Mapping the Developmental Trajectories of Chronic Offenders in Canada

by

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The above committee determined that the thesis is acceptable in form and content and that a satisfactory knowledge of the field covered by the thesis was demonstrated by the candidate during an oral examination. A signed copy of the Certificate of Approval is available from the School of Graduate and Postdoctoral Studies.

ABSTRACT

The current study analyzed convicted chronic offenders that were charged with at least two offences in the region of Hamilton, Ontario, Canada, between 2006 and 2019 (N = 11,426) in order to investigate the relationship between specialization (i.e., committing the same crime type repeatedly) and versatility (i.e., committing a variety of crime types) which have commonly been viewed as mutually exclusive. It aimed to determine whether: (1) committing a certain crime in the past makes an individual more likely to commit that same crime in the future, (2) having an affinity for specific crimes makes an individual more likely to commit certain other crimes, and (3) offenders are likely to move throughout the clusters identified in objective 2 in a consistent fashion. In achieving objective 1, a logistic regression identified that in almost all crime types assessed, a prior conviction for a certain offence increased an individual's chances of being convicted of that same offence in the future. This finding provides support for the overarching goal of policies and regulations that target chronic offenders (e.g., the National Sex Offender Registry). Both objectives 2 and 3 yielded less distinct results, suggesting that specialization and versatility are likely not mutually exclusive and that offenders are likely to repeat certain crimes in tandem with other crimes.

Keywords: chronic offenders, crime specialization, cluster analysis

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M. Pullman

Mari Pullman

STATEMENT OF CONTRIBUTIONS

I hereby certify that I am the sole author of this thesis and that no part of this thesis has been published or submitted for publication. I have used standard referencing practices to acknowledge ideas, research techniques, or other materials that belong to others. Furthermore, I hereby certify that I am the sole source of the creative works and/or inventive knowledge described in this thesis.

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何よりもまず、今日の私を支えるためにしてくれた無数の犠牲に対して、ママとパパに感謝しています。あなたたちの揺るぎないサポートなしでは、これらすべてが可能になりませんでした。ママ、本当にありがとう。

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Mapping the Developmental Trajectories of Chronic Offenders in Canada

In 1986, the U.S. National Academy of Sciences (NAS) Panel on Criminal Career Research produced a report on a new framework known as the criminal career approach (Blumstein, 1986). The criminal career approach is not a theory in and of itself, but rather is an overarching framework wherein theories can be hypothesized and tested. Briefly, this framework suggests that a criminal career has an onset, a point of desistance, a duration, and a frequency. In addition, this framework indicates that there is a specific prevalence rate associated with the proportion of the population who has a criminal career (Blumstein, 1986). The criminal career framework makes a strong distinction between frequency and prevalence. The prevalence defines the proportion of the general population who is committing criminal offences, whereas the frequency defines the rate of offending of a specific offender while they are within the community and therefore, not incarcerated (Blumstein, 1986; Farrington, 1992).

Recognizing and understanding offenders who are on the extreme end of the duration distribution, and more importantly, the frequency distribution, is tremendously valuable because data shows that a small fraction of the offender population is responsible for a disproportionately large amount of crime (Falk et al., 2014; Farrington, 1992; Ruth, 2021). For example, a study that analyzed violent offenders using data from several national registers in Sweden determined that of the total population born between 1958 and 1980, approximately 1% was responsible for 63.2% of all violent convictions, which suggests a very high frequency for a very small number of individuals (Blumstein, 1986; Falk et al., 2014). Of the total population, approximately 4% had at least one violent conviction; therefore, the prevalence rate of violent offenders based on conviction data was approximately 4% (Blumstein, 1986; Falk et al., 2014). Similarly, a report published by the Edmonton Police Commission detailing crime statistics over the four-year-period between May 2017 and April 2021 revealed that approximately "6% of the top offending individuals… amassed 20%... of all violations" (Ruth, 2021, p. 5).

Data consistently shows that a region's top offenders are responsible for a disproportionately large amount of crime; this exemplifies the importance of studying their patterns and behaviours (Falk et al., 2014; Ruth, 2021). Historically, theorists believed that offenders who had long criminal careers exhibited specific typologies in regard to crime type (Clinard & Quinney, 1967; Gibbons, 1965); this concept is known as specialization. However, this perspective has not been supported and overall, the data suggests that an offender, particularly one that persists long-term, will exhibit versatility across crime types over the lifetime of their criminal career (Gibbons, 1975; Gottfredson & Hirschi, 1990; Weinrott & Saylor, 1991). Extending on these two opposing perspectives (i.e., specialization and versatility), research over the last decade or two has questioned whether they should be seen as mutually exclusive (DeLisi et al., 2019; Francis et al., 2004; McGloin et al., 2009). Rather than using a lack of complete specialization to argue versatility, they have aimed to identify the utility in using an offenders' prior criminal behaviour to predict future criminal behaviour while recognizing that other crime types will surely exist. The goal of the current study was to extend this line of inquiry within a Canadian context.

Opinions on Offender Typology versus Versatility

There have been several influential papers that have weighed in on the dispute between chronic offenders' behaviours and whether they tend to specialize within a certain (subset of) crime type(s) and exhibit specific typologies (i.e., specialized or specialist), or whether they exhibit versatility in their crimes over time. Chronologically, the discussion in the early to mid-20th-century, which was led by theorists such as Gibbons (1965) and Clinard and Quinney

(1967), favoured classifying offenders' into certain typologies. Gibbons (1965) distinguished juvenile offender types from adult offender types, and discussed how life circumstances could lead an individual to different criminal pathways exclusively in youth, adulthood, or both. Gibbons proposed fifteen types of adult offenders (e.g., professional thief, automobile thief, violent sex offender) and nine juvenile types (e.g., predatory gang delinquent, drug user, female delinquent).

Although Clinard and Quinney (1967) did begin to depart from the assertion that there were strict delineations of criminals based on their specific crime types, the assumption regarding criminal behaviour types and what kind of individual would fall into each of these types remained. They suggested that there were eight types of criminal behaviour systems, with each having a distinct stance on specific components. An example of one of the eight types that they proposed was the violent personal criminal who takes part in crimes such as murder, assault, and forcible rape. These individuals do not view themselves as criminals because they often do not have a previous record and instead have a certain circumstance that caused them to commit the offence. As outlined by Clinard and Quinney, "[the violent personal criminal's] offences are not directly supported by any group… [their] behaviors are in sharp contrast to the middle-class values of the society, [and there are] strong reaction[s] to [these] offences" (p. 15). These three influential figures (i.e., Gibbons, Clinard, and Quinney) exemplify how staunch forensic and criminological academia were on the specialist side of this debate in the early to mid-20th-century.

Over time, theories on specific offender typologies have further evolved to become more general and suggest broad categories within the offender population arguably less respective of their crimes (Moffitt, 1993; Nagin & Land, 1993). Many of these researchers focused on the developmental trajectories of offenders, as opposed to specific classifications of offenders. In her seminal paper, Moffitt (1993) discussed the factors that encourage deviance to persist after adolescence, making a distinction between adolescence-limited antisocial behaviour and life-course-persistent antisocial behaviour. She argued that a disproportionately large amount of adolescents (compared to other age groups) take part in deviant and antisocial behaviour as a form of social mimicry to attain status and power among their peer groups. However, she argued that a certain subset of adolescents (i.e., life-course-persistent offenders) continue their deviant behaviour past this period when most of their peers (i.e., adolescence-limited offenders) recognize that the risks of deviance outweigh the rewards. Life-course-persistent antisocial behaviour, Moffitt argued, is a result of neuropsychological ailments interacting with their environment which encourages delinquent and later, criminal, behaviour.

Both and Nagin et al. (1995) and Sampson and Laub (2003) analyzed data which suggested that delineating offenders into the two categories (i.e., life-course persistent and adolescence-limited), and making assumptions regarding each's creation and their respective traits, may not be as sound. Based on self-reported measures, Nagin et al. found that adolescence-limited offenders, even at age 32, were at high risk of engaging in theft (particularly from their employer), using illicit drugs, consuming alcohol at high rates, and getting into fights. They suggested that adolescence-limited-offenders are not necessarily foregoing deviant behaviour, but rather are engaging in "circumscribed deviance." Sampson and Laub determined that for all offender groups, including predicted life-course-persistent offenders, crime declined with age. They also found poor evidence for predicting long-term offending based on childhood prognoses.

Recent Empirical Research

In more recent years, the broad scope of this discussion, as evidenced directly above, has been to empirically test the validity of classifying offenders into distinct typologies or general groups, such as “life-course-persistent” or “adolescence-limited” (Nagin et al., 1995; Piquero et al., 2003; Sampson & Laub, 2003). Multiple studies that have measured samples over long periods have suggested that offenders appear to exhibit versatility (Weinrott & Saylor, 1991; Wiesner et al., 2018). Simon (1997) assessed individuals whom they stated are often treated by the public, legal, and mental health system as specialists: perpetrators of intimate partner violence and sex crimes, independently. In both groups, they found a high degree of offending outside of these two categories; most of the individuals in their sample who had committed intimate partner violence had histories of violence outside of the home, and most of the sex crime perpetrator sample had a history of non-sex offences as well. Similarly, Weinrott and Saylor (1991) assessed 99 males who had been convicted of rape or sexual abuse of a child and found that most admitted to committing a non-sex offence in the 12 months prior to their incarceration.

While these studies clearly demonstrate that absolute specialization is extremely unlikely, the debate between versatility and specialization has been seen in “zero-sum terms”, where evidence of general versatility denotes a lack of existence of any specialization (DeLisi et al., 2019, p. 2). Recent researchers (DeLisi et al., 2019; Francis et al., 2004; McGloin et al., 2009) have aimed to expand on whether this is accurate. More specifically, some researchers have suggested that evidence of a) an affinity towards certain crime types across an array of versatile trends, and b) specialization in the short-term, appears to exist (Francis et al., 2004; McGloin et al., 2009; Shover, 1996; Sullivan et al., 2006). Shover (1996) surveyed qualitative data provided by persistent thieves and stated:

> Although there is limited long-term specialization by persistent thieves, the existence of distinct crime preferences combined with "habit [and] familiarity with techniques… [tends] to draw them back towards their 'main line' – the type of crime they [feel] most at home with." As opposed to rigid specialization, therefore, the more common pattern is "what might be called 'short-term specialization,'… periods in which they… become involved in a specific type of crime to the virtual exclusion of others. (pp. 65-66)

This flexible perspective of specialization is what the current thesis utilizes. This definition recognizes that across the lifetime of a chronic offender, they are unlikely to exhibit absolute specialization. However, it acknowledges that being able to identify some patterns, where prior crime can predict the future criminal behaviour of an offender, is valuable. Therefore, this study focuses on the utility of using prior crimes to predict future crimes, rather than attempting to add to the theoretical specialization/versatility debate. While this thesis does incorporate and attempt to balance all previous research cited, it is inspired by the methodology of three specific studies which employed logistic regression (DeLisi et al., 2019) and latent class modelling (Francis et al., 2004; McGloin et al., 2009) to approach specialization in this manner.

Logistic Regression

DeLisi and colleagues (2019) analyzed prior arrests of juveniles who had been incarcerated for homicide, robbery, aggravated assault, simple assault, burglary, and drug sales. They utilized logistic regression to determine how the incidence of a particular prior crime would predict the crime type of the juvenile's most recent conviction (i.e., reason for incarceration). For example, when analyzing individuals whose most recent convictions were homicide, they used a binary indicator of existence of a prior homicide arrest (1 = prior homicide arrest, 0 = no prior homicide arrest) as well as binary indicators for each of the other offences included to predict said recent conviction. They identified that the only significant predictor of most recent homicide conviction was prior homicide arrest. This means that being arrested for homicide in the past did significantly predict conviction for a separate homicide offence in the future, but arrest for a different prior crime did not.

