultural norms. The stereotype was created by European colonizers to prove that Indigenous peoples were "less evolved" and needed European intervention to become civilized and Christianized. In contrast, the *Squaw* stereotype was created by Jesuit missionaries to justify the rape, imprisonment, and enslavement of Indigenous women. The Squaw is a dark-skinned, overweight, inhuman and unattractive woman who lusts after White men. She does not intend to abandon her culture or convert to Christianity. Instead, she is depicted as manipulating White men into sin and spreading sexual diseases (i.e., syphilis). Consequently, Christian missionaries must control her by imprisoning, physically and sexually abusing, and converting her (Acoose 1995). The Squaw is a powerful image that perpetuates stereotypes, and more importantly – as is apparent from the growing number of missing and murdered Indigenous women in Canada – fosters dangerous cultural attitudes that condone violence and imprisonment against Indigenous women. Thus, the increased incarceration of Indigenous women in a continuation of colonial methods to control the Squaw's body and protect the virtue of White Canadian society.

In 2021, Statistics Canada calculated that Indigenous women are 3.5 times more likely than non-Indigenous women to be victims of physical and sexual violence, and are 5 times more likely to die as a result of this violence. Furthermore, Indigenous women (54 percent) are more likely than non-Indigenous women (37 percent) to report the most severe forms of domestic violence, such as being beaten, choked, threatened with a gun or knife, or sexually assaulted. Approximately, 75 percent of Indigenous sexual assault survivors are women under the age of 18, 50 percent are under the age of 14, and 25 percent are under the age of 7 (S. Canada 2021). Victims of domestic and sexual violence have a higher likelihood of long-term injury, post-traumatic stress disorder, challenges with relationships and maintaining stable employment (P. H. A. of Canada 2014).

Of all the assaults committed against Indigenous peoples, perhaps the most infamous was the Residential School System. The schools operated for a period of 100 years and the last school closed in 1997. The effects of the Residential School System have been intergenerational and its violent legacy includes: physical, sexual, mental and emotional abuse; alcoholism, drug and solvent abuse; extreme poverty; low education rates; high unemployment rates; loss of identity; high suicide rates; loss of parenting skills with a high number of Indigenous children in the child welfare system; and a gross over-representation in the criminal justice system (Piotr Wilk and Cooke 2017).

Prior to 1985, First Nations women were stripped of their Indian Status pursuant (to the registration provisions of the Indian Act) if they married a "non-Status Indian" or "non-Indian," started a University education, or registered to vote in federal elections. Furthermore, the Indian Act made it illegal for Status Indigenous women to vote or run for office in Canadian federal or provincial elections until the law was repealed on March 31st 1960. Consequently, Indigenous women have only recently received the right to vote and participate in Canada's political system. By and large, the Indian Act registration provisions led to the dislocation, disenfranchisement and isolation of First Nations women. The Indian Act forced many Indigenous women to leave their families and communities in order to receive their basic human rights. On top of all this, Indigenous women who chose to leave their families in order to marry, become educated, or just vote often faced financial uncertainty and blatant racism (Brodsky 2016).

Indigenous women have been marginalized significantly by the impact of colonization and the Residential School System. Government policies that have impoverished Indigenous communities have left Indigenous girls and women vulnerable to exploitation and violence. Furthermore, racism and discrimination has denied the dignity and self-worth of Indigenous women by making them vulnerable to violence perpetrated against them by men. Therefore, the high number of Indigenous women in federal corrections are likely the result of their collective and individual circumstances.

Canadian federal corrections must address the historical and contemporary needs of Indigenous women in a culturally and gender-appropriate manner. However, to date, the experience of Indigenous women in federal prisons is a continuation of Canada's dark colonial legacy.

3 Data

3.1 The Source of the Data

The dataset we will use is the CSC Offender Management System from 2012 to 2018.

The dataset was collected from the Correction Service of Canada (CSC) Offender Management System and includes seven years worth of entries from 2012 to 2018. Each year is captured as a snapshot of the database on March 31st, the last day of the CSC's fiscal year. The dataset was collected by the Globe and Mail's Tom Cardoso who sent a request to Anne Kelly, the Head of the CSC after submitting a freedom of information request (Cardoso 2020c).

The dataset has 741,738 rows and 25 columns. It documents the lives of 49,165 people (inmates under federal jurisdiction) in custody or supervised release. The dataset lists each inmate's age, gender, race and religion; details about the length of their sentence and their charges; and notes whether they are doing time at a minimum-, medium- or maximum-security facility, or are on parole. The dataset also includes data on five of the CSC's most important risk scores (Cardoso 2020a).

The first risk score is Offender Security Level. The offender's security level determines the layout, operations, and programs offered to inmates. The three security levels are Maximum, Medium, and Minimum (C. S. Canada 2019).

The second risk score is Dynamic/Need. The dynamic risk assessment is performed by psychologists to predict an inmate's likelihood of re-offending. Psychologists measure factors including antisocial behaviour, pro-criminal attitudes, neuroticism, and other personality factors. These scores are used to assess if an inmate can receive parole or early release. The three scores an inmate could receive are High, Medium, and Low (C. S. Canada 2019).

The third risk score is Static/Risk. The static risk assessment is performed by psychologists to predict an inmate's likelihood of re-offending based on their criminal history. The three scores an inmate could receive are High, Medium, and Low (C. S. Canada 2019).

The fourth risk score is Motivation. The motivation score measures if an inmate takes accountability for their crimes and is strongly committed to not re-offending after their release. The three scores an inmate could receive are High, Medium, and Low (C. S. Canada 2019).

The fifth risk score is Reintegration Potential. The reintegration potential assessment is performed by psychologists to predict if an inmate will be able to reintegrate into society (e.g., finding housing, gaining employment, static risk, and dynamic risk). The three scores an inmate could receive are High, Medium, and Low (C. S. Canada 2019).

Within the sample, 34,047 of the inmates are female; 11,751 of these female inmates are Indigenous, 17,831 female inmates are White, and 4,465 female inmates are non-Indigenous racial minorities.

3.2 Original Author

This paper is a reproduction and extension of the Globe and Mail's *Bias Behind Bars* (November 2020) - a two-year investigation by the Globe's crime and justice reporter Tom Cardoso that uncovered systematic bias in Canada's prison system. Cardoso used the same dataset to study reassessment scores by race in federal correction institutions. Cardoso discovered a disturbing pattern – Indigenous and Black people seemed to receive worst scores across a range of assessments more frequently than other groups (Cardoso 2020b).

Cardoso's original study also primarily focused on male inmates because less than 5 percent of the inmates in the dataset were female. Thus, female inmates were removed from some aspects of the original study.

Cardoso's model discovered that Indigenous men were 29.5 percent more likely to end up with a low reintegration score compared to White men, and that Black men were 6.1 percent less likely. He also built a model to test how well the reintegration potential score predicted future offending which returned statistically significant results for Black men and non-significant results for Indigenous and White men. Hence, Cardoso reveals that Black and Indigenous people face significantly disparate outcomes at the hands of the Canadian justice system (Cardoso 2020b).

The following Monday after *Bias Behind Bars* was published, the investigation sparked bipartisan support from MPs who called for an independent study on systematic discrimination in federal prisons, including inmates' risk and security assessments (Group 2020). Cardoso has started a national conversation about systematic racism and bias in Canada's institutions and his reporting has laid down a framework upon which reform can begin.

I hope to add upon Cardoso's research by examining the CSC's reassessment tool's predictive validity and if the tool is also systematically biased against Indigenous women.

I am also making two additional changes from Tom Cardoso's original research:

1. I will not be calculating how many inmates reoffended between 2012 to 2018. I chose not to calculate this because my dataset is limited to a short timeframe. Thus, I cannot confirm if an inmate came into this dataset with a previous criminal history or if they reoffended after 2018.
2. I will also not be using the `Sentence Type` as a control variable in my logistic regression models. Although I believe this is an important variable that should be added to the model, I cannot include it due to time constraints. Tom Cardoso originally converted all 700 sentence types into weights based on Statistics Canada's Crime Severity Index. However, I am unable to do this because the Crime Severity Index is not publicly available and instead you must request access from Statistics Canada. Secondly, the 700 sentence types must be manually converted to weights which is extremely time consuming and this variable is not a focus of my analysis.

I also constructed two new variables that were not part of the original dataset.

1. First, I cleaned up the race column by grouping all the ethnic groups into 22 races. I grouped different ethnic groups into races based on Statistics Canada's *Visible Minority and Population Group Reference Guide, Census of the Population, 2016*. I put different groups into races because the race column mixes races and ethnicities, and also uses different names for the same racial group (e.g., Black, African American, Nigerian; White, Euro-Canadian, British).
2. Second, my analysis is strictly focused on CSC scores for Indigenous women. Consequently, I created a new column that puts all Indigenous women under the umbrella term "Indigenous, all White women under the umbrella term"White", and all other racialized minorities under the umbrella term"Other".

3.3 Data Ethics

In addition to potential biases that may have occurred when the data was collected by the CSC and initially cleaned by Thomas Cardoso, we must also consider the ethical implications of choosing to use this dataset, our decisions when cleaning the data, and how we interpret the model's results. We must be especially careful because our research question is geared towards vulnerable and racialized groups in Canada.

To guide our ethical questions, I will use danah boyd, Solon Carocas, Kate Crawford, and numerous other scholars' guidance on the *10 Simple Rules for Responsible Big Data Research* (2017) The 10 rules include (Matthew Zook and Pasquale 2017):

1. Acknowledge that data are people and can do harm.
2. Recognize that privacy is more than a binary value.
3. Guard against re-identification of your data.
4. Practice ethical data sharing.

5. Consider the strengths and limitations of your data; big data does not automatically mean better.
6. Debate the tough, ethical choices.
7. Develop the code of conduct for your organization, research community, or industry.
8. Design your data and systems for auditability.
9. Engage with the broader consequences of data and analysis practices.
10. Know when to break the rules.

First, I must acknowledge my own racial and social biases before beginning my analysis. I am a cis, White, able-bodied, educated, and financially privileged woman. I have also never been or know someone who was incarcerated. I have never experienced structural racism and I have undoubtedly benefited from white privilege. I have benefited from colonization and the dehumanization of Indigenous peoples because I am settler on Indigenous land. Therefore, my implicit and unconscious bias will influence how I frame the research question, conduct my experiment, and interpret the results which may be incorrect, racist, and perpetuate systematic discrimination against Indigenous peoples. I will use anti-racist tools to reduce my unconscious bias by educating myself on the historical context from a diversity of sources and pedagogies, recognize peoples' individuality and humanity, actively working for anti-racist policies and reparations, cultivating empathy, critically examining my own bias and thoughts, ensuring my research is open to debate and criticism, and using my privileged position to center important and less-privilieged voices (Kendi 2019).

Second, I will protect privacy by ensuring the dataset's attributes will not contain personally identifiable information. The dataset also does not include information about the individual's location and does not record an inmate's name or date they were incarcerated. Therefore, it is very difficult to trace back each row to an individual person unless a person had access to the inmate's sentence id or offender number. However, this data is kept at the CSC and is highly confidential and secure.

Third, I will ensure the results can be audited by making the data, code, and results publicly available via a GitHub repository. This ensures that my work is reproducible as well as methodologically robust.

Fourth, a tough ethical choice I debated when interpreting the data was how do we classify an inmate's gender and ethnic identity. The "GENDER" field strictly reports two values – "Male" or "Female." Although these are the two biological sexes, individuals may identify with a gender that is different from their sex given at birth or they may identify with a non-traditional notion of gender. However, transgender inmates are currently placed in prisons based on their gender assigned at birth. Thus, there may be self-identified female inmates missing from the dataset and self-identified male inmates included in the dataset which may skew the results. Also, the CSC's decision to omit this gender identity also discourages more meaningful analysis and research questions about how transgender inmates are impacted by the Canadian prison system and how their reassessment scores may also reflect structural bias towards transgender individuals. A second question is how the dataset defines "Indigenous" and who is included in the category. According to Tom Cardoso, the "RACE" feature is based on inmates self-identified ethnic identity when they first arrived at prison. Additionally, the dataset does not account for mixed-race oe multi-ethnic identities because inmates are forced to choose one race. Therefore, the dataset is missing nuance because we cannot examine the impact of being mixed-race on risk reassessment scores and many individuals may be omitted from the Indigenous category if they choose to identify with another race.

Fifth, I had to make the tough choice to exclude races other than Indigenous and White from my analysis. While Tom Cardoso's investigation revealed that Black men are more likely to receive worst risk assessment scores compared to White men, I unfortunately do not have enough data to make a similar comparison using female inmates. While it is crucial to study and analyze data on this overlooked population, the fact that our sample does not include enough data on non-Indigenous and non-White female inmates could lead to my models making incorrect conclusions with low internal and external validity.

Lastly, I must consider the impact my research may have on the racial groups I chose to analyze. For instance, if I discover that Indigenous women get higher dynamic and static risk scores compared to White women, I risk perpetuating the stereotype that Indigenous women are violent, deserve to be imprisoned, and

Table 1: Number of Female Inmates in Federal Prisons (2012-2018)

Number of Inmates	Average Age	Average Sentence Length (Years)
34047	37.04	3.36

dehumanized. Thus, I will try to reduce perpetuating racist stereotypes and prejudice by beginning this paper with a brief overview of Indigenous women's' history, listing qualitative sources about incarcerated Indigenous women in the bibliography, and including methods and strategies proposed by Indigenous women and their communities to empower Indigenous women and reduce the female incarceration rate in a way that is gender- and culturally-appropriate.

3.4 Descriptive Analysis

3.4.1 There were 34,047 Female Inmates in Federal Custody Between 2012 and 2018

Table 1 (Table 1) illustrates that there are 34,047 female inmates in the sample. The average age for a women in federal custody is 37.04 years and the average sentence length is 3.36 years.

The table was constructed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and KableExtra (Zhu 2020).

3.4.2 Indigenous Women Represent 34.51% of Female Inmates, but Only 4% of the Canadian Female Population

Table 2 (Table 2) shows that Indigenous women are overrepresented in federal custody. Indigenous women represent 34.51 percent of all federally incarcerated women between 2012 and 2018, but only represent 4% percent of Canadian women in the same time period (S. Canada 2016). Indigenous women are also below the average age for a female inmate at 34.52 years and serve a shorter average sentence length of 3.13 years.

In contrast, White women are unrepresented in federal custody at 52.54 percent of inmates while representing 80 percent of all Canadian women. White women are also slightly above the average age for a female inmate at 38.62 years and are right on the average sentence length of 3.36 years.

The racial group that has the highest average age are South Asian women at 39.40 years and the racial group with the lowest average age are inmates "Unable to Specify" at 30.96 years. The "Unable to Specify" category does not mean that an inmate is multiracial, but instead that they did not disclose their racial identity when they entered custody.

The racial group with the highest average sentence length are Latin American women at 5.35 years and the racial group with the lowest average sentence length are "Unable to Specify" at 2.69 years. Unfortunately, the representation of non-Indigenous racialized minorities will not be covered in this analysis, but it does open up opportunities for further study.

The table was constructed using R (R Core Team 2020), janitor (**citeJanitor?**), tidyverse (Wickham et al. 2019), and kableExtra (Zhu 2020).

Figure 1 (Figure 1) visualizes the number of female inmates per race in federal custody. The graph demonstrates that Indigenous women are the second largest racial group represented in federal custody between 2012 and 2018.

The figure was constructed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and ggplot (Wickham 2016).

Since the distribution of CSC risk scores for non-Indigenous racialized women is beyond the scope of this analysis, I encourage you to explore and discover patterns on your own using this Shiny app here.

Table 2: Number of Female Inmates in Federal Prisons (2012-2018)

Ethnic Group	Number of Inmates	Average Age	Average Sentence Length (Years)	Percent of Female Inmates
White	17891	38.62	3.36	52.5479484
Indigenous	11751	34.52	3.13	34.5140541
Black	1892	37.59	4.44	5.5570241
East Asian	839	44.08	3.86	2.4642406
Unable to Specify	540	30.96	2.69	1.5860428
Multiracial	390	31.14	3.68	1.1454754
South Asian	288	39.40	4.16	0.8458895
West Asian	173	33.06	3.60	0.5081211
Other	149	37.77	3.27	0.4376303
Latin American	134	36.96	5.35	0.3935736

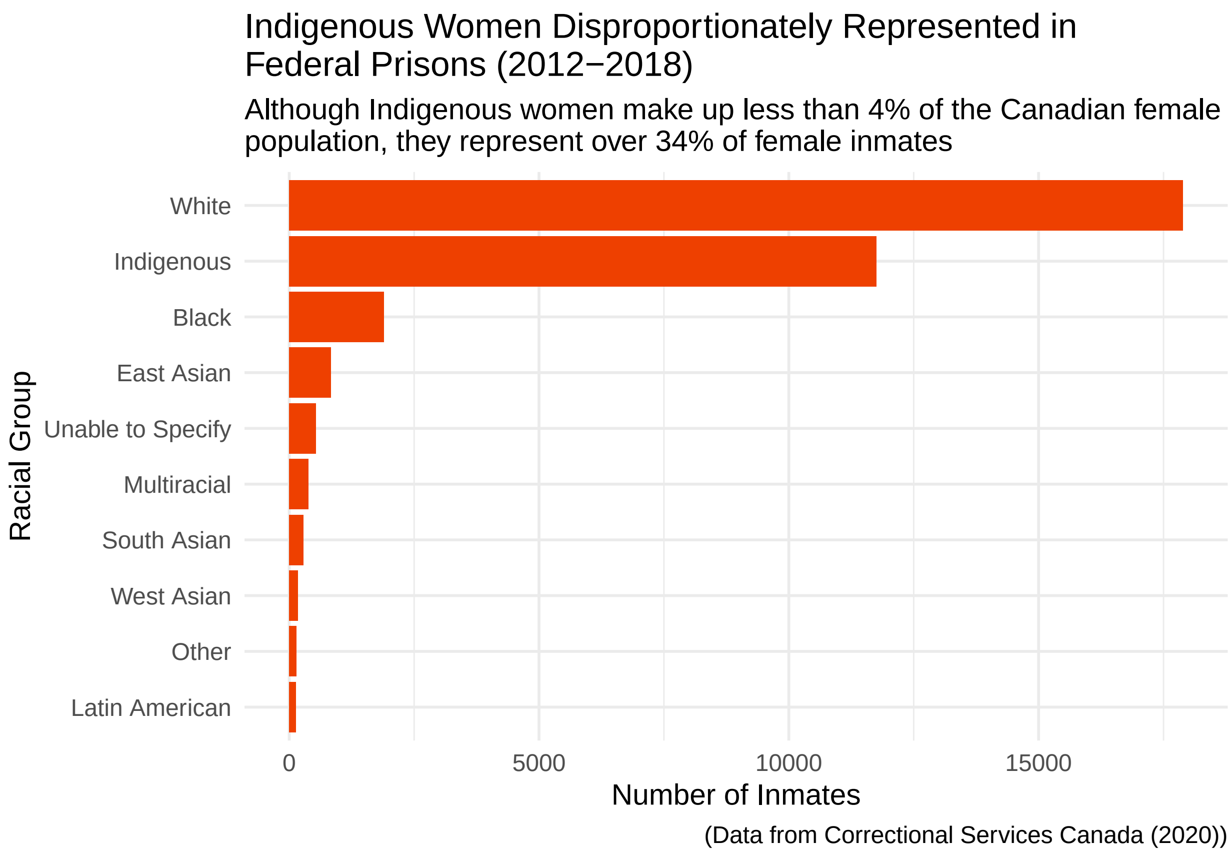

Figure 1: Indigenous Women Disproportionately Represented in Federal Prisons (2012-2018)

Table 3: Number of Female Indigenous Inmates by Ethnicity (2012-2018)

Indigenous Ethnic Group	Number of Inmates	Average Age	Average Sentence Length (Years)	Percent of Indigenous Female Inmates
North American	8403	35.03	3.02	71.508808
Metis	3217	33.32	3.43	27.376393
Inuit	131	31.54	2.68	1.114799

3.4.3 North American First Nations Women Represent the Majority of Indigenous Women in Federal Custody

Table 3 (Table 3) demonstrates that North American First Nations women represent 71 percent of Indigenous women in federal custody. The three Indigenous groups are all below the average age for a female inmate. North American First Nations women have the highest average age at 35.03 years and Inuit women the lowest at 31.54 years. We see a similar pattern in the average aggregate sentence length with Inuit women serving the shortest average sentence while Metis women serve the longest. These results are very interesting because most Inuit people live in the Canada's three territories where they have majority representation in the territorial governments (Gocke 2011). Thus, there may be a pattern between political representation and representation in federal custody, but this is just an assumption that requires further research.

The table was constructed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and KableExtra (Zhu 2020).

Similarly, Figure 2 (Figure 2) visualizes that North American First Nations women are the largest Indigenous group represented in federal custody.

The figure was constructed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and ggplot (Wickham 2016).

3.4.4 Indigenous Women are More Likely to Receive a Maximum Security Level

The offender security level, which can be set to minimum, medium, and maximum, is used to assign inmates to institutions and treatment programs. A security level classification is assigned by the warden of the federal prison based on if the inmate is a threat to other inmates' safety, they require a high level of supervision, or if they have a higher chance of escaping. An inmate who receives a maximum-security classification will typically be assigned to a maximum security prison, area or facility (C. S. Canada 2019).

Figure 3 (Figure 3) demonstrates that Indigenous women are more likely to be receive a Maximum Security Level compared to White and other racial minority inmates. Indigenous women are also the least likely to receive a minimum security level.

These results are very significant because women who receive a maximum security level have the highest level of supervision and are not allowed to leave their cells except for 1 hour of supervised exercise each day. They are also given no privileges and are banned from communicating with other inmates. Thus, women in this security level are extremely isolated and controlled. Furthermore, it is impossible for women in a maximum security prison to receive a high reintegration potential score. Consequently, these women are not eligible for shorter sentences or parole.

In contrast, women who receive a minimum security level need less supervision and are granted more privileges. Women in minimum security prisons are allowed to leave the prison to work, receive career training, or attend school. They are also given more privileges such as increased access to visitors, more exercise time, eat their meals with other inmates, use the prison library, and associate with other inmates. They are also given better living conditions such as larger cells. Women in minimum security prisons are also eligible to receive a shorter sentence or parole. Consequently, women in minimum security are less isolated and have more opportunities to shorten their sentence.

Therefore, Indigenous women receive stricter sentences, harsher living conditions, and less opportunities for early release compared to White and other racialized minority inmates.