This pattern, wherein prior arrest for a certain crime was the only significant positive predictor of a conviction for said crime type in the future, was repeated across all crime types that the authors analyzed. In other words, the only positive predictor of current homicide conviction was prior homicide, current robbery conviction was prior robbery, current drug sales conviction was prior drug sales, etc. These results suggest that when classifying specialization by identifying the existence of the same crime type across an offender's criminal career, as opposed to the absence of other crime types, we can recognize valuable patterns of repeated behaviour.

Latent Class Modelling

Along with the study conducted by DeLisi et al. (2019), the current study was inspired by two prior papers that expanded on this "middle-ground" that straddles the line between versatility and specialization (Francis et al., 2004; McGloin et al., 2009). Both papers investigated the same general research question. Given that data and research overwhelmingly appear to suggest that offenders exhibit versatility over the life course, can we find evidence of specialization in the short-term? In addition, they both used cluster analytic techniques – Francis et al. used latent class analysis (LCA) and McGloin et al. used a longitudinal version of LCA, latent transition analysis (LTA) – to analyze short-term specialization. Similar analyses were used in the current study and a more in-depth summary of the statistics behind this method are described in the methods' Latent Class Modelling section. However, in brief, LCA (and as an extension, LTA) is a subset of structural equation modelling which identifies clusters (i.e., latent classes) within multivariate categorical data. After identifying these clusters, the technique assigns cases to one of these clusters based on maximum likelihood of membership. LTA extends on this by estimating the probabilities of transition among latent classes overtime (Lazarsfeld & Henry, 1968; McCutcheon, 1987).

Francis and colleagues (2004) analyzed conviction data of offenders born in England and Wales in 1953 over a 40-year-period in 5-year intervals. They used an LCA longitudinally to assess specialization by including the time interval as a secondary variable, along with crime type, instead of an LTA. The LCA revealed a nine-cluster solution for the male sample and a three-cluster solution for the female sample. They determined that while most of these clusters were not clean-cut delineations between crime types (i.e., most involved versatility), there were some interesting patterns that emerged. For example, approximately half of the offenders with a shoplifting conviction were specialized offenders who almost exclusively shoplifted. They also determined that male offenders, in particular, were more likely to specialize as they got older. This second point may provide some support for Moffit's (1993) theory on the life-course persistent offender and the strength of such an environment as an offender ages.

As they had a rich dataset that spanned multiple decades, they were also able to assess not only specialized offenders, but also those they defined as probable switchers and desisters. Therefore, they analyzed both those who remained in their respective clusters overtime, as well as how likely offenders in one cluster during one time-interval/age-group (as all offenders in this sample were the same age) may move during the next time-interval (i.e., their developmental trajectory). Visually, in essence, this allowed Francis and colleagues (2004) to create a more complex web of what DeLisi et al. (2019) identified. For example, they identified that of the 739 individuals who had been grouped into the “vehicle theft” cluster (G) at age 16-20, 3.8% had also been grouped in the same cluster at < 16, and 6.0% had been grouped at age 21-25.

McGloin et al. (2007) used an LTA to analyze self-reported data collected between 1989 and 1990 from incarcerated male offenders in Nebraska. They interviewed the respondents on their criminal behaviour during that calendar year along with the two prior and split this data into 1-year intervals. They used an LCA to determine that four clusters were apparent within the sample: (1) no/low offending, (2) mixed offending, (3) drugs, and (4) burglary/theft. They then used an LTA to determine where offenders that were grouped into these clusters in Year 1 appeared in Year 2, and then again in Year 3 (i.e., developmental trajectory). They found that 41.8% of individuals remained in the low/no offence cluster and 6.0% remained in the mixed cluster, which does not suggest specialization. However, approximately 29.3% appeared in the drugs cluster across all three years and 8.1% of the sample appeared in the theft/burglary cluster across all three years. McGloin et al.’s findings suggest that some level of specialization existed within approximately 37% of the sample over the three-year period.

Indeed, when taking a more flexible approach to analyzing specialization, some prior studies that used a lack of complete specialization to argue for the existence of total versatility can be seen with a new perspective. For example, in the study noted above by Simon (1997), they found that perpetrators of intimate partner violence were very likely to be generalists who committed violence outside of the home as well; however, they also identified that 40% of “first-offence wife assaulters” reoffended within a two-and-a-half year window. This finding, and its’ potential utility for policy and corrections, should not be overlooked. While it may be simpler for the theoretical debate between specialization and versatility to see the two concepts as mutually exclusive, a recognition that the world does not operate in “black and white” is imperative.

Current Study

The goal of the current study was to expand on existing research to: (1) identify whether committing a specific crime in the past predicts committing the same offence in the future, (2) identify whether distinct clusters of offenders, based on crimes committed, appear in the data, and (3) identify whether distinct developmental trajectories appear in the data. Objective 1 required the use of logistic regression while the latter two objectives required latent transition analysis (LTA). This thesis aimed to expand on previous research while filling in some of the gaps that existed in their respective methodologies. The current study also tested these methods using a new geographic sample (i.e., a Canadian sample). Furthermore, it aimed to combine these two methods (i.e., logistic regression and LTA) using the same sample of offenders to identify whether elevated chances of repeated/predictable criminal behaviour would be captured using logistic regression or LTA and whether one was a more appropriate method to identify offender trajectories.

Alterations to Prior Research

Foundational research by Shover (1996), DeLisi et al. (2019), Francis et al. (2004), and McGloin et al. (2009), among others, provides compelling evidence for why the topic of specialization should be investigated further. The report published by the NAS' Panel on Criminal Career research (Blumstein, 1986) provides a strong backdrop for studying chronic offenders (i.e., high frequency) in comparison to one-time offenders (i.e., low frequency). To study offending behaviour longitudinally, the current study used a dataset that spanned 16 years.

As mentioned, the current study employed logistic regression and LTA. Specialization research does not require the use of these methods; indeed, other researchers have used a multitude of other techniques, such as the forward specialization coefficient (Farrington et al., 1988), the diversity index (McGloin et al., 2007), smallest space analysis (Trojan & Salfati, 2016), and Markov chain analysis (Stander et al., 1989). However, as initially noted by McGloin et al. (2009), and for the purposes of the current analysis, the aim of objectives 2 and 3 were to find a method that itself derives the crime clusters that existed within the data, as opposed to using the researcher's prospective assumptions. Additionally, LTA is advantageous because it "focuses on the individual-level rather than aggregate offending patterns" and can plant the pathways that reveal transitions among the clusters over time (McGloin et al., 2009, p. 248). Therefore, based on McGloin and colleagues' suggestions, LTA was seen as the most appropriate method for the two latter objectives of the current analysis.

The current study closely aligned with prior research conducted by DeLisi et al. (2019), Francis et al. (2004), and McGloin et al. (2009). However, there are several key elements that separated it from existing research. One of the largest distinctions between these three papers is the data they collected; DeLisi et al. used both conviction and arrest data, Francis et al. used solely conviction data, and McGloin et al. used self-reported data from incarcerated offenders. There are strengths and limitations to all of these approaches. The advantage of using self-report data, when available, is that respondents can provide details regarding their behaviour that are not captured by official records. However, offenders are typically less likely to disclose some types of offences compared to others, which disproportionately represents some crime types over others (Chaiken & Chaiken, 1984). In contrast, conviction data can be advantageous to use because large sample sizes can be obtained, and compared to an offenders' self-report responses, less of a bias should exist in favour of, or against, certain types of crimes (Gibbons, 1965). However, using conviction data can mean that the researcher is only identifying trends that exist within the criminal justice system in their sample's respective region, which results in systematic bias. Although there are strengths and limitations to using any kind of crime data in research, the goal in the current study was to obtain Canadian crime data regarding charges that were laid by police, as opposed to conviction data, to gather as much data as possible. However, upon inspection of the data provided, a decision was made to focus on convictions as opposed to charges as a whole. This decision is further elaborated upon in the methods.

In addition, in order to mirror the strengths of both Francis et al. (2004) and McGloin et al.'s (2009) methodologies for objective 3 in particular, longitudinal data from multiple cohorts spanning 16 years was used. Francis et al.'s design was advantageous as it allowed for multiple periods of short-term specialization to be analyzed which could allow for flexibility in the intervals being studied, and the researcher was also able to observe trends that occurred over time as opposed to only at one point in history. However, they only used one age cohort (i.e., individuals born in 1953), which may have introduced cohort effects. Additionally, due to the binary nature of how individuals are coded for within each time interval in latent class modelling designs, and the fact that they had intervals that spanned five years, an individual who committed 12 thefts during a 5-year-span, for example, would have been coded the same as an individual who committed one (even though these two should not arguably be weighted the same). This is a complex situation to weigh as having more intervals would require a substantial number of variables to be added (potentially causing the model to not converge) but having too few can mean that patterns are not being identified. Both of the issues noted in Francis et al.'s design were mitigated in McGloin et al.'s design. More specifically, they included a general sample of incarcerated male offenders with intervals of one year each, but their study excluded female offenders and only spanned three years total. With all these points in mind, the current study gathered data of all charges laid within a Canadian city (Hamilton, Ontario) over 16 years and aimed to mitigate some of these potential issues.

Practical Implications

The value of the current study is the practical utility that it provides to the criminal justice system and relevant policies. The ability to map developmental trajectories of offenders (objective 3), based on the crimes they have committed (objective 2) can allow researchers to map important times for intervention, and to determine which crime types may be precursors to those deemed most serious (objectives 1 and 2). More specifically, laws and policies that target chronic and/or specialized offenders may be under scrutiny based on evidence (or the lack of) supporting such policies. For example, the National Sex Offender Registry (NSOR) was formed in Canada based on the assumption that sex offenders are highly specialized chronic offenders who are driven to commit these crimes. The NSOR restricts offenders' abilities to find employment and housing, and to travel, as well as requiring them to report personal information on an annual basis (Royal Canadian Mounted Police [RCMP], 2020). Evidence that finds support for sex offenders being highly chronic and specialized would provide a strong argument to maintain these resources; however, this evidence appears to be sparse (Weinrott & Saylor, 1991).

The NSOR and mandatory sentencing laws in Canada assume that without some form of monitoring or incarceration, these offenders will continue to offend at high rates. However, if data suggests that offenders who commit offences that carry mandatory sentences in Canada (e.g., impaired driving, firearms offences, sexual offences) are unlikely to repeat the same crimes, should they be incapacitated at disproportionately greater rates? This question is further exacerbated when considering that according to Correctional Service Canada (2014), their "goal is to assist inmates to become law-abiding citizens." However, research routinely shows that the effects of prisonization often have negative effects on the communities into which offenders are released (DeLisi & Walters, 2011; Gendreau et al., 1999). The current study aimed to determine whether examining crime data provides evidence in support for some of the harshest penalties that exist based on assumptions regarding offender behaviour. While consequences should certainly exist for those who commit serious crimes, particularly against children, the interventions should be data-driven to increase community safety as opposed to potentially jeopardizing it.