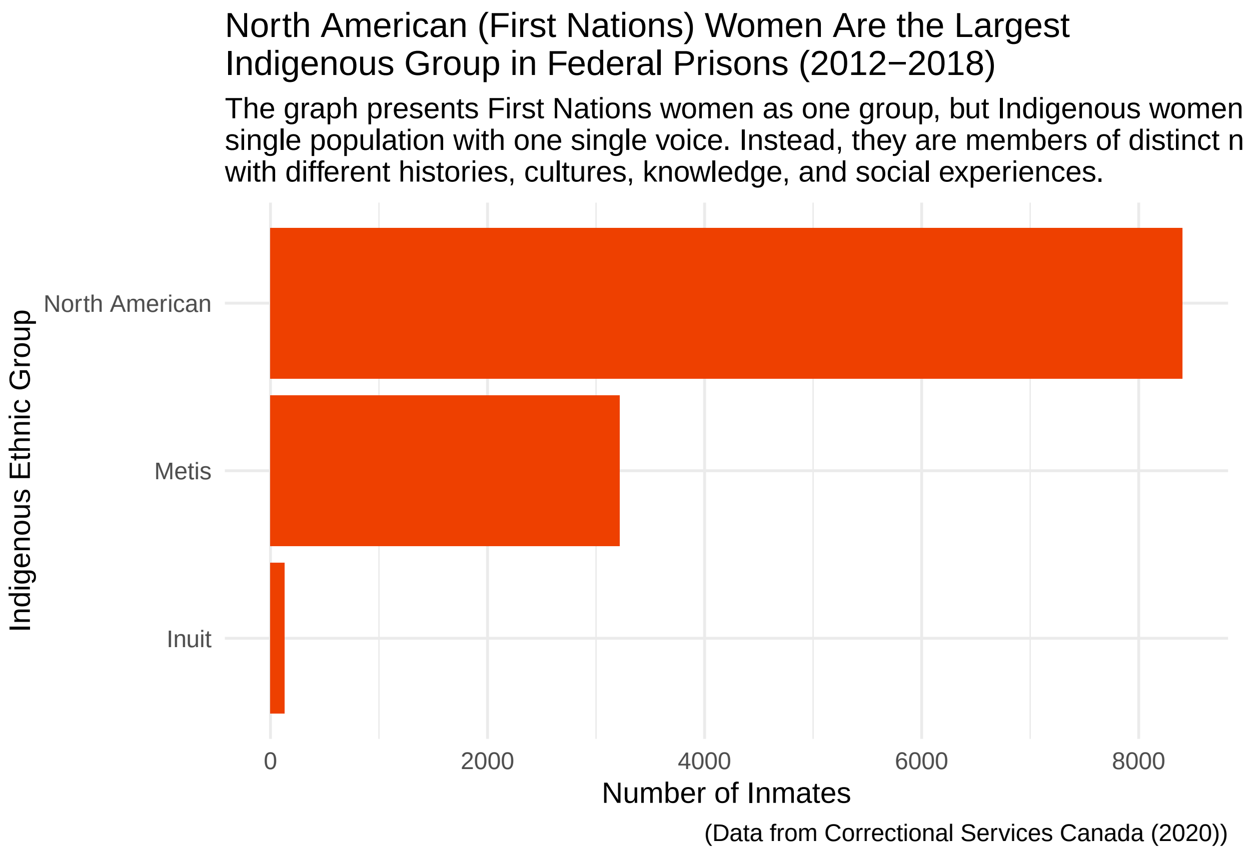

Figure 2: North American (First Nations) Women Are the Largest Indigenous Group in Federal Prisons (2012-2018)

The figure was constructed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and ggplot (Wickham 2016).

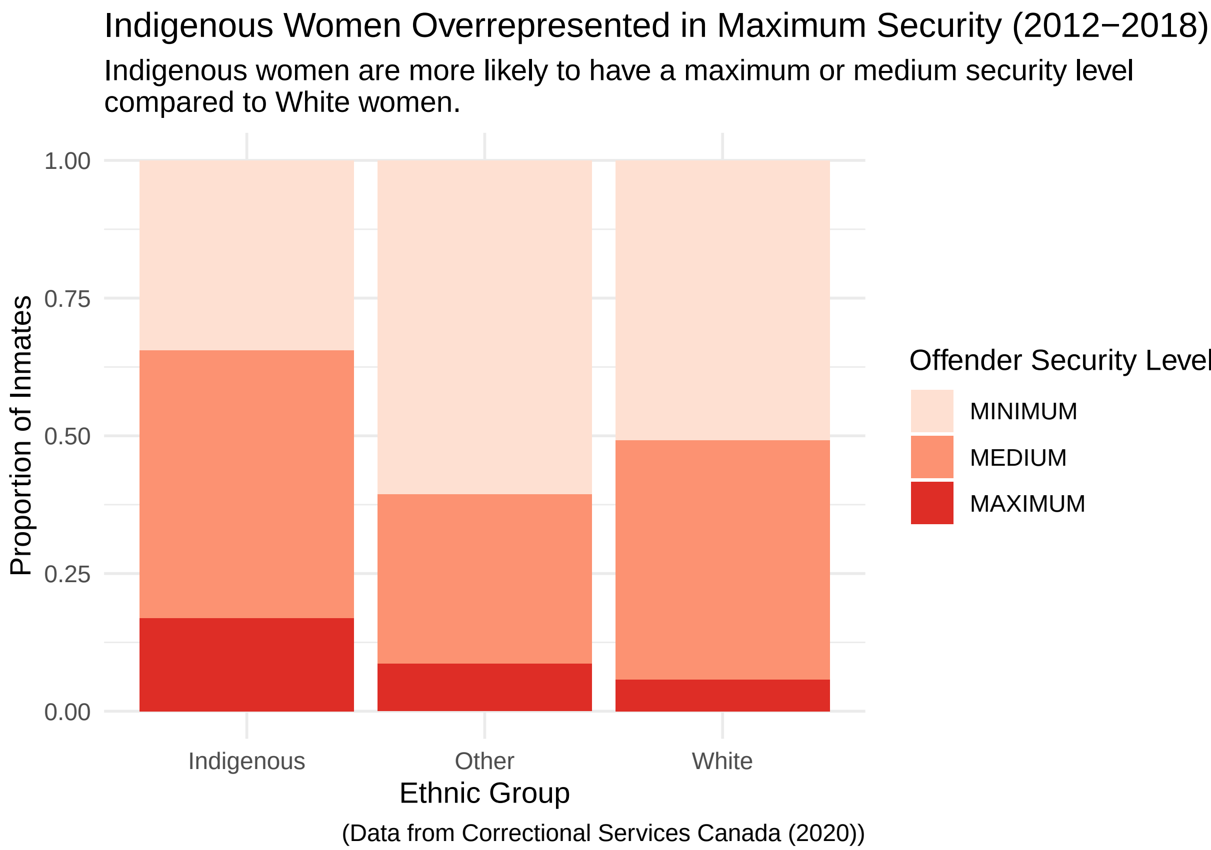

Figure 3: Indigenous Women Overrepresented in Maximum Security (2012-2018)

3.4.5 Indigenous Women are More Likely to Receive a High Dynamic Risk Score

The dynamic/need score is assigned to inmates based on their results from the CSC's *Dynamic Factor Identification and Analysis Revised Assessment Report*. The Dynamic score predicts whether an individual will commit a crime based on their family, educational, and professional background, including (C. S. Canada 2019):

1. Academic History: More years of education and educational achievement leads to lower score.
2. Work History: More years of employment, not being unemployed at time of arrest, and stable job history leads to lower score.
3. Work Skill Set: Marketable and in-demand skills leads to lower score.
4. Work Attitudes: Offender's belief they can reintegrate into the workforce and strong work ethic leads to lower score.
5. Childhood: Strong attachment to family unit, no history of being abused during childhood, and no criminally active family members leads to lower score.
6. Intimate Relationships: Being in a long-term relationship and no history of being a victim/perpetrator of domestic abuse leads to lower score.
7. Parenting: Strong parental skills and no history of child abuse leads to lower score.
8. Criminal: No relationships with other criminals leads to lower score.

9. Prosocial Support: Ability to receive financial support from a partner, family, or friend upon release leads to lower score.
10. Substance Abuse and Drug Use: No history of substance abuse or drug use leads to lower score.
11. Community Functioning: Rarely changing residences during the last year, financial stable, constructive hobbies, and strong attachment to the community leads to lower score.
12. Personal/Emotional: Openness to new experiences, strong problem-solving, strong critical thinking, low anxiety, high self-regulation, planning for the future, strong interpersonal skills, and low aggression leads to a lower score.
13. Attitudes: Displaying negative attitudes towards crime, destruction of property, and violence leads to lower score.
14. Responsitivity: English fluency (verbal and written), high concentration, extroversion, no mental health issues, and no disabilities leads to a lower score.

The dynamic risk score is very important because it is a factor in the reintegration potential score.

Figure 4 (Figure 4) highlights that Indigenous women are the most likely to receive a high dynamic score and the least likely to receive a low dynamic score compared to White and other racialized minority inmates.

The figure was constructed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and ggplot (Wickham 2016).

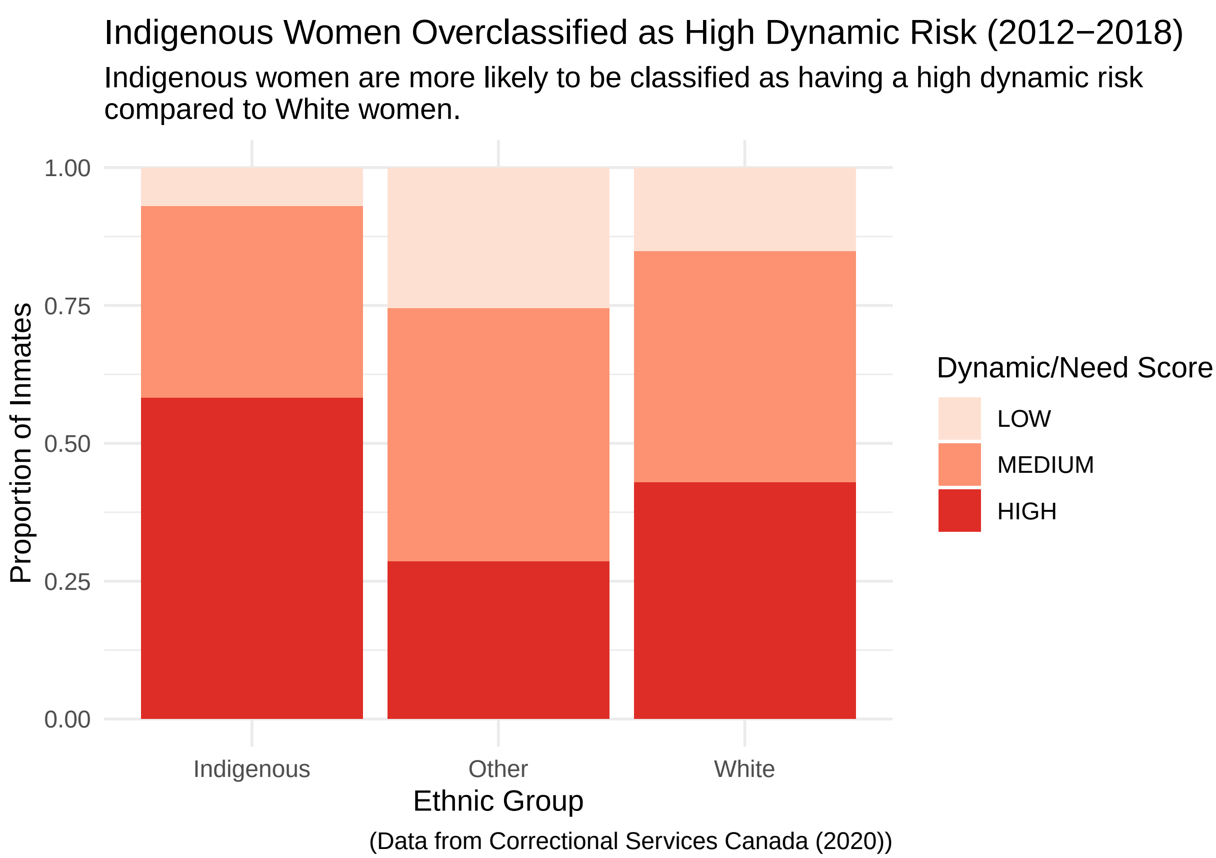

Figure 4: Indigenous Women Overclassified as High Dynamic Risk (2012-2018)

3.4.6 Indigenous Women Overclassified With a High Static Risk Score

The static risk score is assigned to inmates after completing the CSC's *Static Factor Assessment*. It is based on the inmate's personal history in the criminal justice system. The result of the score is a factor in an inmate's potential reintegration score. An inmate can receive a high, medium, or low rating (C. S. Canada 2019).

The guidelines for determining the overall rating for static risk are (C. S. Canada 2019):

1. A rating of HIGH reflects a case in which: the Criminal History Record reflects a considerable involvement in the criminal justice system, the Offense Severity Record reflects considerable harm on society and their victims, and the Sex Offense History Checklist demonstrates a considerable history in sex offending.
2. A rating of LOW reflects a case in which: the Criminal History Record reflects a low involvement in the criminal justice system, the Offense Severity Record shows little or no harm on society and their victims, and the Sex Offense History reflects little or no sex offending.
3. A rating of MEDIUM signifies that the offender is not a low criminal risk, but not a high criminal risk either.

Figure 5 (Figure 5) suggests that Indigenous women are significantly more likely to receive a high static risk score and are the least likely to receive a low static risk score compared to White and other racialized minority women.

The figure was constructed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and ggplot (Wickham 2016).

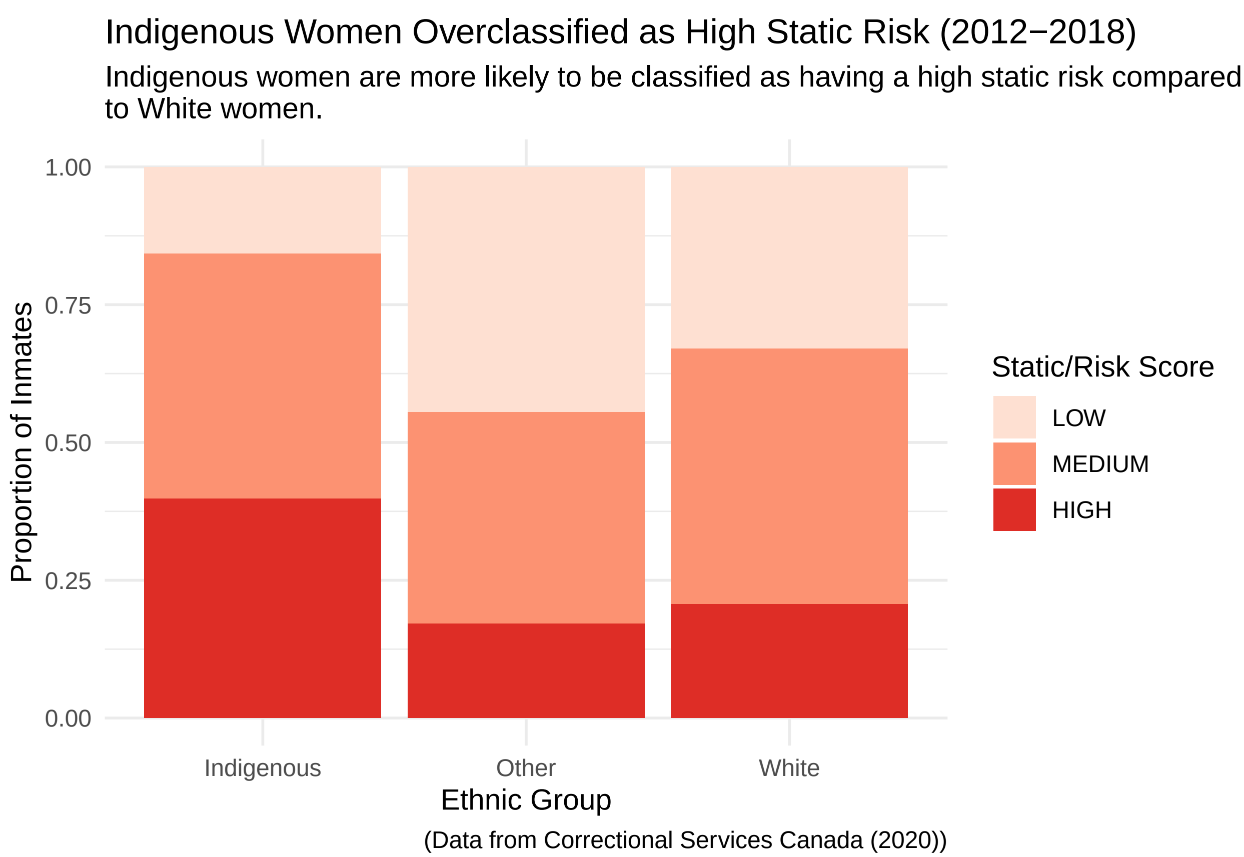

Figure 5: Indigenous Women Overclassified as High Static Risk (2012-2018)

3.4.7 Indigenous Women are Overrepresented as Having a High Motivation to Recommit After Release

The motivation score determines if an inmate has a criminal motivation to recommit their crime(s) after they are released. The test is performed by a psychologist and the offender must prove to the psychologist that they have no desire to recommit their crimes. The psychologist asks the inmates questions in eight categories: education, employment, marital/family, associates, substance abuse, community functioning, personal/emotional orientation, and attitudes (C. S. Canada 2019).

There are three possible scores (C. S. Canada 2019):

1. HIGH: The offender fully recognizes a need requiring intervention and is fully ready to start intervention. They are committed to change and are already engaging in behavior related to change. They are motivated by internal reasoning (e.g., religion, improving themselves, being a better mother, etc.).
2. MEDIUM: The offender may not fully know or accept their deficit, but participate in the recommended programs or other interventions. They are not genuinely committed to change and are motivated by external benefits (i.e., securing a shorter sentence, more privileges and freedoms, etc.).
3. LOW: The offender has no motivation to change their behaviour or genuine commitment to change.

Figure 6 (Figure 6) illustrates that Indigenous women are slightly overclassified as having a low motivation to reform and change their behaviour by participating in the recommended programs. Similarly, they are also the least likely to receive a high motivation score compared to White and other racialized minority inmates.

The figure was constructed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and ggplot (Wickham 2016).

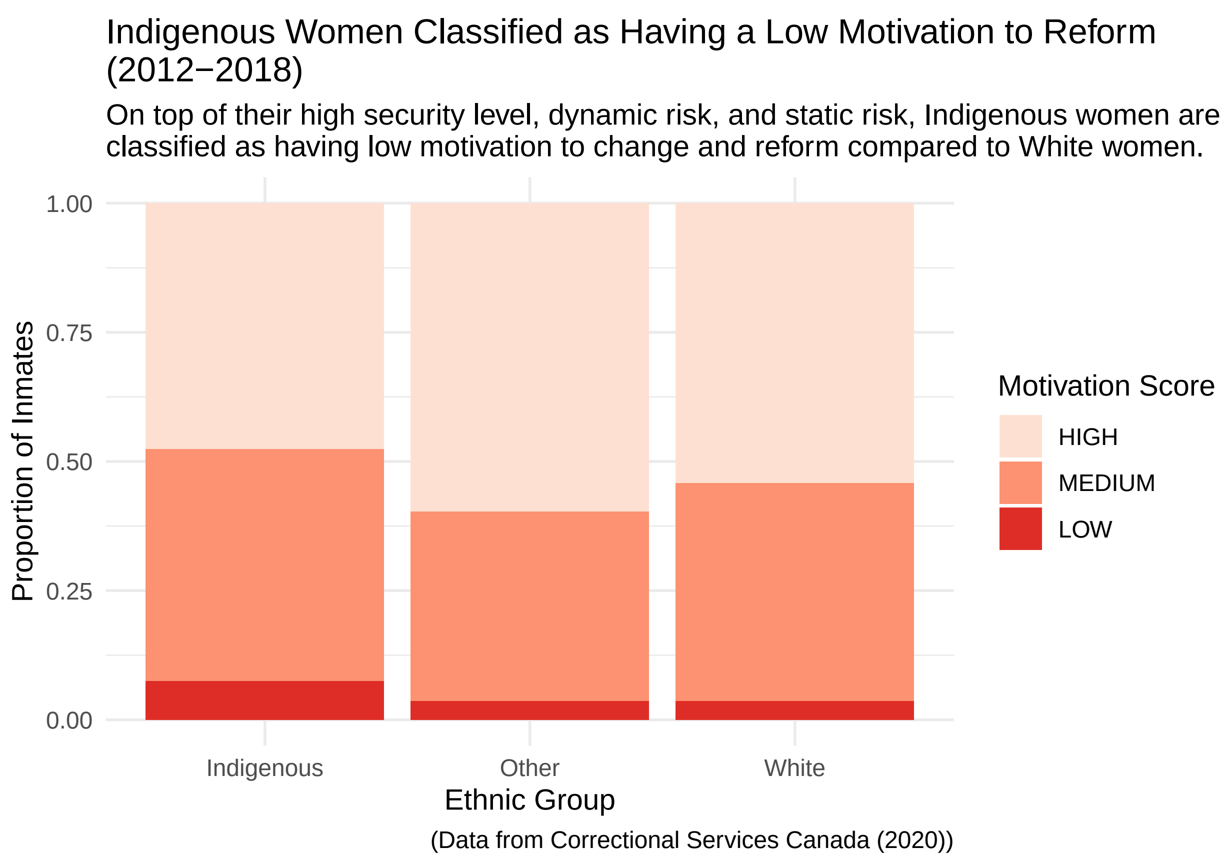

Figure 6: Indigenous Women Classified as Having a Low Motivation to Reform (2012-2018)

3.4.8 Indigenous Women are Significantly Less Likely to Receive a High Reintegration Potential

The final score an inmate receives is the Reintegration Potential Score. The reintegration potential score is determined by an inmate's security level, dynamic risk score, static risk score, and motivation score. Reintegration scores are extremely important for inmates because they determine if an inmate receives more privileges and freedoms within the prison, and a high reintegration potential increases their likelihood of receiving parole (C. S. Canada 2019).

The Reintegration Potential includes three scores (C. S. Canada 2019):

1. LOW: an inmate received the worst score in two or more of the four tools.
2. MEDIUM: an inmate received the worst score in any one tool and one moderate score in at least one tool.
3. HIGH: an inmate who did not receive the worst score in any four of the tools and received at least three best scores in three or more of the four tools.

Figure 7 (Figure 7) shows that Indigenous women are the least likely to receive a high reintegration score so they can secure early release. Indigenous women are also significantly more likely to receive a low reintegration potential compared to White and other racial minority inmates. Consequently, the five scores together suggest that the CSC's risk assessment tools may be trapping Indigenous women in a cycle of trauma and crime.

The figure was constructed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and ggplot (Wickham 2016).