Current Study Summary and Hypotheses

The current study consisted of three parts or phases. Part 1 determined whether committing a certain offence in the past makes an individual more likely to commit that same offence in the future. Part 2 determined whether distinct clusters in regard to crime type existed within the data. For example, is there a cluster of predominantly sexual offenders? Part 3 determined whether certain trajectories appeared when mapping these clusters identified in Part 2 longitudinally. For example, how likely are those grouped into the hypothetical sexual offences cluster to transition into the hypothetical aggravated assault cluster? Part 1 required the use of logistic regression whereas Parts 2 and 3 required the use of latent transition analysis (LTA). The overarching goal was to determine whether the two methods would align to provide evidence for specialization and predictive patterns. While Part 1 would only reveal if having committed a certain offence in the past was a better predictor than having committed another offence in the past (regardless of the other offences committed), Parts 2 and 3 would reveal some level of exclusion to these other offences (as the clusters would be distinct). This, in essence, allowed the question of whether specialization and versatility are mutually exclusive to be targeted.

Based on the results obtained by DeLisi et al. (2019), it was hypothesized that evidence for specialization would be found in Part 1. More specifically, it was assumed that a given offender who had committed a certain crime would be more likely to have committed that same offence in the past compared to other crimes. For Parts 2 and 3, based on the findings of Francis et al. (2004) and McGloin et al. (2009), it was hypothesized that evidence for clustering would be identified. However, due to the discrepancy in the number and composition of the clusters (most likely due to differences in samples), Parts 2 and 3 were largely exploratory. As such, there were no a priori hypotheses regarding the specific clusters that would appear and/or the trajectories that those grouped into these clusters would take.

Method

Data

The data used within this thesis was provided by the Hamilton Police Service who serves the city of Hamilton, Ontario, Canada. As of 2021, Hamilton is a city of 569,353 residents, 140,950 of which identify as a visible minority, with a median age of 40.8 years old (Statistics Canada, 2023). As of 2018, in terms of police reported crime, Hamilton (3,953 incidents / 100,000 population) had a rate similar to the rest of Ontario (4,113 incidents / 100,000 population) but was below Canada as a whole (5,488 incidents / 100,000 population) (Statistics Canada, 2020).

This data included all charges that were laid in the region between the years 2006 and 2022 (N = 328,574). A request was made to receive all possible charges, not just those listed under the Criminal Code of Canada. This information was in the data provided under the variable name “Charge Type” and included the Criminal Code of Canada (n = 263,326), the Highway Traffic Act (n = 19,139), the Controlled Drug and Substances Act (n = 31,955), other Provincial statutes (n = 3,649), the Youth Criminal Justice Act (n = 5111), the Liquor License & Control

Act (*n* = 4,586), the Cannabis Act (*n* = 773), the Canada Shipping Act (*n* = 17), and other Federal statutes (*n* = 38). In respect to charge types, several other variables were provided; namely, “Charge Section,” “Charge Subsection,” and “Charge Wording.” The charge section and subsection denoted where in the act, statute, or code the specific charge was retrieved from, and the charge wording provided a description of the charge. For example, a charge laid under subsection 1 of section 264.1 of the Criminal Code is: “Utter Threat to Cause Death or Bodily Harm.”

In total, the dataset included 941 distinct charges within the different statutes and acts. This was narrowed down to focus specifically on the 503 charge types that were listed under the Criminal Code for two main reasons. First, the goal of the current inquiry was to analyze and map offender behaviour and patterns. As a result, it did not appear intuitive to focus on charges that did not suggest any criminal motivation or behaviour. For example, section 101 under the Canada Shipping Act is “operating pleasure craft without copy of license on board.” The concern with including these charges was that it would muddle the output obtained by the LCA as those who exhibit criminal behaviour would be analyzed within the same pool as those with incidents such as driving without their boating license. While the latter is still problematic and should not be minimized, it does not suggest criminal intent, which is precisely why it is not listed under the Criminal Code. Second, while having 503 charges is still a large quantity to consider within the LCA, 941 almost doubles this value. In an effort to strive for parsimony and obtain interpretable and practical results, it seemed to be a better decision to attempt to reduce the number of potential types that an individual could be charged under. This reduced the total number of charges laid under the Criminal Code in Hamilton region during the specified period to 263,316.

It should be noted that although the Controlled Drug and Substances Act and Youth Criminal Justice Act do encompass crimes that display criminal intent, a decision was made to solely focus on Criminal Code convictions. This was done for a couple of reasons. First, in alignment with what has already been noted above, including these two charge types would have added a substantial number of crimes to the dataset which was not wanted. Second, although some incidents involving offenders under age 18 were charged under the Criminal Code, a potential confound (i.e., age) could have been introduced by including a large quantity of young adult offenders. Therefore, in an effort to control the scope of the current study, convictions under the Controlled Drug and Substances Act and Youth Criminal Justice Act were excluded from the current analyses. However, this could be a valuable future direction of this research.

Several other variables were provided within this dataset. The “Occurrence ID,” “Occurrence Year,” “Offender ID,” “Offender Age,” and “Offender Gender” provided a description of the offender, and the timing of the crime incident (rather than the timing of the conviction) was provided as well. Although each row in the dataset was propagated by a single charge that was laid, occurrence ID could be repeated as there could have been several charges laid due to one incident that occurred (e.g., an offender who committed robbery may be charged with robbery and level one assault if both occurred during the same incident). The offender ID is unique to each offender that the Hamilton Police Service encounters and therefore, if the same offender committed one crime in 2006 and then again in 2017, for example, this would allow the analyst to track the offender over time.

For charges involving a victim, their characteristics were also provided within the dataset requested. More specifically, their age (Victim Age), gender (Victim Gender), race (Victim Race), and relationship to the perpetrator (Victim Relationship), along with a “Victim ID,” which is a unique identifier provided to each victim that the Hamilton Police Service encounters (similar to the Offender ID) were all included in the dataset. Lastly, two more variables were provided – the “Charge Status” and “Most Serious Weapon” used during the incident if one was present. The charge status listed for each charge was one of 31 potential statuses, with the most frequent being “withdrawn” (n = 113,414), “conviction” (n = 88,304), “in progress” (n = 26,300), and “no further process” (n = 18,160). Due to the large quantity of charges within the dataset that did not lead to a conviction, and without knowing the reason(s) why a conviction did not occur, it seemed unwise to include these charges. This was because a conviction may not have occurred due to lack of evidence or evidence that the accused did not commit the offence. Therefore, a decision was made to narrow the scope further to only include individuals who had committed offences under the Criminal Code of Canada AND were convicted for said offences (N = 88,304).

Several other points were considered within the context of the goal of the current analysis. First, as mentioned, the data spanned the years 2006 to 2022, which included the period of the COVID-19 pandemic and associated shutdowns and lockdowns. Research has noted how the pandemic and associated regulations affected crime rates. For example, Boman and Mowen (2021) surveyed the crime statistics for 27 cities in 23 countries and identified that on average, crime decreased by 37% due to the pandemic and associated shutdowns. In an effort to provide results that were practical and interpretable outside of the context of the COVID era, a decision was made to conduct analyses on data spanning between the years 2006 to 2019 (N = 77,811 convictions). Second, as the aim was to identify the patterns and trajectories of offenders who commit multiple crimes over their lifetime, those with less than two offences within the entire dataset were excluded. At this point, the final dataset to be analyzed in subsequent steps comprised of 11,426 individuals who had been convicted of 67,453 total crimes of 346 potential types. The dataset was then divided to be able to conduct analyses on the female (*N* = 1,834) and male (*N* = 9,594) offenders separately.

Procedure

Logistic Regression

After narrowing down the dataset to its final size, it was then used in two separate ways (i.e., for Part 1 separately from Parts 2 and 3). To conduct the logistic regression analysis modelled after DeLisi et al. (2019), the dataset for males was narrowed down to include the 15 charges with the greatest number of occurrences. Due to the public debate about sexual offenders, particularly with young victims, and the common perception that these offenders specialize (as further elaborated upon in the review of the literature), offenders who were convicted of sexual assault and those who committed sexual offences against children were included in the male sample. For the female sample, as there were fewer crime types to begin with, the 10 charges with the greatest number of occurrences were included in the analyses. For both datasets, if a given offender had been convicted of one of these charges (17 for males and 10 for females) at least twice throughout the span of the dataset, they were included in the sample. For Part 1, 3,747 male and 686 female offenders were analyzed. Table 1 denotes the recoded charges that were analyzed for males and females.

Table 1

Recoded Charges Included in Logistic Regression Analyses

Males		**Females**	
Final conviction	***n***	**Final conviction**	***n***
Level 1 assault	528	Theft under $5,000	255
Theft under $5,000	698	Level 1 assault	78
Mischief (property)	444	Mischief	75
Utter threat	234	Fraud under $5,000	49
Breaking & entering	223	Operation while impaired	95
Operation while impaired	588	Breaking & entering	37
Possession of a weapon	249	Weapon assault	20
Weapon assault	88	Forge/counterfeit	42
Property obtained through crime under $5,000	144	Communicate/benefit from prostitution	17
Possession under $5,000	87	Utter threat	18
Robbery	46		
Fraud under $5,000	92		
Assault (other)	36		
Dangerous driving	104		
Possession of a firearm	109		
Sex offence (child victim)	35		
Sex offence	42		
Total	3,747	**Total**	686

At this point, 17 new variables were created for the males and 10 new variables for the females. These variables were binary indicators identifying whether a given offender’s last conviction (within the dataset) was one of the 17 or 10 charges. Then, 17 and 10 new variables were created to identify which charges that offender had been convicted of in the past, prior to the final conviction. These were also coded in a binary format. For example, if an offender whose last conviction was robbery had committed sexual assault, level 1 assault, and robbery prior to the final conviction throughout the span of the data, they would be coded as “1” for “last conviction – robbery,” “past conviction – sexual assault,” “past conviction – level 1 assault,” and “past conviction – robbery” and as “0” for all other last and past convictions.

Seventeen logistic regression analyses were conducted for the male sample and 10 for the female sample. For a given iteration, a specific “last conviction” variable was included as the outcome variable and all other “past conviction” variables were included as the indicators. In line with the study conducted by (DeLisi et al., 2019), and to maintain the scope of the current thesis, interactions between predictors (i.e., prior conviction variables) were not included. The ‘glm’ command which comes with the base package of R (R Core Team, 2021) was used to produce the final models; a binomial function was specified as these were logistic regressions. Figure 1 provides an example of the code that was used to assess male offenders whose last conviction was theft under $5,000.

Figure 1

Example Code Used for Logistic Regressions (Male)

```
glm(last_theft_under ~ past_1_assault + past_theft_under +
past_mischief_property + past_threat + past_be_commit + past_operation_impair
+ past_possess_weapon + past_weapon_assault + past_prop_crime_under +
past_possession_under + past_robbery_gen + past_fraud_under + past_assault +
past_dang_operation + past_possess_firearm + past_offense_child + past_sex_a,
data = reg_data, family = "binomial"())
```

Latent Class Modelling Preparation

To prepare the data to conduct the latent transition analysis (LTA) modelled after Francis et al. (2004) and McGloin et al. (2009), several steps were taken. Some crime types were condensed with others when one of two criteria were met: (1) they appeared within the entire dataset less than 50 times, or (2) the charges undoubtedly pointed to the same criminal behaviour or criminal intent, to obtain a male dataset with 67 and a female dataset with 34 types of crimes (rather than 503). This followed a similar methodology to Francis et al.; while they did use a minimum of 10 offences as opposed to 50, this approach led them to 71 crime types. Therefore, in an effort to arrive at a value within a reasonable range of Francis et al. (2004) and to try to improve the statistical power of the model (by not having certain crimes with too low of a frequency), the current inquiry used 50 as the benchmark.