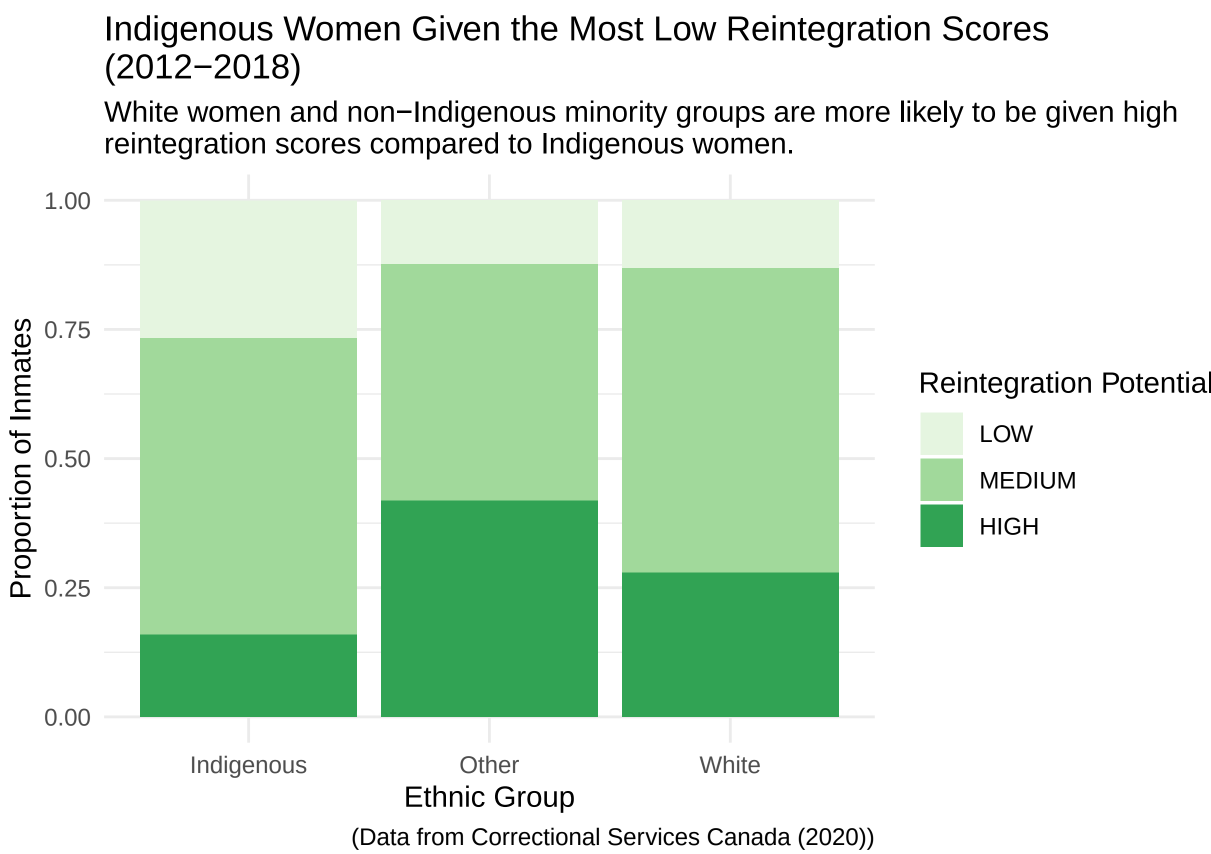

Figure 7: Indigenous Women Given the Most Low Reintegration Scores (2012-2018)

4 Model

4.1 Multiple Logistic Regression Model(s)

In order to understand if a relationship exists between race and CSC risk assessment scores, I performed five multiple logistic regressions for each risk score. The model was appropriate for finding the likelihood that race influences an inmate's risk of receiving the worst score because I converted the worst risk score into a binary variable. The logistic regression models will be used to describe the data and explain the relationship between one dependent binary variable and one or more nominal and interval independent variables. Through multiple logistic regression, I am unable to decisively conclude results or the strength of that relationship, but rather explore if any relationship exists. The software used to run the logistic regression models is R (R Core Team 2020)

I also chose to use a logistic regression model rather than a linear regression model because the security scores are ordinal categorical variables rather than a quantitative dependent variable. Additionally, I chose not to use a Chi-Square test, T-Test, ANOVA or correlation models because I wanted to account for potential confounding variables in my model(s) such as age and aggregate sentence length. Thus, I needed a statistical model for multivariate analysis rather than bivariate analysis.

The formula for logistic regression is:

$p(X) = \frac{e^{\beta_0+\beta_1 X}}{1+e^{\beta_0+\beta_1 X}}$

Where p is the probability of X (the mean of the dependent variable), e is the base of the natural logarithm (about 2.718), and β_0 and β_1 are the parameters of the model (y-intercept and slope respectively).

The first model (1) is the probability of getting the maximum security level:

$p(X) = \frac{e^{\beta_0+\beta_1 X+\beta_2 X}}{1+e^{\beta_0+\beta_1 X+\beta_2 X}}$

Where p is the probability of X (the mean of the is_maximum_security), e is the base of the natural logarithm (about 2.718), and β_0 and β_1 are the parameters of the model (y-intercept and slope respectively) for race and age.

The second model (2) is the probability of getting a high dynamic risk score:

$p(X) = \frac{e^{\beta_0+\beta_1 X+\beta_2 X}}{1+e^{\beta_0+\beta_1 X+\beta_2 X}}$

Where p is the probability of X (the mean of the is_high_dynamic), e is the base of the natural logarithm (about 2.718), and β_0 and β_1 are the parameters of the model (y-intercept and slope respectively) for race and age.

The third model (3) is the probability of getting a high static risk score:

$p(X) = \frac{e^{\beta_0+\beta_1 X+\beta_2 X}}{1+e^{\beta_0+\beta_1 X+\beta_2 X}}$

Where p is the probability of X (the mean of the is_high_static), e is the base of the natural logarithm (about 2.718), and β_0 and β_1 are the parameters of the model (y-intercept and slope respectively) for race and age.

The fourth model (4) is the probability of getting a low motivation score:

$p(X) = \frac{e^{\beta_0+\beta_1 X+\beta_2 X}}{1+e^{\beta_0+\beta_1 X+\beta_2 X}}$

Where p is the probability of X (the mean of the is_low_motivation), e is the base of the natural logarithm (about 2.718), and β_0 and β_1 are the parameters of the model (y-intercept and slope respectively) for race and age.

The fifth model (5) is the probability of getting a low reintegration potential score:

$p(X) = \frac{e^{\beta_0+\beta_1 X+\beta_2 X+\beta_3 X}}{1+e^{\beta_0+\beta_1 X+\beta_2 X+\beta_3 X}}$

Where p is the probability of X (the mean of the is_low_motivation), e is the base of the natural logarithm (about 2.718), and β_0 and β_1 are the parameters of the model (y-intercept and slope respectively) for race, age and aggregate sentence length.

For this project, the models will need to have a 0.05 significance level to be considered statistically significant. This is a common standard for logistic regression models. Arriving at a finding with a 5 percent significance threshold is like flipping a coin 100 times and getting heads (or tails) at least 60 times (Sander Greenland and Altman 2016).

4.2 Control Variables

Control variables help researchers establish a co-relational or causal relationship between variables by enhancing internal validity.

The first control variable is age. I chose age as a control variable because Tom Cardoso's original study demonstrated that age does have an effect on reintegration potential scores because younger inmates are more likely to receive higher reintegration potential scores because they have a shorter criminal history (static risk score). Thus, I chose to control for age in all the logistic regression models so it will not influence the final model.

The second control variable is aggregate sentence length. This control variable is only used in the reintegration potential score model because reintegration potential is the only score that is recalculated every year an inmate is in prison. In contrast, the other four scores are determined at the beginning of an inmate's sentence (C. S. Canada 2019). Thus, I controlled for aggregate sentence length to determine if an inmate was only receiving a higher reintegration potential score because of the time they spent in prison.

4.3 Logistic Regression Model Weaknesses

Logistic regression models have multiple weaknesses that could influence my ability to test a causal relationship between race and risk assessment scores.

First, when I created the logistic regression models I may have omitted important variables that were not included in the original dataset. Although I used age and aggregate sentence length as control variables in my models, I did not include the inmate's crime which led to them being imprisoned. Omitting this variable may lead to the estimate of the regression coefficient for the variables in the model to be either too high or too low. For instance, Indigenous women may be more likely to commit first degree murder which leads to a these women receiving maximum security levels and low reintegration potential scores. Thus, race is not the cause of the relationship but the confounding variable "type of crime." Additionally, there may be confounding qualitative variables that cannot be captured in a dataset or placed into a statistical model such as an individual's personal history, family background, and psychology.

Second, logistic regression models could have multicollinearity. Multicollinearity is a situation when two or more independent variables are highly correlated with each other. Multicollinearity leads to unreliable and unstable estimates of the regression coefficients and result in the reduction of their significance. For instance, the true relationship may be between age and race, rather than race and risk assessment scores.

Third, logistic regression's results are limited by the sample size. The sample size has a profound effect on tests of statistical significance. The CSC dataset may not include enough examples to justifiably determine if there is a causal relationship between race and risk assessment scores. Thus, the results of my logistic regression may be due to a small sample size that has low external validity and low internal validity.

Lastly, there may be intervening or mediating variables that are influencing my logistic regression models' results. For instance, the age variable may mediate the effect of the race variable on risk assessment scores. Thus, younger Indigenous inmates may receive worst risk assessment scores compared to White women while older Indigenous women have a similar risk score distribution as White women.

4.4 Model Validation

The logistic regression models will be validated by splitting the dataset into training and testing sets, building the logistic regression model using the training set, using the testing set to make predictions, and then use an Above the Curve plot to determine the percentage of inmates where the model correctly predicted the risk assessment score.

The Area Under the Curve (AUC) measures the logistic regression model's classification performance. AUC uses the proportion of positive data points that are correctly predicted positive and the proportion of negative data points that are mistakenly predicted as positive. I will also generate a plot that shows the trade-off between the rate at which the model correctly predicted the variable and the rate the model incorrectly predicted the variable. The area under the curve represents the number of true positive predictions. The metric ranges between 0.50 to 1.00, and values above 0.80 indicate that the model has high validity and predicts the correct value 80% of the time. The higher the AUC,the better the performance of the model at distinguishing between the positive and negative classes. An AUC score of 50% means that the model does slightly better than flipping a coin (random chance) (Narkhede 2018).

I will create the AUC plots and scores using the ROCR (Sing et al. 2005) and caret (Kuhn 2020) packages.

5 Results

5.1 Inmate Security Level Logistic Regression Model for Race

To test the effect of race on an inmate's security level, the first logistic regression model examines the likelihood that female inmates would end up with the worst possible security level- maximum - against the odds they would receive a medium or minimum one. Since, this project is focused on Indigenous women, the three race categories are Indigenous, White, and Other. The model will control for age. The logistic regression was created using R (R Core Team 2020), forcats (Wickham 2021) and huxtable (Hugh-Jones 2021). We will use logistic regression because our response variable is binary (maximum security level: yes or no).

Our null and alternative hypothesis are:

H0: There is no relationship between race and receiving a maximum security level in a Canadian federal prison.

H1: There is a relationship between race and receiving a maximum security level in a Canadian federal prison.

The inmate security level is very important because it is a factor in the reintegration potential score.

The security level model (Table 4) arrived at statistically significant results for all three racial categories.

The logistic regression results demonstrate that for every one unit increase in the number of Indigenous women who receive a maximum security level, the log odds that a White women and other racialized minority will receive a maximum security level decreases by 1.068 and 0.646 respectively. The p-value for Indigenous women in maximum security is less than 0.01, well below my alpha threshold of 0.05. Therefore, the p-value flags the data as being unusual if all the assumptions used to compute it (including the test hypothesis) are correct. Thus, we can reject the null hypothesis that there is no difference between a female inmate's race and their likelihood of being assigned a maximum security level (Sander Greenland and Altman 2016).

The Area Under the Curve model (Table 5) (Figure 8) demonstrates that our model correctly predicted 72.31% of inmates as having a maximum security level or not using their race and age. Thus, the maximum security model has moderatly high validity.

5.2 Dynamic/Need Score Logistic Regression Model for Race

To test the effect of race on an inmate's dynamic risk score. The second logistic regression model examines the likelihood that female inmates would end up with the worst possible dynamic risk score - high - against the

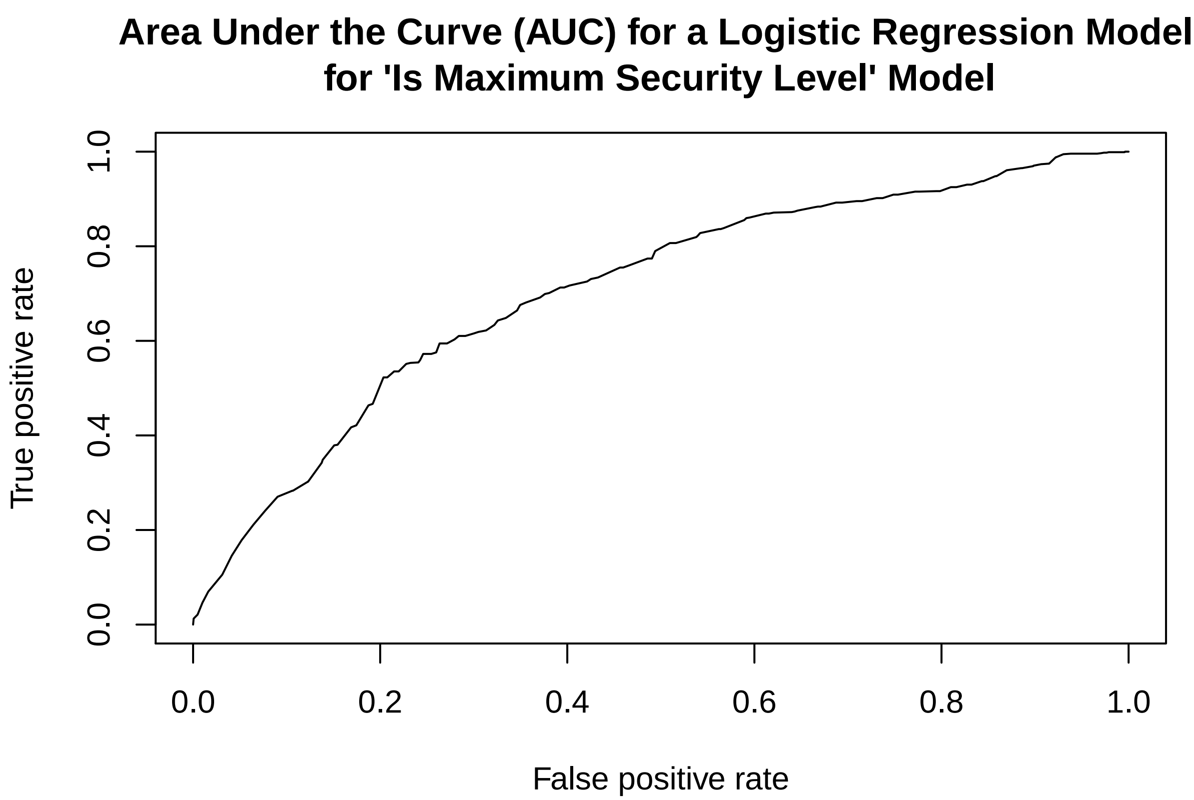

Figure 8: Area Under the Curve (AUC) for a Logistic Regression Model for ‘Is Maximum Security Level’ Model

Table 4

	Logistic Regression Model Predicting a Maximum Security Score Using Race and Age
(Intercept)	**0.20628 ****
	(0.07516)
race_analysisOther	**-0.64646 *****
	(0.06346)
race_analysisWhite	**-1.06826 *****
	(0.04316)
age	**-0.05446 *****
	(0.00224)
N	30725
logLik	-9243.45684
AIC	18494.91368

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 5: Area Under the Curve (AUC) for a Logistic Regression Model for 'Is Maximum Security Level' Model

x
0.7074783

odds they would receive a medium or low one. Since, this project is focused on Indigenous women, the three race categories are Indigenous, White, and Other. The model will control for age. The logistic regression was created using R (R Core Team 2020) and huxtable (Hugh-Jones 2021). We will use logistic regression because our response variable is binary (high dynamic score: yes or no).

Our null and alternative hypothesis are:

H0: There is no relationship between race and receiving a high dynamic score in a Canadian federal prison.

H1: There is a relationship between race and receiving a high dynamic score in a Canadian federal prison.

The dynamic risk model (Table 6) arrived at statistically significant results for all three racial categories.

The logistic regression results demonstrate that for every one unit increase in the number of Indigenous women who receive a high dynamic score, the log odds that a White women and other racialized minority will receive a high dynamic score decreases by 0.493 and 1.189 respectively. The p-value for Indigenous women with a high dynamic risk is less than 0.01, well below my alpha threshold of 0.05. Therefore, the p-value flags the data as being unusual if all the assumptions used to compute it (including the test hypothesis) are correct. Thus, we can reject the null hypothesis that there is no difference between a female inmate's race and their likelihood of being assigned a high dynamic risk score (Sander Greenland and Altman 2016).

The Area Under the Curve model (Table 7) (Figure 9) demonstrates that our model correctly predicted 62.44% of inmates as having a high dynamic score or not using their race and age. Thus, the dynamic risk score model predictions are slightly better than chance and the model has moderate validity.

Table 6

	Logistic Regression Model Predicting a High Dynamic Risk Score Using Race and Age
(Intercept)	**1.62697 *****
	(0.04261)
race_analysisOther	**-1.18851 *****
	(0.04014)
race_analysisWhite	**-0.49312 *****
	(0.02527)
age	**-0.03710 *****
	(0.00108)
N	32266
logLik	-21021.11099
AIC	42050.22199

*** p < 0.001; ** p < 0.01; * p < 0.05.

Table 7: Area Under the Curve (AUC) for a Logistic Regression Model for 'Is High Dynamic' Model

x
0.6477986

5.3 Static Risk Score Logistic Regression Model for Race

To test the effect of race on an inmate's static risk score. The second logistic regression model examines the likelihood that female inmates would end up with the worst possible static risk score - high - against the odds they would receive a medium or low one. Since, this project is focused on Indigenous women, the three race categories are Indigenous, White, and Other. The model will control for age. The logistic regression was created using R (R Core Team 2020) and huxtable (Hugh-Jones 2021). We will use logistic regression because our response variable is binary (high static score: yes or no).

Our null and alternative hypothesis are:

H0: There is no relationship between race and receiving a high static score in a Canadian federal prison.

H1: There is a relationship between race and receiving a high static score in a Canadian federal prison.

The static risk model (Table 8) arrived at statistically significant results for all three racial categories.

The logistic regression results demonstrate that for every one unit increase in the number of Indigenous women who receive a high static score, the log odds that a White women and other racialized minority will receive a high static score decreases by 0.965 and 1.187 respectively. The p-value for Indigenous women with a high dynamic risk is less than 0.01, well below my alpha threshold of 0.05. Therefore, the p-value flags the data as being unusual if all the assumptions used to compute it (including the test hypothesis) are correct. Thus, we can reject the null hypothesis that there is no difference between a female inmate's race and their likelihood of being assigned a high static risk score (Sander Greenland and Altman 2016).

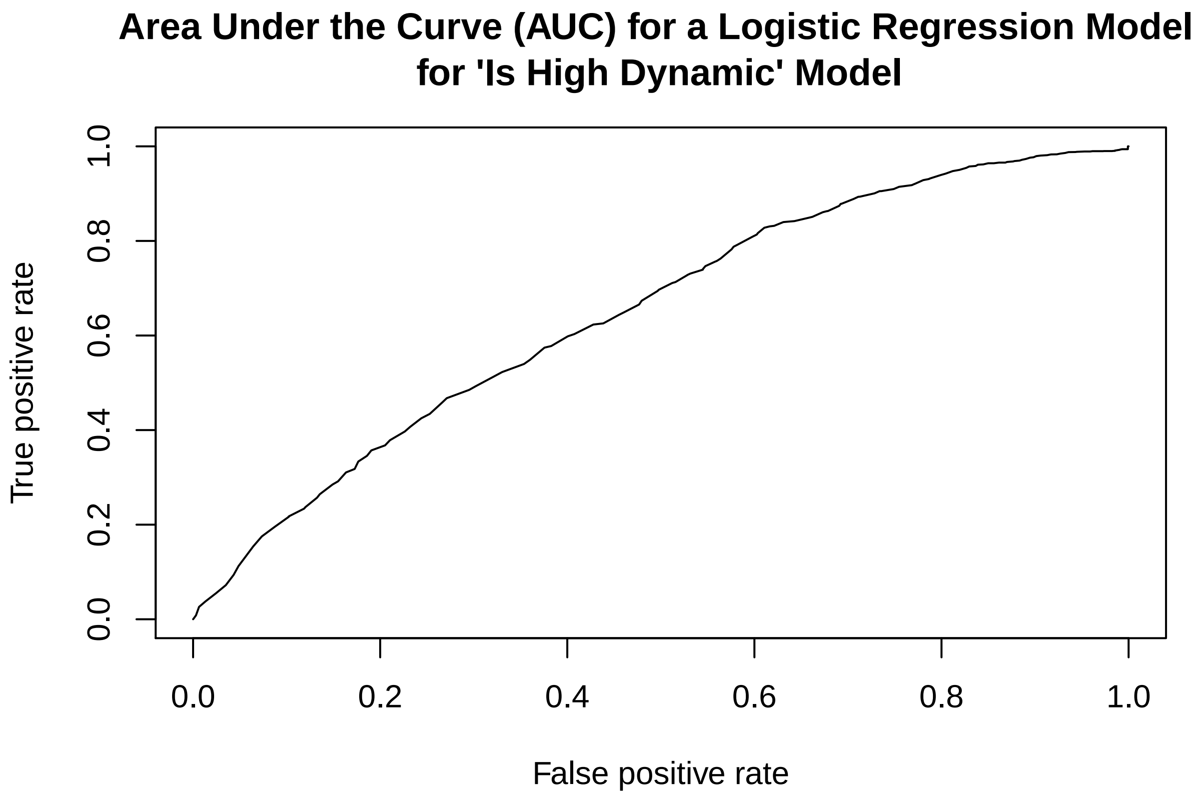

Figure 9: Area Under the Curve (AUC) for a Logistic Regression Model for 'Is High Dynamic' Model

The Area Under the Curve model (Table 9) (Figure 10) demonstrates that our model correctly predicted 64.03% of inmates as having a high static score or not using their race and age. Thus, the static risk score model predictions are slightly better than chance and the model has moderate validity.