In only one instance was a group of crimes separated. In the Criminal Code of Canada, while some sexual offences perpetrated against children are separated from other crimes (e.g., sexual interference, luring a child <14 via a computer), others are not (e.g., sexual assault). Therefore, after condensing several of these sexual offences into one category, the male dataset did have an additional crime type created to distinguish sexual offences committed to a victim under the age of 13. The female dataset did not have enough sexual offences within the sample (N = 55, combined with several other crime types) and therefore, perpetrators with younger victims were not separated from the rest of the sample.

At this point, the data was separated into five time periods: T1 (2006 – 2008), T2 (2009 – 2011), T3 (2012 – 2014), T4 (2015 – 2017), and T5 (2018 – 2019). The crime rate in Hamilton throughout the total period appeared to increase. Therefore, while the last timepoint did unfortunately have one less year of data, the frequencies across the five time periods still balanced to some degree. For a given time period (e.g., T1), each offender occupied a single row and each charge type occupied a given column. If a given offender had committed said crime during this period, they were coded as “1” and if not, they were coded as “0.” An example of this data can be seen in Appendix A. The decision to have five time periods was made in order to generate intervals short enough in duration and enough intervals to identify valuable patterns while also not overloading the software with too many variables (as each crime type at each time period occupied a single column).

Latent Class Modelling

The use of analytic methods to assess latent variables in the social sciences has become more popular in the last few decades. The underlying premise when studying latent variables is that the "covariation… observed among the manifest (observed) variables is due to each manifest variable's relationship to the latent variable – that the latent variable 'explains' the relationship between the observed variables" (McCutcheon, 1987, p. 5). Early work that analyzed latent variables focused mainly on factor analysis, which typically reveals continuous latent variables (i.e., factors) based on continuous observed variables (McCutcheon, 1987). However, the more recent use of latent class models allows researchers to assess both the observed indicators and the latent variable as discrete (Green, 1951). For example, you may use a factor analysis to analyze religiosity as a latent variable on a scale between 1 and 10 based on continuous observed indicators (e.g., number of times goes to church a week, amount of money donated to the church, etc.). In contrast, you may want to analyze individuals presenting with distinct symptoms into potential diseases they may have – both of which would be discrete and categorical in nature. For this analysis, you would want to use a latent class model. Classes/clusters are mutually exclusive, meaning that cases (i.e., respondents in the current study) can only be grouped into a single class/cluster. Latent class models can be advantageous because they allow you to: (1) assess discrete variables, (2) use indicators measured at both the nominal and ordinal level, and (3) do not require one to abide by the assumption of multivariate normality or the continuity of measurement (McCutcheon, 1987).

Summary of Latent Class Modelling

A brief description of binary latent class modelling/ analysis will follow; see Lazarsfeld and Henry (1968) or McCutcheon (1987) for more. To simplify this example, suppose the analysis only contained two manifest items, petty theft (variable *A*) and assault (variable *B*), and that this initial analysis was only using data from the first time-interval (i.e., disregarding the influence of time). Let *X* represent the latent variable, which is crime cluster in this example, and assume *X* has an unknown number of levels within it (i.e., *C*; also referred to hereafter as classes and clusters). This latent variable with an unknown number of levels within it is represented by X_c. Given that the response input for this analysis is binary, the levels for both variable *A* and *B* (*I* and *J*, respectively) can only be 1 or 0 (i.e., 1 if the respondent did commit the crime during said time interval and 0 if not).

The goal of latent class modelling is to reveal two parameters: (1) latent class probabilities (γ) and (2) item-response probabilities (ρ) (McCutcheon, 1987). Latent class probabilities describe how many classes of the latent variable there are (represented by *C*) and what proportion of the sample is located within each of these classes. Item-response probabilities can be thought of as being similar to factor loadings in factor analyses, with an item-response probability representing the likelihood of a case (i.e., respondent) having at least one conviction for offence *B* (for example) given that their case belongs to class *c* of the latent variable *X* (McCutcheon, 1987). In brief, LCA does this by first producing an estimated model based on estimated parameters (Bray, 2019). Then, for each value of *C*, it identifies a model using the maximum likelihood estimation (MLE). The models produced for each value of *C* are then compared to one another to determine which best describes the data. This final model will have the best fit in terms of the number of classes (*C*), and values for both latent class probabilities (γ) and item-response probabilities (ρ).

Model Estimation

Let *Y* represent all possible response patterns and *y* represent a particular response pattern. In our example, we would have y_1, y_2, y_3, y_4 (2 x 2 response options). For example, y_1 may denote responding "Yes" to previously committing petty theft (A_1) and "Yes" to previously committing assault (B_1). Now, let *M* represent all manifest items (variable *A, B, … Z*) and let r_m represent all potential responses (response *I* and *J* in our case), for each item (*m*). Based on this, the likelihood of providing a particular response pattern (y_1 in our example noted) can be demonstrated as shown in Equation 1 (Bray, 2019). This is the fundamental equation that is used in latent class modelling to build initial parameter estimates for each cell that would appear in a hypothetical contingency of responses.

$$P(Y_i = y_i) = \sum_{c=1}^{C} \gamma_{\mathrm{c_i}} \prod_{m=1}^{M} \prod_{R_m=1}^{R_m} \rho_{mr_m|c}^{I(y_m=r_m)} \tag{1}$$

(γ_c) represents the latent class probability, and therefore, is the probability of membership in latent class *c*. ($\rho_{mr_m|c}^{I(y_m=r_m)}$) represents the conditional probability of response r_m to indicator *m*, conditional on membership to latent class *c*. Now, we have estimated the parameters, but this must be compared against the observed data to determine whether this model truly represents said data.

Model Identification

The model fit is identified for each potential value of *C* before a final model is produced. Even with an exploratory LCA, a general idea of the number of classes of the latent variable would be advantageous to have in mind. Therefore, if you believe there may be around 10 classes (i.e., *C* = 10), you would want to identify a model which best describes a one-cluster solution, two-cluster solution, all the way to most likely a 14- or 15-cluster solution. Most researchers opt to determine the fit of the model using maximum likelihood estimations (MLE) to identify the parameters which best fit the observed data (Newsom, 2021a). The software would iterate through different potential values of the parameters to select values that when placed into Equation 1, most closely align with the true data. At this point in the process, you would be left with 14 or 15 well-identified models which each represent a different cluster solution in value. Then, these will be compared to one another to determine which cluster solution best represents the data (i.e., to determine how many classes actually appear in the data).

Model Selection

Once a well-identified model has been selected for each potential value of *C*, these can then be compared using either absolute model fit or relative model fit (Bray, 2019) . An absolute model fit will compare the identified model to the data, typically using the G^2-test. However, using an absolute model fit can be problematic for LCA because data within the contingency table may be sparse which can cause the G^2 statistic to not be approximately distributed as a chi-square. For example, the cell within a given hypothetical contingency table that represents individuals who have an armed robbery conviction but have no petty theft conviction may be empty (it can be assumed that those who have an armed robbery charge would most likely have a previous petty theft charge). Occurrences like this would leave the contingency table with a distribution not in the formation of a chi-square (Bray, 2019) . For this reason, researchers suggest using a relative model fit to assess the best model for the LCA (Francis et al., 2004).

There are multiple ways to assess relative model fit as well (e.g., bootstrap likelihood ratio test), but a common method is to use a fit criterion, which optimizes the balance between fit and parsimony (Bray, 2019). More simply put, information criterion will determine the best model identified that explains the greatest amount of variation in the data while using the fewest possible values of *C*. Both the Akaike Information Criterion (AIC) statistic and Bayesian

Information Criterion (BIC) statistic have been suggested for this method (Newsom, 2021a). The current study will use the BIC statistic, as others have recommended its use because it corrects for the number of parameters fitted, and the size of the sample, within the data (Bray, 2019; Newsom, 2021a; Nylund et al., 2007). See Equation 2 below on how to calculate the BIC statistic, where *n* represents the sample size, and *p* represents the number of parameters estimated in the model (Bray, 2019) .

$$BIC = G^2 + [log(n)][p] \quad (2)$$

At this point, the model with the lowest BIC value – which suggests best fit – would be selected. Now, the researcher has identified the number of classes (C), as well as the values of latent class probabilities (γ) and item-response probabilities (ρ), which best represents the data (Bray, 2019). Using the current study as an example, you would then be able to compute cluster profiles breaking down the probability of an individual that was grouped into a specific cluster having been convicted of a specific charge. For example, what is the likelihood that an individual grouped into Cluster II had a conviction for aggravated assault? Based on individuals with common charges being grouped into the same cluster, the researcher would then be able to form an idea of what that cluster represents (e.g., primarily drugs, primarily property damage, etc.)

Latent Transition Analysis

By using the LCA, probable classes (i.e., crime clusters) for specific time intervals can be identified. Latent transition analysis (LTA) extends on this by allowing researchers to: (1) identify the clusters in an almost identical way to LCA and (2) determine the probability of individual case's (i.e., respondent's) stability and change across these clusters over time intervals (*T*). In this way, it is similar to latent Markov modelling, which other researchers have used to model specialization (Collins & Wugalter, 1992; Stander et al., 1989) and is a type of autoregressive model (McGloin et al., 2009). The predictive portion of this model (i.e., predicting group membership at a later interval based on prior membership) is a (multinomial) logistic model (Newsom, 2021b).

Again, let *Y* represent all possible response patterns and *y* represent a particular response pattern. $I(y_{m,t} = r_{m,t})$ represents the indicator function which would be computed as 1 if the response to item *m* at time *t* were "Yes" and 0 if it were "No." Based on this, a very similar equation to the latent class model can be formed to represent the latent transition model and the probability of observing response pattern *y*.

$$P(Y_i = y_i) = \sum_{c_1=1}^{C} \cdots \sum_{c_T=1}^{C} \delta_{c_1} \tau_{c_2|c_1} \cdots \tau_{c_t|c_{t-1}} \prod_{t=1}^{T} \prod_{m=1}^{M} \prod_{r_{m,t}}^{R_m} \rho_{t,m,r_{m,t}|c_t}^{I(y_{m,t}=r_{m,t})} \quad (3)$$

δ_{c_1} represents the probability of membership in latent class c_1 at Time 1 (Bray et al., 2021). $\tau_{c_t|c_{t-1}}$represents the probability of membership in latent class c_t at time *t* conditional on membership to class c_{t-1} at time *t*-1. $\rho_{t,m,r_{m,t}|c_t}$ represents the probability of response $r_{m,t}$ to variable *m* at time *t*, conditional on membership in latent class c_t at time *t* (Bray et al., 2021; Newsom, 2021b). After these values are derived, the researcher now has estimated the parameters and they would move onto model identification and selection in the same manner noted in the above sections. After selecting an adequate model based on the BIC-statistic, the researcher can map cluster profiles (as exemplified in Appendix B, using data from Francis et al., 2004) across time intervals. This gives the researcher the ability to see the transition probabilities across time intervals among clusters.

The procLTA package accessed through SAS software, Version [9.4] was used to conduct these analyses. For further information, refer to Lanza et al. (2007). See Appendix B for an example of code used for the final model fitted for male offenders.