5.4 Motivation Score Logistic Regression Model for Race

To test the effect of race on an inmate's motivation score. The second logistic regression model examines the likelihood that female inmates would end up with the worst possible motivation score - low - against the odds they would receive a medium or high one. Since, this project is focused on Indigenous women, the three race categories are Indigenous, White, and Other. The model will control for age. The logistic regression was created using R (R Core Team 2020) and huxtable (Hugh-Jones 2021). We will use logistic regression because our response variable is binary (low static score: yes or no).

Our null and alternative hypothesis are:

H0: There is no relationship between race and receiving a low motivation score in a Canadian federal prison.

H1: There is a relationship between race and receiving a low motivation score in a Canadian federal prison.

The motivation model (Table 10) arrived at statistically significant results for all three racial categories.

The logistic regression results demonstrate that for every one unit increase in the number of Indigenous women who receive a low motivation score, the log odds that a White women and other racialized minority will receive a low motivation score decreases by 0.792 and 0.794 respectively. The p-value for Indigenous women with a low motivation is less than 0.01, well below my alpha threshold of 0.05. Therefore, the p-value flags the data as being unusual if all the assumptions used to compute it (including the test hypothesis) are correct. Thus, we can reject the null hypothesis that there is no difference between a female inmate's race and their likelihood of being assigned a low motivation score (Sander Greenland and Altman 2016).

Table 8

	Logistic Regression Model Predicting a High Static Risk Using Race and Age
(Intercept)	**-0.67286 *** **
	(0.04410)
race_analysisOther	**-1.18716 *** **
	(0.04587)
race_analysisWhite	**-0.96502 *** **
	(0.02755)
age	**0.00746 *** **
	(0.00114)
N	32306
logLik	-18053.36401
AIC	36114.72801

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 9: Area Under the Curve (AUC) for a Logistic Regression Model for 'Is High Static' Model

x
0.6354341

The Area Under the Curve model (Table 11) (Figure 11) demonstrates that our model correctly predicted 61.52% of inmates as having a low motivation score or not using their race and age. Thus, the motivation score model predictions are slightly better than chance and the model has moderate validity.

5.5 Reintegration Potential Score Logistic Regression Model for Race

To test the effect of race on an inmate's reintegration potential score. The second logistic regression model examines the likelihood that female inmates would end up with the best possible reintegration potential score - high - against the odds they would receive a medium or low one. Since, this project is focused on Indigenous women, the three race categories are Indigenous, White, and Other. The model will control for age and aggregate sentence length because the reintegration potential score is recalculated throughout the inmate's sentence. The logistic regression was created using R (R Core Team 2020) and huxtable (Hugh-Jones 2021). We will use logistic regression because our response variable is binary (high reintegration potential score: yes or no).

Our null and alternative hypothesis are:

H0: There is no relationship between race and receiving a high reintegration potential score in a Canadian federal prison.

H1: There is a relationship between race and receiving a high reintegration potential score in a Canadian federal prison.

The reintegration potential model (Table 12) arrived at statistically significant results for all three racial

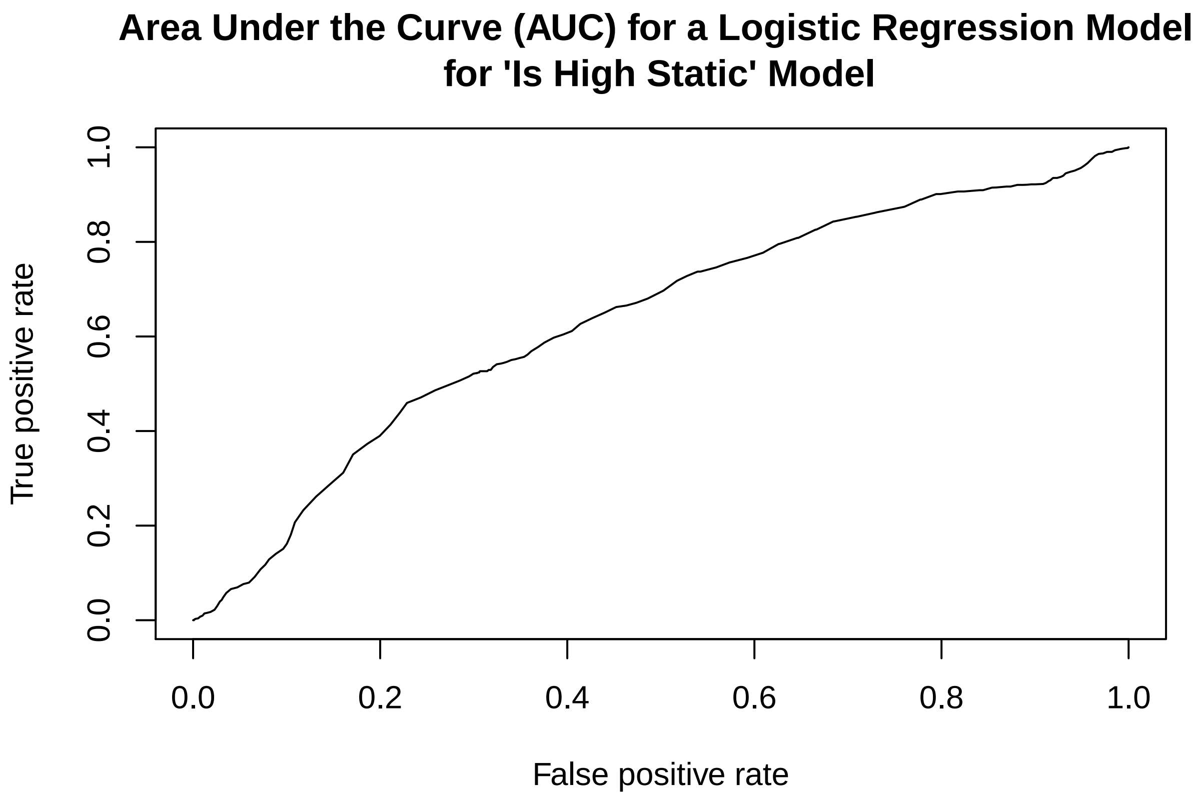

Figure 10: Area Under the Curve (AUC) for a Logistic Regression Model for 'Is High Static' Model

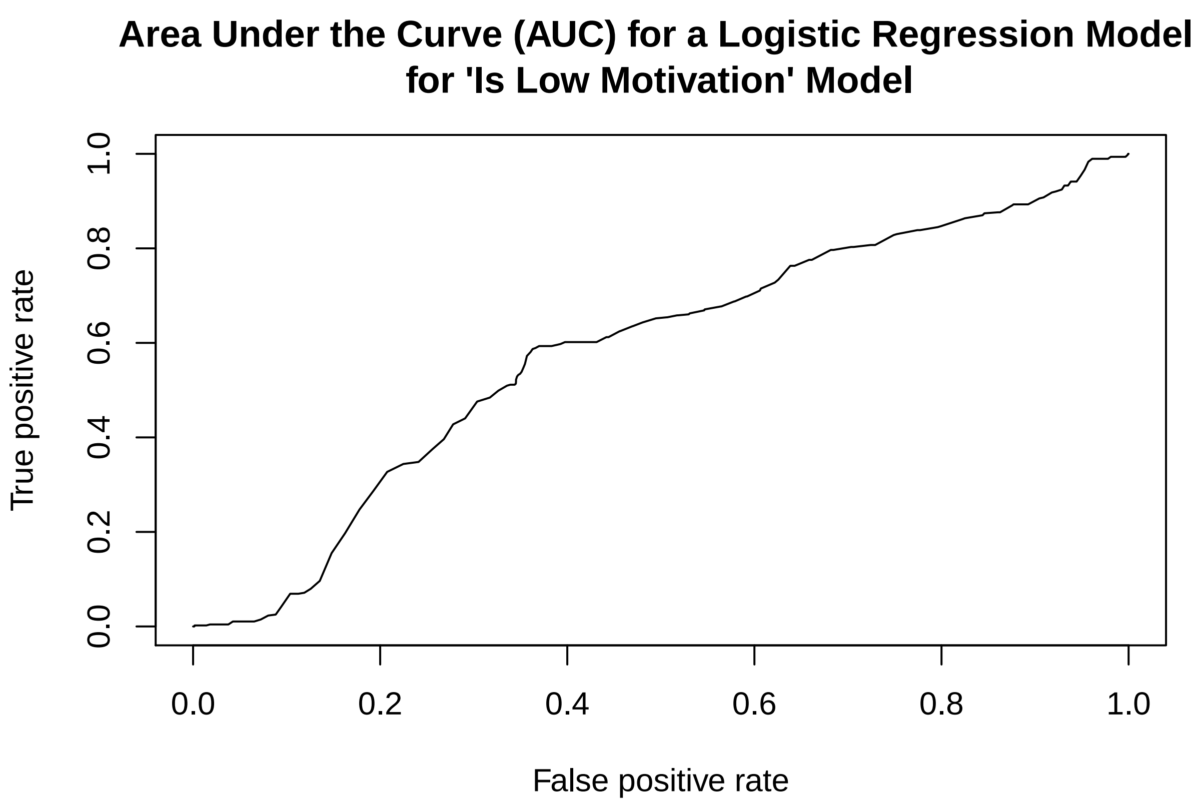

Figure 11: Area Under the Curve (AUC) for a Logistic Regression Model for 'Is Low Motivation' Model

Table 10

	Logistic Regression Model Predicting a Low Motivation Score Using Race and Age
(Intercept)	**-2.60867 ***** **(0.08835)**
race_analysisOther	**-0.79454 ***** **(0.09153)**
race_analysisWhite	**-0.79298 ***** **(0.05545)**
age	0.00295 (0.00231)
N	32230
logLik	-6260.68325
AIC	12529.36650

*** p < 0.001; ** p < 0.01; * p < 0.05.

Table 11: Area Under the Curve (AUC) for a Logistic Regression Model for 'Is Low Motivation' Model

x
0.5807858

categories.

The logistic regression results demonstrate that for every one unit increase in the number of Indigenous women who receive a high reintegration potential score, the log odds that a White women and other racialized minority will receive a high reintegration potential score increases by 0.579 and 1.295 respectively. The p-value for Indigenous women with a high reintegration potential score is less than 0.01, well below my alpha threshold of 0.05. Therefore, the p-value flags the data as being unusual if all the assumptions used to compute it (including the test hypothesis) are correct. Thus, we can reject the null hypothesis that there is no difference between a female inmate's race and their likelihood of being assigned a high reintegration potential (Sander Greenland and Altman 2016).

The Area Under the Curve model (Table 13) (Figure 12) demonstrates that our model correctly predicted 67.20% of inmates as having a high reintegration potential score or not using their race, age and aggregate sentence length. Thus, the reintegration potential model's predictions are slightly better than chance and the model has moderate validity.