Summary of Analyses

In brief, Part 1 used a logistic regression by mapping prior convictions onto last convictions within the dataset to determine whether having committed the same offence in the past would be a better predictor of future conviction than any other prior offence. Part 2 used an LTA to identify clusters of offenders, probability of membership of an offender into a given cluster (i.e., latent class membership) and their likelihood of having been convicted of a specific offence given that they were included in said cluster (i.e., item-response probability) for the former. Furthermore, Part 3 used the LTA to identify how offenders moved amongst these clusters overtime.

Results

The demographics of the 9,594 males and 1,834 females included in this analysis can be seen in Table 2. For the male offenders, the majority were White (76.2%), with an average age of 32.94 years old (*SD* = 11.94) at first conviction within the dataset date range (i.e., from 2006 to 2019) and had an average of 6.04 convictions (*SD* = 6.83). The number of convictions for male offenders ranged from 2 (as only chronic offenders were included) to 81. For the female offenders, the majority were White (82.8%), with an average age of 32.75 years old (*SD* = 11.04) at first conviction within the dataset and had an average of 5.17 convictions (*SD* = 5.16). The number of convictions for females ranged from 2 (as only chronic offenders were included) to 54.

Table 2

Offender Demographics

Variable		**Males**	**Females**
Race	Indigenous	371 (4.0%)	116 (6.5%)
	Black	1048 (11.3%)	129 (7.2%)
	Hispanic	202 (2.2%)	19 (1.1%)
	Mixed	19 (0.2%)	6 (0.3%)
	Middle Eastern	222 (2.4%)	8 (0.4%)
	Asian	138 (1.5%)	9 (0.5%)
	Southeast Asian	196 (2.1%)	19 (1.1%)
	White	7049 (76.2%)	1480 (82.8%)
	Other	7 (0.1%)	2 (0.1%)
Age	< 12	1 (0.01%)	0
	12 – 17	610 (6.4%)	88 (4.8%)
	18 – 29	3895 (40.6%)	774 (42.2%)
	30 – 39	2442 (25.5%)	492 (26.8%)
	40 – 49	1711 (17.8%)	335 (18.3%)
	50 – 59	724 (7.5%)	124 (6.8%)
	60 – 69	181 (1.9%)	20 (1.1%)
	> 69	30 (0.3%)	1 (0.1%)
Number of Occurrences	2	3276 (34.2%)	647 (35.3%)
	3 - 5	3314 (34.6%)	681 (37.1%)
	6 - 10	1581 (16.5%)	307(16.7%)
	11 - 20	977(10.2%)	155(8.5%)
	21 - 40	380 (4.0%)	41(2.2%)
	41 – 60	60 (0.6%)	3 (0.2%)
	> 60	3 (0.03%)	0
Total		**9594**	**1834**

Part 1

Male Offenders

Logistic regression analyses were conducted on 15 of the most frequent recoded charge types that appeared within the dataset and two more (i.e., sexual assault and sexual offence against a child) that were of particular interest within the current inquiry (expanded upon more in the methods). This was done to determine whether prior convictions for a given offence would be a stronger predictor for a conviction of that same offence in the future (compared to any other prior convictions). Seventeen binary indicators identifying whether a given offender had previously been convicted of each of the 17 crimes were regressed onto a binary output variable which identified if the last conviction for that offender was one of the 17 given crimes. All offenders included in this analysis were male and had been convicted of at least one of these 17 crimes at least twice throughout the span of the dataset. The 17 crimes were: level 1 assault, theft under $5,000, mischief (damaging property), utter a threat, break & enter (commit), operating a vehicle while impaired, possession of a weapon, assault with a weapon, property obtained through crime under $5,000, possession under $5,000, robbery (general), fraud under $5,000, assault (other), dangerous operation of a vehicle, possession of a firearm, sexual assault, and child sex offence.

Appendix C outlines the odds ratios and significant associations between all variables that were identified through these analyses. A focus was placed only on significant positive associations as significant negative associations denote that having not committed a particular prior offence predicts being convicted of the last crime in question. For example, if prior robbery was negatively associated with the last conviction being a child sex offence, this would mean that NOT committing robbery in the past significantly predicts that you will be convicted of a child sex offence in the future. This may be interesting to investigate in the future as it could in theory be used for profiling applications. For example, using the negative odds ratios may help to identify that a given offender who has committed crime A now likely has not committed crime B previously. With this information, the investigator may be able to narrow down their suspect pool by identifying that a given offender did commit crime B previously and likely can be excluded from the pool. However, this was beyond the scope of the current thesis which aimed to identify how a conviction of a given crime would increase the chances that an individual would commit another given crime in the future (i.e., a positive association).

For the male offenders, the only positive predictors of the final conviction being level 1 assault were prior level 1 assault conviction (odds ratio [*OR*] = 1.91, 95% CI = [1.57, 2.33], z = 6.48, $p < .001$) and a prior utter threat conviction (*OR* = 1.66, 95% CI = [1.28, 2.14], z = 3.90, $p < .001$). Those who had been convicted of level 1 assault in the past were 1.91 times more likely than those who had not been convicted of it, to be convicted of it in the future. Those who had been convicted of uttering a threat in the past were 1.66 times more likely than those who had not been convicted of it, to be convicted of level 1 assault in the future.

A prior conviction for theft under $5,000 was the sole (positive) predictor for the same conviction in the future. Those who had previously been convicted of theft under $5,000 were 9.03 times more likely than those without said prior conviction to be convicted of it in the future (95% CI = [7.36, 11.11], z = 21.00, $p < .001$).

Those who had previously been convicted of mischief (damage to property) were 2.71 times more likely than those who had not been to be convicted of the same offence in the future (95% CI = [2.13, 3.43], z = 8.16, $p < .001$). Those who had previously been convicted of level 1 assault were 1.67 times more likely than those who had not been to be convicted of mischief (damage to property) in the future (95% CI = [1.36, 2.06], z = 4.85, $p < .001$). Lastly, those who had been convicted of assault with a weapon were 1.82 times more likely than those who had not been to be convicted of mischief (damage to property) in the future (95% CI = [1.32, 2.47], z = 3.77, $p < .001$).

Offenders who had previously been convicted of uttering a threat were 2.02 times more likely to be convicted of the same offence in the future than those who had not (95% CI = [1.45, 2.78], $z = 4.26$, $p < .001$). Those who had been convicted of level 1 assault were 1.39 times more likely to be convicted of uttering a threat in the future than those who had not ($OR = 1.39$, 95% CI = [1.05, 1.82], $z = 2.32$, $p = .020$). Lastly, those who had been convicted of assault with a weapon were 1.73 times more likely to be convicted of uttering a threat in the future than those who had not (95% CI = [1.13, 2.56], $z = 2.64$, $p = .008$).

Those who had previously been convicted of breaking and entering were 13.3 times more likely than those who had not been to be convicted of the same offence in the future (95% CI = [9.58, 18.46], $z = 15.48$, $p < .001$). Those who had previously been convicted of possession under $5,000 were 1.92 times more likely than those who had not been to be convicted of breaking and entering in the future (95% CI = [1.12, 3.18], $z = 2.47$, $p = .014$). Lastly, those who had been convicted of assault (other) were 1.96 times more likely than those who had not been to be convicted of breaking and entering in the future (95% CI = [1.09, 3.34], $z = 2.36$, $p = .018$).

A prior conviction for operating a vehicle while impaired was the sole (positive) predictor for the same conviction in the future. Those who had been convicted of operating a vehicle while impaired in the past are 6.97 times more likely to be convicted of said offence in the future when compared against those who had a different prior conviction (95% CI = [5.25, 9.30], $z = 13.32$, $p < .001$).

Those who had a prior conviction for possession of a weapon were 5.09 times more likely than those who did not to be convicted of possession of a weapon in the future (95% CI = [3.66, 7.05], $z = 9.73$, $p < .001$). Those with a prior conviction for possession of a firearm were 6.59 times more likely than those who did not to be convicted of possession of a weapon in the future (95% CI = [4.45, 9.72], $z = 9.44$, $p < .001$). Those with a prior conviction for uttering a threat were 1.77 times more likely than those without said prior conviction to be convicted of possession of a weapon in the future (95% CI = [1.21, 2.56], $z = 3.00$, $p = .003$). Lastly, those with a prior conviction for robbery were 1.83 times more likely than those without said prior conviction to be convicted of possession of a weapon in the future (95% CI = [1.03, 3.11], $z = 2.16$, $p = .03$).

Offenders with a prior conviction for assault with a weapon were 3.39 more likely than those without one to be convicted of the same offence in the future (95% CI = [1.94, 5.68], $z = 4.47$, $p < .001$). Furthermore, those with a prior conviction of robbery were 3.23 times more likely than those without said conviction to be convicted of assault with a weapon in the future (95% CI = [1.39, 6.65], $z = 2.99$, $p = .002$).

Those with a prior conviction for obtaining property under $5,000 through a crime (i.e., property under $5,000) were 5.29 times more likely than those without said prior conviction to be convicted of property under $5,000 (95% CI = [3.19, 8.59], $z = 6.61$, $p < .001$). Those with a prior conviction for breaking and entering were 1.69 times more likely than those without to be convicted of property under $5,000 (95% CI = [1.02, 2.72], $z = 2.10$, $p = .036$). Those with a prior conviction for possession of a weapon were 1.91 times more likely than those without to be convicted of property under $5,000 (95% CI = [1.15, 3.08], $z = 2.59$, $p = .009$). Lastly, those with a prior conviction for fraud under $5,000 were 2.16 times more likely than those without to be convicted of property under $5,000 in the future (95% CI = [1.04, 4.13], $z = 2.21$, $p = .027$).

Those who had a prior conviction for possession under $5,000 were 6.99 times more likely to repeat the same offence in the future than those without said prior conviction (95% CI = [3.91, 12.18], $z = 6.79$, $p < .001$). Those with a prior conviction for dangerous operation of a vehicle were 2.87 times more likely than their counterparts without said conviction to be convicted of possession under $5,000 in the future (95% CI = [1.25, 5.88], $z = 2.69$, $p = .007$).

The only significant positive predictor for a conviction of robbery was the same conviction in the past. Those with a prior conviction for robbery were 35 times more likely than those without one to be convicted of robbery in the future (95% CI = [18.41, 68.14], $z = 10.72$, $p < .001$).

Offenders with a prior conviction for fraud under $5,000 were 29.61 times more likely than those without said conviction to be convicted of fraud under $5,000 in the future (95% CI = [17.35, 50.47], $z = 12.48$, $p < .001$). Furthermore, those with a prior conviction for property under $5,000 were 2.52 times more likely than those without said conviction to be convicted of fraud under $5,000 in the future ($OR = 2.52$, 95% CI = [0.98, 5.83], $z = 2.04$, $p = .041$).

Those with a prior conviction for dangerous operation of a vehicle were 13.85 times more likely than those without said prior conviction to be convicted of the same offence in the future ($OR = 13.85$, 95% CI = [8.08, 23.29], $z = 2.55$, $p = .011$). Those with a prior conviction for breaking and entering were 2.26 times more likely than those without said prior conviction of being convicted of dangerous operation of a vehicle in the future (95% CI = [1.16, 4.11], $z = 9.77$, $p < .001$).

Those with a prior conviction for possession of a firearm were 22.41 times more likely than those without said prior conviction to be convicted of the same offence in the future (95% CI = [13.95, 36.23], $z = 12.80$, $p < .001$). Moreover, those with a prior conviction for possession of a weapon were 4.53 times more likely than those without said prior offence to be convicted of possession of a firearm in the future (95% CI = [2.68, 7.54], $z = 5.74$, $p < .001$).

A prior conviction for sexual offence against a child was the sole (positive) predictor of the same conviction in the future. Those with a prior conviction for a sexual offence against a child were 108 times more likely than those without said prior conviction for the offence to be convicted of the same offence in the future (95% CI = [46.19, 270.03], $z = 10.46$, $p < .001$).

Offenders with a prior conviction for sexual assault (victim above age 13) were 65.06 times more likely than those without said prior offence to be convicted of the same offence in the future (95% CI = [31.24, 140.44], $z = 10.95$, $p < .001$). Furthermore, those with a prior conviction for sex offence against a child were 3.41 times more likely than those without said prior offence to be convicted of sexual assault in the future (95% CI = [1.13, 10.09], $z = 2.22$, $p = .036$).

Female Offenders

Logistic regression analyses were conducted on 10 of the most frequent recoded charge types that appeared in the dataset comprised of female chronic offenders. Ten binary indicators that identified whether a given offender had previously been convicted of each of the 10 crimes were regressed onto a binary output variable that identified if the last conviction for that offender was one of the 10 given crimes. The final conviction within the dataset for all offenders included was one of the 10 following crimes: breaking and entering, forgery and counterfeiting, fraud under $5,000, mischief, level 1 assault, operation of a vehicle while impaired, theft under $5,000, uttering a threat, assault with a weapon, and communicating for the purpose of prostitution.

Appendix D outlines the odds ratios and significant associations between all variables that were identified through these analyses for female offenders. Only significant positive associations were detailed as noted above. Female offenders with a prior conviction for theft under $5,000 were 9.36 times more likely than those without said conviction to be convicted of the same offence in the future (95% CI = [6.29, 14.15], $z = 10.83$, $p < .001$).

Those with a prior conviction for level 1 assault were 2.69 times more likely than those without said prior offence to be convicted of level 1 assault in the future (95% CI = [1.60, 4.52], $z = 3.73$, $p < .001$). Furthermore, those with a prior conviction for mischief were 3.06 times more likely than those without to be convicted of level 1 assault in the future (95% CI = [1.40, 6.48], $z = 2.88$, $p = .004$).

Those with a prior conviction for mischief were 3.35 times more likely than those without said prior conviction to be convicted of mischief in the future (CI = [1.60, 6.77], $z = 3.31$, $p < .001$). Those with a prior conviction for level 1 assault were 2.16 times more likely than those without said prior conviction to be convicted of mischief in the future (95% CI = [1.28, 3.61], $z = 2.91$, $p = .004$).

Offenders with a prior conviction for fraud under $5,000 were 16.27 times more likely than those without said prior conviction to be convicted of fraud under $5,000 in the future (95% CI = [7.97, 33.85], $z = 7.59$, $p < .001$). Furthermore, those with a prior conviction for forgery/counterfeiting were 3.89 times more likely than those without said prior conviction to be convicted of fraud under $5,000 in the future (95% CI = [1.62, 9.07], $z = 3.10$, $p = .002$).

The only positive predictor for a future conviction of operating a vehicle while impaired was itself. Those with a prior conviction for operating a vehicle while impaired were 18.93 times more likely to be convicted of the same offence in the future when compared to their counterparts without this prior conviction (95% CI = [8.23, 48.01], $z = 6.60$, $p < .001$).

Similarly, the only positive predictor for a future conviction of breaking and entering was itself (*OR* = 7.95, 95% CI = [3.23, 18.75], $z = 4.66$, $p < .001$). Those with a prior conviction for breaking and entering were 7.95 times more likely to be convicted of the same offence in the future when compared against their counterparts without this prior conviction.

Those with a prior conviction for assault with a weapon were 3.18 times more likely than those without said prior conviction to be convicted of assault with a weapon in the future (95% CI = [0.93, 9.32], $z = 2.01$, $p = .045$). Those with a prior level 1 assault conviction were 2.97 times more likely than those without said prior conviction to be convicted of assault with a weapon in the future (95% CI = [1.17, 7.79], $z = 2.28$, $p = .023$). Finally, those with a prior conviction for uttering a threat were 5.34 times more likely that those without to be convicted of assault with a weapon in the future (95% CI = [1.32, 18.10], $z = 2.57$, $p = .010$).

The only significant predictor for a future conviction of forgery/counterfeiting was a prior conviction of the offence itself. Those with a prior conviction for forgery/counterfeiting are 7.67 times more likely to be convicted of the same offence in the future compared to those without said prior conviction (95% CI = [3.46, 16.84], $z = 5.08$, $p < .001$).

Similarly, the only significant predictor for a future conviction for communicating for the purposes of prostitution was as prior conviction of the same offence. Females with a prior conviction for communicating for the purposes of prostitution were 71.73 times more likely to be convicted of the same offence again in the future when compared to those without said prior conviction (95% CI = [19.00, 326.91], $z = 6.00$, $p < .001$).

Lastly, those with a prior conviction for uttering a threat were 8.31 times more likely than those without said prior conviction to be convicted of the same offence in the future (95% CI = [2.25, 27.86], $z = 3.37$, $p < .001$). Those with a prior conviction for level 1 assault were 3.96 times more likely to be convicted of uttering a threat when compared against those without a prior conviction for level 1 assault (95% CI = [1.45, 11.67], $z = 2.63$, $p = .009$).

Part 2

Male Offenders

Part 2 aimed to identify whether certain clusters of offenders (in terms of crime type) appeared within the data. A four-cluster solution was identified as the most representative model for the male sample. This cluster solution was selected based on the latent transition analysis (LTA) that outputted the lowest Bayesian Information Criterion (BIC) value. Appendix E demonstrates the estimated cluster proportions and item-response probabilities for the male sample at Time 1. The latent class probability for Cluster I (γ_1) was 62.38% of the sample, Cluster II (γ_2) was 15.61% of the sample, Cluster III (γ_3) was 17.57% of the sample, and Cluster IV (γ_4) was 4.45% of the sample. The latent class probabilities for the respective clusters at Time 2, 3, 4, and 5 (along with Time 1) can be seen in Table 3.

Table 3

Latent Class Probabilities at All Time Points (Males)

	Cluster I	Cluster II	Cluster III	Cluster IV
Time 1	62.38%	15.61%	17.57%	4.45%
Time 2	61.96%	20.07%	13.07%	4.91%
Time 3	63.10%	17.95%	9.14%	9.82%
Time 4	64.67%	16.85%	6.17%	12.31%
Time 5	74.50%	15.74%	7.60%	2.16%

Based on the item-response probabilities (ρ) for the respective clusters seen at Time 1 within Appendix E, Cluster I can be described most aptly as a low-offending cluster. All item-response probabilities captured within this cluster were extremely low and suggest that even amongst the group of offenders included within the sample analyzed (i.e., males who had committed at least two crimes), those accounted for by Cluster I had been convicted of very few crimes.

Across Clusters II, III, and IV, there are several crime types that appear quite frequently that have been identified within this thesis as secondary crimes. These include crimes such as failure to attend court, failure to comply with probation, breach of probation, and failure to reattend court. While it is acknowledged that these crimes do appear to be more probable than others across all three clusters, Clusters II and III appear to exhibit these crimes at a much greater likelihood than Cluster IV. Beyond these crime types for Cluster II, theft under $5,000 exhibits the highest item-response probability with a 34.07% likelihood that an offender grouped into this cluster had this conviction. This value is followed by possession (of property obtained by a crime) under $5,000 with a 16.61% likelihood and breaking and entering (commit) with a 12.22% likelihood of conviction for a given offender grouped into the cluster. It appears as though this cluster could aptly be seen as the property or theft cluster as all crimes exhibiting a high item-response probability would arguably fall under this scope.

The item-response probabilities in Cluster III suggest that a given offender who was grouped into the cluster would have a 41.08% chance of having a level 1 assault conviction. This is followed by mischief (damages property) at 16.29% of the sample and uttering a threat at 16.23% of the sample. This cluster may be best described as the violent crime/assault cluster as all crimes with a > 10% item-response probability involve either threatening behaviour or verbiage. Furthermore, as mentioned, both Cluster II and III reveal that the incidence of secondary crimes within these clusters is high. It may be that those who are more likely to commit property crime and violent crimes are also more likely to fail to attend court (26.84% and 27.51% for Cluster II and III, respectively), fail to comply with probation (35.05% and 44.58%, respectively), breach their probation (19.79% and 14.18%), and fail to reattend court (16.15% and 8.11%, respectively).

The item-response probabilities in Cluster IV suggest that a given offender who was grouped into the cluster would have a 62.01% chance of have a conviction for operating a vehicle while impaired, a 14.89% chance of driving while disqualified, and a 10.91% chance of being convicted of refusing a sample when ordered to by an officer. This clearly demonstrates that those who are grouped into Cluster IV could be considered the repeat “drunk drivers” within the sample. Altogether, the male chronic offender sample appears to have a low-offending cluster which comprises 62.38% of the sample, a property/theft cluster which comprises 15.61% of the sample, a violent/assault cluster which comprises 17.57% of the sample, and an impaired driving cluster which comprises 4.45% of the sample at Time 1.

Female Offenders

Only a two-cluster solution was identified for the female sample based on the cluster solution identified through the LTA that outputted the lowest BIC value. Appendix F outlines the estimated cluster proportions for the female sample at Time 1. The latent class probability for Cluster I (γ_1) was 26.69% of the sample and Cluster II (γ_2) was 73.31% of the sample at Time 1. The latent class probabilities for the respective clusters at Time 2, 3, 4, and 5 (along with Time 1) can be seen in Table 4.

Table 4

Latent Class Probabilities at All Time Points (Females)

	Cluster I	**Cluster II**
Time 1	26.69%	73.31%
Time 2	28.63%	71.37%
Time 3	30.65%	69.35%
Time 4	26.53%	73.47%
Time 5	23.87%	76.13%

The item-response probabilities (seen in Appendix F) for Cluster I suggest that those who were grouped into this cluster had a high likelihood of having been convicted of the same secondary crimes identified in clusters II and III within the male sample. These crimes include failure to comply (42.49% item-response probability at T1), failure to comply with a court order (41.26%), failure to reattend court (28.76%), and breach of probation (29.21%). Furthermore, those who were grouped into this cluster had a 12.95% chance of having been convicted of theft under $5,000 (24.98%), communicating for the purposes of prostitution (14.30%), and level 1 assault (12.95%). None of these crimes, particularly the last three, present any underlying common intent and suggest that this cluster is comprised of those females within the sample with a higher affinity for criminal behaviour. This assertion is further supported by the existence of only one other cluster identified by the model and that a survey of Cluster II's item-response probabilities' show no crimes with a high likelihood. This cluster would be comparable to Cluster I within the male sample. These findings suggest, therefore, that at T1, approximately 27% of the female chronic offender sample could be classed as high-frequency offenders and that approximately 73% could be considered low-frequency offenders.

Part 3

Male Offenders

Part 3 aimed to identify whether the clusters of offenders identified in Part 2 could be tracked longitudinally. The latent transition probabilities for the male sample can be seen in Appendices G(i) to G(iv). In terms of the stability/specialization within clusters, there was remarkable stability amongst Cluster I; 65.98% of those grouped into Cluster I at T1 remained in the same at T2, 64.81% of those at T2 remained at T3, 67.13% of those at T3 remained at T4, and 81.35% of those at T4 remained at T5. Between consecutive time periods, this averages to approximately 70% of those grouped into the low-frequency offender cluster at a given two-year time interval being grouped into it at the next two-year time interval.