6 Discussion and Future Research

6.1 Discussion of Research Findings

The Canadian Security Service's (CSC) risk assessment scores ultimately risk trapping Indigenous women in a cycle of trauma and crime because Indigneous women are more likely to receive worst scores for factors outside their control. This makes it more difficult for these women to access educational programs, find employment

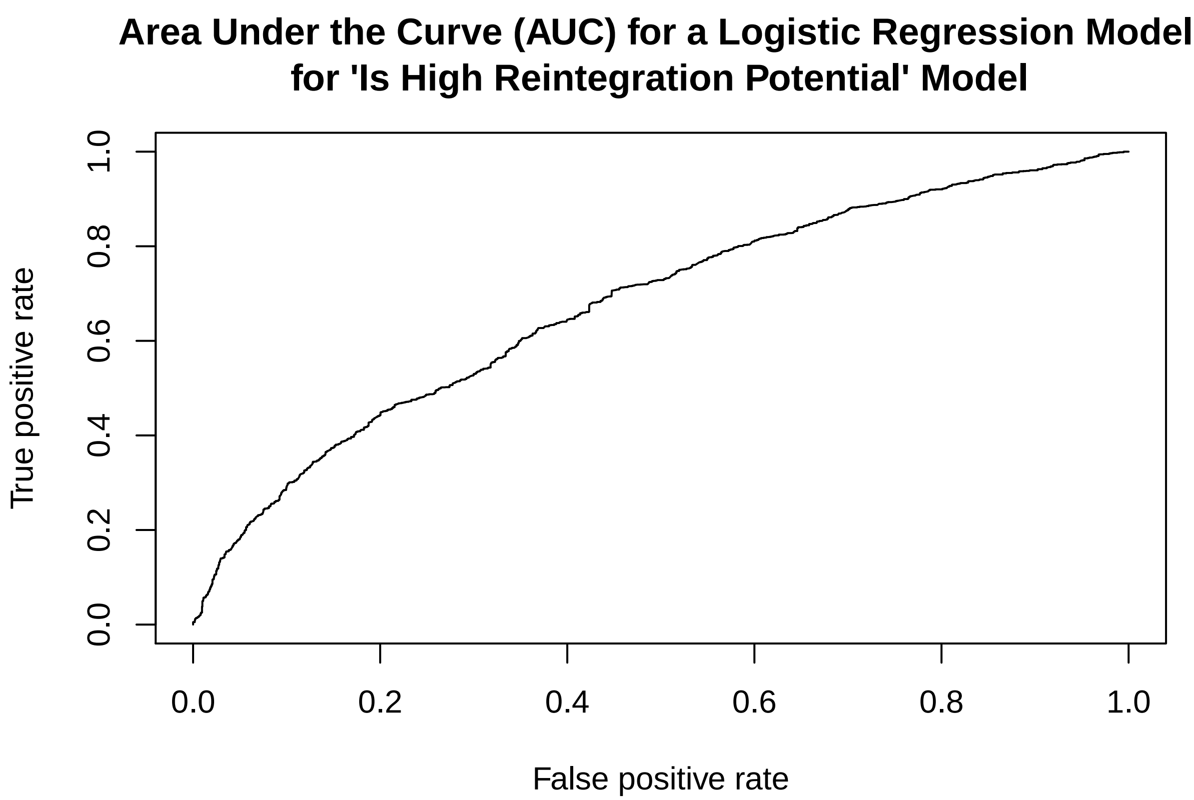

Figure 12: Area Under the Curve (AUC) for a Logistic Regression Model for 'Is High Reintegration Potential' Model

Table 12

	Logistic Regression Model Predicting a High Reintegration Potential Using Race, Age and Aggregate Sentence Le
rcept)	**-2.93875**
	(0.0509
_analysisOther	**1.29452**
	(0.0418
_analysisWhite	**0.57913**
	(0.0316
	0.03751
	(0.0011
egate_sentence_length	**-0.00007**
	(0.0000
	32419
k	-17239.491
	34488.982

< 0.001; ** $p < 0.01$; * $p < 0.05$.

Table 13: Area Under the Curve (AUC) for a Logistic Regression Model for 'Is High Reintegration Potential

x
0.6752971

opportunities, and campaign for early release which could decrease their likelihood of recommitting.

First, the maximum security level is a valuable tool for ensuring dangerous prisoners are supervised and isolated in order to protect the health and safety of other inmates. Additionally, maximum security inmates can also work towards a medium security level and eventually a minimum security level through good behaviour. However, the overrepresentation of Indigenous women in maximum security prisons opens questions about why Indigenous women are more likely to receive the "worst" score compared to White women. Unfortunately, the dataset does not explain why these women received a maximum security score. The reason may be the "Squaw" stereotype that depicts Indigenous women as more violent and dangerous compared to White femininity. However this statistic is particularly troublesome because women in maximum security facilities are constantly under strict supervision and solitary confinement which risks exacerbating their dynamic score - particularly mental health and extroversion.

Second, I argue that the dynamic score must be removed from the CSC's risk assessment evaluations. The dynamic score is based upon factors that are outside an inmate's control and disciplines women who have been victims of crime. For instance, the dynamic score punishes women who are survivors of domestic violence and pedophilia by giving a lower score to abused women. However, the most concerning aspect is that if their abuser was a family member and was convicted of their crime, these women are still punished by the dynamic score because they have a criminals in their family unit. Thus, the dynamic score criminalizes physical and sexual abuse-survivors and delegitimizes the seriousness of violent crimes against Indigenous women. The dynamic score implies that abused women must be locked up, hidden away and neglected rather than empowered.

Additionally, the dynamic score benefits financially privileged, educated, and white-collar criminals. Residential schools infamously stripped Indigenous women of a high-quality education and contributed to serious mental health issues through physical, sexual, and emotional abuse. Since the closure of the last residential school in Canada, its traumatic legacy lives on. Residential school survivors are more likely to live in poverty at the time of arrest compared to non-Indigenous women (S. Canada 2016). Furthermore, residential school survivors are more likely to be involved in the sex trade, have a mental illness, drop out of high school, not pursue a higher education and have addictions. Many of these women's crimes are poverty-related such as theft under $5,000, soliciting sex work in public areas, selling illicit substances and resisting arrest (Piotr Wilk and Cooke 2017).

In contrast, the dynamic risk score rewards the most privileged with the best scores. For instance, individuals who have a post-secondary education, were employed at the time of rest, have in-demand skills, come from a privileged family with no history in the criminal justice system, and are financially secure are significantly more likely to get a lower dynamic risk score. I argue that the dynamic risk score exacerbates the historical, racial and gendered impact of colonization and poverty on crime. This score reinforces that federal custody is used to control the most marginalized members of Canadian society rather than oppose large social structure that contribute to more Indigenous women coming in conflict with the law. Hence, the dynamic risk score demonstrates that the CSC needs to develop culturally-appropriate crime prevention strategies that address structural inequalities experienced by Indigenous women. These strategies would in turn reduce the static risk score for future generations of Indigenous women.

Third, the motivation score does not address why more Indigenous inmates are less motivated to reform and not recommit their crimes in the future. The dataset does not capture the reasons Indigenous inmates are less enthusiastic to participate in reintegration programming and change their behaviours towards crime. Nevertheless, the three risk assessment scores above suggest that Indigenous women may be less motivated because of their negative experiences with Canada's criminal justice system. The security level, dynamic need and static risk scores demonstrate that the current system is biased against Indigenous peoples, and does not respond to the needs or realities of Indigenous women. The CSC's decision to lock a disproportionate number of Indigenous women in maximum security where they cannot participate in educational or employment opportunities, limits these women's ability to upgrade their skills, pursue additional education, and find employment opportunities outside the prison. Additionally, the dynamic risk score penalizes Indigenous women for being survivors of abuse, being impoverished, coming from an impoverished household, and having a mental illness. Thus, current correctional programming abandons Indigenous women by limiting their opportunities to reintegrate into society. Thus, the data suggests that these women may have a low motivation score because they feel like the CSC's current programs and risk assessment tools are inadequate for addressing the underlying criminogenic factors of Indigenous women.

Lastly, these four scores all impact an inmate's reintegration potential score. By being more likely to receive the worst scores in all four categories, it is severely unlikely that an Indigenous women will be able to secure a shorter sentence or earn additional freedoms. Hence, the CSC risk assessment tools contribute to the overrepresentation of Indigenous women in Canadian federal prisons because they reduce these women's access to economic, social and educational resources which all contribute to the higher rate of incarceration and for longer periods of time.

6.2 Limitations of Research Findings

Viewed as a whole, the CSC dataset provides a strong overview for how an individual's race and experiences with racism impact their risk assessment scores when they are in federal custody. These risk assessment scores may play a large role in the criminalization and overrepresentation of such an alarming number of Indigenous women in Canada, as well as the strengths and failing of the criminal justice system. However, the findings generated by this research project are subject to a number of limitations, which ought to be kept in mind.

As I have tried to stress throughout my work, the dataset only covers a short time period and does not capture the historical and individual experiences of Indigenous women. Consequently, it is not the physical appearance of a women that causes her to receive the worst risk assessment scores. Instead, Indigenous women receive the worst scores because of the isolation, disenfranchisement, and discrimination Indigenous women received and continue to receive in Canadian society.

Furthermore, each of the individual's captured in this dataset have their own unique story. The results of this research cannot be extrapolated across criminalized Indigenous women as a monolithic whole. Rather, they must be interpreted as a mere overview of what scores an Indigenous woman is more likely to receive when they enter federal custody. Additionally, the dataset has a relatively small number of inmates because the data is focused on federally incarcerated inmates rather than the entire criminal justice system. This means that further and more specific qualitative and quantitative research would need to be undertaken to determine if the logistic regression models' results are consistent with those of other criminalized Indigenous women in Canada.

Unfortunately, certain aspects of my project design may have perpetuated dangerous stereotypes. For example, the inmates represented in the dataset are all in federal custody and those in federal custody typically commit more severe crimes. The dataset does not represent women incarcerated at the provincial or municipal level between 2012 to 2018. This biases the results towards criminalized women at the federal level. Moreover, the participants that were given the race label "Indigenous" must have their Indian Status and thus the model's results may not necessarily reflect the experiences of non-Status Indigenous women who do not live on reserves or had an experience with a residential school prior to being incarcerated.

6.3 Suggested Avenues for Future Research

Over the course of this project, I have identified a number of potential avenues for future quantitative and qualitative research with criminalized Indigenous women in Canada. Central among these is quantitative research into the experiences of Indigenous women in provincial prisons and remand centres, which has been gravely understudied. Provincial prisons use the same CSC risk assessments on incarcerated women and the data may reflect a different reality for incarcerated women at the provincial level. Provincial prisoners also typically commit less severe crimes than those in federal custody (Dyck 2013).

Another issue deserving of further examination is a difference-in-differences analysis for Indigenous inmates who received culturally- and gender-appropriate programming and interventions. The CSC is committed to introducing interventions for Indigenous communities such as healing circles, implementing Indigenous pedagogies into educational programming, helping Indigenous women find employment opportunities on reserves, and more (Services 2019). It would be interesting to study if women who receive this programming are more likely to have higher motivation and reintegration potential scores compared to Indigenous women who did not receive this programming.

The final subject that requires further research would be the extent to which systematic racism within the criminal justice system may be inhibiting Indigenous women's prospects for successful reintegration into society upon release from incarceration. The models' results demonstrate that there is a great deal more the CSC can do to tackle cultural and racial biases towards Indigenous women that may be contributing to them getting the worst scores. We could do a difference-in-difference analysis on the risk assessment scores after psychologists administering the test receive equity, diversity and inclusion training.

However, as this research project has attempted to illustrate, the crisis of Indigenous over-incarceration goes much deeper than mere statistics, however shocking. While it is easy to use graphs and percentages to demonstrate the severity of Indigenous overrepresentation within Canada's federal prisons, we really ought to talk about people rather than figures. When an Indigenous women, or any person for that matter, goes to prison, it is not only their life trajectory that is negatively affected. The trickle down affects of Indigenous over-incarceration will lead to future generations being caught in this tenacious web of trauma, poverty, and crime. If we do not take time to stop, listen, learn and act, there is little hope that this grave injustice will simply continue unabated. Instead of locking people up on reserves, Canada will simply lock them up in prison instead.

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