For Cluster II, 2.04% of those grouped into Cluster II at T1 remained in the same at T2, 33.24% of those at T2 remained at T3, 30.45% of those at T3 remained at T4, and 34.35% of those at T4 remained at T5. The rate of stability appears to be relatively consistent but the transition between T1 and T2 seems to exhibit some irregularity. Regardless, approximately 25% of those who are considered primarily theft/property offenders continue to be so for the next two-year time interval.

For Cluster III, 5.20% of those grouped into Cluster III at T1 remained in the same cluster at T2, 35.99% of those at T2 remained at T3, 35.72% of those at T3 remained at T4, and 49.04% of those at T4 remained at T5. Again, the transition between T1 and T2 seems to exhibit some anomaly but some level of consistency in stability does appear to exist with an overall average of 31.49% of those grouped into Cluster III at a given time being grouped into the same cluster at the next time point. Approximately 31% of those considered to be violent offenders continue to be so for the next two-year time interval.

Lastly, for Cluster IV, 25.27% of those who were grouped into the cluster at T1 were grouped into the same cluster at T2, 26.31% of those at T2 remained at T3, 17.45% of those at T3 remained at T4, and 1.49% of those at T4 remained at T5. Apart from the anomaly that the transition between T4 and T5 presents, the chance of remaining within the cluster between consecutive time points does remain relatively consistent around the overall average of 17.63%. Approximately 18% of those considered dangerous/impaired drivers continue to be so for the next two-year time interval.

All clusters exhibited a high transition probability in regard to transitioning from their respective clusters to Cluster I. The average transition probability of this pattern (i.e., Cluster II → I, Cluster III → I, or Cluster IV → I) was 58.39%. This means that an offender grouped into Cluster II, III, or IV had approximately a 58% chance of being grouped into Cluster I at the next time period. Among clusters II, III, and IV, the lowest likelihood of transition from a given cluster to Cluster I was Cluster III (violent offending) at a 42.58% likelihood of transition, followed by Cluster II (property offending) at a 62.63% likelihood of transition and Cluster IV (dangerous/impaired driving) at a 69.96% likelihood of transition to Cluster I. As mentioned, all other latent transition probabilities can be viewed in Appendices G(i) to G(iv).

Female Offenders

The latent transition probabilities among the female sample can be seen in Appendices H(i) to H(iv). Overall, there is relative stability within the low offending cluster (Cluster II), 79.01% of those grouped into this cluster at T1 remained at T2, 72.81% of those at T2 remained at T3, 76.55% of those at T3 remained at T4, and 80.81% of those at T4 remained at T5. Those who were grouped into the low offending cluster at a given time period had a 77.30% likelihood of being grouped into the same cluster at the next time period on average. For the high-frequency offending cluster, 43.41% of those grouped into the cluster at T1 remained at T2, 34.25% of those at T2 remained at T3, 28.63% of those at T3 remained at T4, and 38.99% of those at T4 remained at T5. Therefore, those grouped into the high-frequency offending cluster at a given time period had a 36.32% likelihood of remaining in the cluster at the subsequent time period.

Movement into the low-offending cluster (II) from the high-frequency cluster (I) was much more common than movement in the opposite direction. Those grouped into Cluster I at T1 had a 56.59% likelihood of moving into Cluster II at T2, those in the cluster at T2 had a 65.75%

likelihood of moving at T3, those in the cluster at T3 had a 71.37% likelihood of moving at T4, and those at T4 had a 61.01% likelihood of moving at T5. Overall, this suggests that those who were grouped into the high-frequency offending cluster (I) had a 63.68% chance of being grouped into the low-offending cluster (II) at the subsequent time period.

Those grouped into Cluster II at T1 had a 20.99% likelihood of moving into Cluster I at T2, those in the cluster at T2 had a 27.19% likelihood of moving at T3, those in the cluster at T3 had a 23.45% likelihood of moving at T4, those in the cluster at T4 had a 19.19% likelihood of moving at T5. Those who had been grouped into the low-offending cluster (II) at a given time period had a 22.71% likelihood of being grouped into the high-frequency cluster (I) at the next time period. The pattern here demonstrates that females tend to occupy and transition into the low-offending cluster; this is further elaborated upon in the Discussion below.

Discussion

The current study utilized both logistic regression analysis and latent transition analysis (LTA) to identify whether: (1) an individual who commits a given crime is more likely to have committed that same crime in the past than any other crimes, (2) there are distinct groupings of crime types (i.e., are offenders with affinities for specific types of crimes more likely to commit other distinct crimes?), and (3) there are distinct developmental trajectories moving from one cluster to another. The crime data used for the analyses was acquired from the Hamilton Police Service and contained all charges that were placed in the region of Hamilton, Ontario between 2006 and 2022. For reasons previously mentioned in the Method section, only conviction data that spanned from 2006 to 2019 was used, with the male and female offender samples analyzed separately.

Research Question 1

The logistic regressions for male offenders was conducted using the 15 most common crime types along with two that are commonly discussed as being a “specialist” activity – sexual offences against children, in particular, and sexual assault (with an adult victim) as a comparison. The findings from the logistic regression conducted on the male sample clearly indicate that in almost all instances, the strongest predictor for the last conviction of a given offender was a history of that same conviction (compared to another conviction). Male offenders with a prior conviction for level 1 assault were almost 2 times more likely to be convicted of it in the future when compared against individuals without said prior conviction; prior theft under $5,000 increased odds by a magnitude of approximately 9, mischief (property) by 3, utterance of a threat by 2, breaking and entering by 13, operating a vehicle while impaired by 7, assault with a weapon by 3, property under $5,000 (i.e., obtaining property under $5,000 through a crime) by 5, possession under $5,000 by 7, robbery by 35, fraud under $5,000 by 30, dangerous operation of a vehicle by 14, possession of a firearm by 22, sexual offence against a child by 108, and sexual assault by 65, when compared against their respective counterparts (i.e., not having committed said prior crime).

The only instances in which a prior conviction for the same offence was not the strongest predictor for a future offence for the male sample was in the cases of assault (other) and possession of a weapon. For the former, none of the indicators appear to have met formal significance thresholds. For the latter, while a conviction for possession of a weapon was a significant predictor of the same conviction in the future, possession of a firearm was an even stronger predictor. Depending on the given incident, a firearm can be classified as a weapon and therefore, this finding was not surprising.

The female sample was tested using 10 indicator variables. Again, the findings from these analyses indicate that in almost all instances, the strongest predictor for a given conviction was a history of that same conviction (compared to other convictions). Female offenders with a prior conviction for theft under $5,000 were 9 times more likely than those without said prior conviction to be convicted of theft under $5,000 in the future; prior mischief increased odds by a magnitude of 3, fraud under $5,000 by 16, operation of a vehicle while impaired by 19, breaking and entering by 8, forgery/counterfeiting by 8, communicating/materially benefiting from prostitution by 72, and uttering a threat by 8.

The only instances in which a prior conviction for a given offence was not the strongest predictor for perpetration of that offence in the future for the female sample was in the case of level 1 assault and assault with a weapon. For the former, while a prior level 1 assault conviction was still a significant predictor of a conviction in the future, mischief was a stronger predictor. For the latter, while a prior assault with a weapon conviction was also a significant predictor of a conviction in the future, uttering a threat was a stronger predictor. For a majority of the most common crimes committed for each sample (15/17 for males and 8/10 for females), having committed said offence in the past makes an individual much more likely to commit said offence in the future than a counterpart who has committed other prior offences.

Research Question 2

The LTA identified a four-cluster solution for the male sample and a two-cluster solution for the female sample at Time 1. For the male sample, a low-frequency (62% of sample), property/theft (16%), violent/assault (18%), and impaired driving (4%) cluster were identified. The large low-frequency cluster is unsurprising, as McGloin et al. (2009) identified a similar group that they called low/no offending which comprised 42% of their sample. Furthermore, Francis et al. (2004) had a cluster (19% of total sample) which they deduced exhibited a "marginal lifestyle with versatile offending" (p.65). While the current analysis did try to minimize the size of this group by excluding offenders with less than two convictions, some offenders in the sample did have over 50 convictions. Even during one time interval, there would have been discrepancies in the number of convictions for given offenders, which may have caused the low-frequency male offenders to be grouped together and placed into the first cluster. Regardless of the name used to refer to this group of offenders, it appears to be a prominent group within male offender populations identified in Hamilton, ON (current study), Nebraska (McGloin et al., 2009), and the UK (Francis et al., 2004).

Apart from the low-offending cluster, three crime-specific clusters were identified within the male sample. These findings can be interpreted to mean that within Time 1, male offenders that were grouped into the property/theft cluster were likely to have committed and have been convicted of crimes such as theft under $5,000, breaking and entering, and possession under $5,000, and unlikely to commit other types of crimes. Furthermore, those grouped into the violent/assault cluster had a high probability of having been convicted of level 1 assault, mischief (which can be an overt destruction or violence committed towards some form of property), and uttering a threat. Lastly, those grouped into the impaired driving cluster had a high probability of having been convicted of operating a vehicle while impaired, driving while disqualified, and refusing a sample when ordered by an officer.

As noted, male offenders who were grouped into the violent/assault cluster and property/theft cluster in the current dataset had a greater likelihood of being convicted of what has been defined as secondary crimes (although it was relatively common across all three crime-specific clusters). This includes convictions such as failure to attend court, failure to comply with probation, breach of probation, and failure to reattend court. This may be due to the criminal motivation behind driving while impaired in comparison to property crimes or violent crimes. While all three crime subsets/types can occur under some altered state of mind, driving while impaired almost guarantees that this is a factor. This, combined with the high prevalence of alcohol use and drug use disorder found within perpetrators of driving while impaired, indicates that “psychiatric comorbidity likely contributes to [it]” (Shaffer et al., 2007, p. 795). The criminal intent behind driving while impaired is typically different than the intent behind violent crime and property crime. While these two crimes/subtypes can occur under an altered state of mind, there presumably is more intent that is required to commit, and knowledge that some victim will be harmed (whether physically or the owner of a property). While driving while impaired can have dire consequences and in the most severe cases, can even result in death, this is not guaranteed. It is likely that those who commit violent and property crime recognize (to some extent) that they are committing a crime. However, an individual who drives while impaired has likely not actively chosen to commit said crime and if they have, this decision most likely was not made until they were of unsound mind.

The assertion that violent and property crime may stem from some level of criminal intent, but that driving while impaired does not, could potentially be supported by the odds ratios provided by the logistic regression in Part 1. Operation while impaired is not significantly associated with any prior convictions except for itself. Therefore, it may be that male offenders who exhibit some form of affinity for crime (i.e., violent and property offenders in this case) are further propelled to commit other crimes including secondary crimes such as failing to attend court or failing to abide by probation regulations.

The same number of clusters (i.e., four) was identified as McGloin et al. (2009) for their sample of male offenders, but the item-response probabilities and associated clusters differed. More specifically, McGloin et al. identified a low-offending cluster (as mentioned), a drugs cluster, a general (i.e., versatile) cluster, and a burglary/theft cluster. While the current study did identify a theft cluster, a drugs cluster was not identified. This discrepancy is most likely due to a multitude of factors, including the fact that McGloin et al. only used seven indicator variables. Francis et al. (2004) identified a nine-cluster solution for their male sample. It may be that there is more consistency in offending behaviour across age and having a single cohort aided in parsing out clusters that were more distinct at given time intervals. However, as previously mentioned, the current study aimed to mitigate such cohort effects and identify general trends. Furthermore, Francis et al. did not use a traditional LTA and included the entire dataset (i.e., across all time points) within the LCA to identify clusters; having all datapoints available most likely did strengthen the distinctions between clusters leading to a greater number of them. As the current study aimed to use these clusters identified in research question 2 to answer the quandary posed in research question 3, the approach laid out by Francis et al. was not utilized.

For the female sample, only two clusters were identified: (1) a low-frequency offending cluster (73% of the total female sample) and (2) a high-frequency offending cluster (27%). Amongst the high-frequency offending cluster, the crime types with the highest item-response probabilities were level 1 assault, theft under $5,000, and communicating for or materially benefiting from prostitution, along with similar secondary crimes to the male sample. The prevalence of these three crime types alone reveals that amongst the offending group, a specific crime or subset of crimes does not appear to be most prominent. While McGloin et al. (2009) did not survey female offenders, Francis et al. (2004) identified a three-cluster solution for their female sample. They indicated that these clusters were: (1) versatile offending, (2) shoplifting, and (3) trust violation. The versatile offending is relatively comparable to the current study's low-offending cluster, but the other two clusters were not parsed apart. This may have occurred for the same reasons listed above for the male sample, along with the fact that there were far fewer females than males with two or more convictions. In other words, it may be that differences in sampling led to this distinction.

To conclude, while distinct clusters were identified primarily for the male sample, this only surmounted to a handful. This suggests that clean-cut delineations between offenders and their clusters do not exist. While several groups of male offenders do appear to exist (i.e., property/theft, violent/assault, impaired driving), these are broad categories with little utility from a practical standpoint. The findings of this research question, and how it pairs with the two other questions, are elaborated upon below.

Research Question 3

The findings from the LTA were also used to identify how stable offenders were within their respective clusters and how likely they would be to switch into other clusters. Some level of in-group consistency was identified for both male and female offenders. For the male sample, the group with the greatest consistency was the low-frequency offending cluster (70%) followed by the violent/assault cluster (31%), property/theft cluster (25%), and lastly, the impaired driving cluster (18%). The rates of transition were variable, with the most probable being from crime-specific clusters to the low-offending cluster. An individual grouped into any crime-specific cluster (i.e., property/theft, violent/assault, impaired) at a given time interval had a 58% chance of being grouped into the low-offending cluster at the next time interval. More specifically, those grouped into the violent/assault cluster at a given time interval had the lowest rate of transition into the low-offending cluster at the next interval (43%), followed by the property/theft offenders (63%), and then those convicted of impaired driving (70%). This latter finding speaks to the points noted above under "Research Question 2." The fact that those grouped into the impaired driving cluster were the least likely to remain in their initial cluster and instead, were the most likely to move into the low-offending cluster suggests that they have a lower inclination (compared to those within the other two crime-specific clusters) to repeat a crime. This may be because they have a lower affinity for criminal behaviour to begin with.

For the female offenders, those grouped into the low-frequency offending cluster had a 77% likelihood of remaining in the same cluster at the next time interval and those in the high-frequency offending cluster had a 36% likelihood of remaining in the same cluster. Furthermore, movement from the high-frequency offending cluster to the low-frequency offending cluster was much more common than in the opposite direction, at 64% probability. Those who were grouped into the low-offending cluster had only a 23% likelihood of moving into the high-frequency offending cluster for the next time interval. Amongst female chronic offenders, the general trend appears to be an affinity for low-frequency offending.

Connections

The findings from each component of this thesis can be complicated to analyze as a whole. In brief, Part 1 demonstrated that an offender – male or female – who is convicted of a particular offence is significantly more likely to be convicted of that same offence in the future compared to a counterpart who has been convicted of a separate prior offence. Part 2 demonstrated that while several distinct clusters do exist (particularly for male offenders), there are too few to be of practical utility. Essentially, within a given time interval, there are very few consistent patterns of linked offences. Part 3 demonstrated that stability within a given crime-specific cluster (i.e., not the low-offending cluster) is rare and that most offenders move into the low-offending cluster over time.

Put together, the logistic regression (Part 1) demonstrates that on the individual crime-specific level, an offender who commits a given crime is highly likely to have committed that same crime in the past. However, Part 2 demonstrates that these trends do not transcend to the aggregate level across crime types. For example, while a prior conviction for assault with a weapon may predict a future conviction for the same offence (as shown in the current study), when analyzed across all crime types, the LTA would aim to identify how a conviction for assault with a weapon is associated with possession of a weapon, level 1 assault, assault (other), etc. While hypothetical Offender A may have convictions for assault with a weapon and possession of a weapon at Time 1, Offender B may have convictions for assault with a weapon and assault (other). In this way, the LTA cannot parse out consistent linkages across the sample even if at the individual crime level, prior conviction does predict future conviction.

Furthermore, while the logistic regression identified that prior conviction does predict a greater likelihood of a conviction for that same offence in the future, Part 3 (through conducting an LTA) did not find strong evidence for stability. Granted, the LTA may be seen as a more thorough analysis, as it did have five time points compared to the logistic regression which essentially only had two (i.e., past and last conviction). However, as previously mentioned regarding the differences in how the logistic regression compared to the LTA would analyze patterns (i.e., crime-specific vs. aggregate), the same notes would be applied to Part 3. Due to the procedure used by LTA, a hypothetical offender that was convicted of operating a vehicle while impaired at Time 1 and then operating a vehicle, theft under $5,000, and breaking and entering at Time 2, would most likely be grouped into the impaired cluster at Time 1 and then the property/theft cluster at Time 2 (these nuances are demonstrated in the item-response probabilities in Appendix G and H). While it is arguably extremely important for the user to be able to identify that this hypothetical offender has repeatedly committed driving while impaired, the LTA would not demonstrate this within its' results, thus, portraying this offender to not be a specialist.

In its earliest definition, yes, this hypothetical offender would not be considered a specialist because they have committed a variety of offences. However, by defining specialization as repeated perpetration of a certain crime regardless of others committed (as defined in this thesis), it is evident that this hypothetical offender is specializing in impaired driving. By pairing both the logistic regression and LTA together, the current study has been able to demonstrate that the concepts of specialization and versatility are not mutually exclusive. In other words, within a litany of versatile offending, an individual offender can indeed exhibit some sort of affinity for certain offences. The former is demonstrated by Parts 2 and 3 using the LTA and the latter by Part 1 using the logistic regression. Furthermore, these patterns exist on the crime-specific level, not the aggregate.

Use of Logistic Regression and LTA within Specialization Research

By testing both methods (i.e., the logistic regression and LTA), it appears to suggest that the LTA has little utility in outputting results that hold any useful application within this context. This stance supports the statements made by DeLisi et al. (2019) that some of the prior research on this topic may be too complex or technical to identify valuable indicators for future conduct and it casts doubt on using LTA as a means to identify specialization amongst offenders for applied purposes (note that it may still be useful for theoretical discussions). A specific goal for the current study was to assess whether making alterations to the data used to analyze the offenders (e.g., shorter time-intervals, all crime types, only including offenders with >1 convictions, no cohorts, etc.) would result in stronger evidence for clustering, which could have practical utility for corrections. Unfortunately, this was not the case and only broad categories of offenders (i.e., property/theft, violent/assault, impaired driving) were identified.

Future Research and Implications

As noted, the low-offending cluster identified through the LTA for both the male and female samples were quite large. A suggestion that could be made to expand upon the current inquiry would be to analyze highly-chronic offenders to determine whether trends or observations change. As shown in Table 2, even amongst a sample of chronic offenders, a majority of individuals had been convicted of less than six offences during this period. However, 443 male offenders and 44 female offenders were convicted of at least 21 offences. The motivation, attitudes, behaviour, and deviance of these two groups may be significantly different. As discussed in the review of the literature, numerous studies have demonstrated that it is a small fraction of the most chronic offenders in any region that are disproportionately responsible for the majority of crime that occurs (Falk et al., 2014; Ruth, 2021). If distinct patterns between low-frequency and high-frequency chronic offenders do exist, there would be practical utility in researchers analyzing the high-frequency group. Furthermore, while the LTA arguably failed to provide valuable insight into clustering that occurs when both low- and high-frequency chronic offenders were included in the sample, more pronounced clusters, which reflect a seasoned offender’s affinities and tendencies may be evident if analyses focused solely on the high-frequency offenders.

The use of logistic regression to identify indicators for future offending behaviour appears to be promising. Future research may aim to use additional predictors to detect whether offenders with certain characteristics are more likely to specialize and repeat their crimes if not apprehended. For example, Piquero et al. (1999) previously identified that older offenders were more likely to specialize. Demographic variables, collected through crime or court data, or additional indicator variables (e.g., socioeconomic status, education level, experience of adverse childhood experiences, etc.) collected through self-report, may add to the strength of these predictive models. Future researchers might be able to identify who is most likely to evolve to become a chronic offender, and who is most likely to specialize in certain crime types/subsets (this would be most significant for extremely destructive/harmful crimes). These models could then be used to identify where to apply more interventions and resources and at what time.

The most important result from the current study was that a prior offence does indeed indicate perpetration of that same crime type in the future. This provides some level of support for laws and policies that target specialized chronic offenders. The National Sex Offender Registry (NSOR) in Canada, for example, restricts an offender's housing and travel once they have been placed on the list following conviction for certain sexual offences (Royal Canadian Mounted Police [RCMP], 2020). The findings from the current study suggest that an individual who has committed a sexual offence against a child is over 100 times more likely to commit this crime in the future than a counterpart with a prior conviction for a different crime type. While this does provide evidence that sex offenders are highly-specialized offenders driven to repeat their crimes, the NSOR was instated in 2004, which means that it was in place (with some modifications at certain time periods) during the entirety of the span of this dataset.

Given that the current study did not include data from before the NSOR existed, no direct comparison can be made to identify trends from before and after the introduction of the NSOR. However, the finding that an individual who has been convicted of committing sexual offences against children is 100 times (the largest odds ratio produced across all logistic regressions) more likely to be convicted of the offence in the future when compared to an individual who has been convicted of other crimes is surprising. This means that an individual who has been convicted of a sexual offence against a child, and faces the repercussions and restrictions outlined in the NSOR, is still 100 times more likely to commit and be convicted of the same crime than an individual who has never been convicted of a sexual offence against a child (and therefore, has never had to follow such regulations/restrictions). To conclude, either the NSOR has reduced the likelihood of a chronic offender repeating this crime and the odds were even more staggering prior to its introduction, or it has failed to meet its objective.

Driving while impaired, sexual interference (against a child), possession of a firearm, and possession of a weapon are convictions that carry a mandatory minimum sentence (sometimes for repeated offenders) in Canada (Government of Canada, 2023). Amongst all of these crimes analyzed in Part 1, having been convicted of that crime in the past did most strongly indicate a future conviction for that same offence (although prior conviction for possession of a firearm did predict possession of a weapon most strongly). Again, similar to identifying the efficacy of the NSOR, a direct comparison between trends of repeated perpetration of these crimes before and after the introduction of each mandatory minimum sentence was not made. These sentencing policies were put in place at varying time points and it may be that the laws have worked to reduce the odds to the level that they are now. However, the ratios for these crime types were not below the ratios for the other crime types analyzed which do not carry mandatory minimum sentences and therefore, direct evidence either in support of or against the use of mandatory minimum sentences could not be obtained through this thesis.

While the current study did demonstrate that prior conviction does make having a repeated conviction significantly more likely compared to a counterpart without said prior conviction, one valuable research question for future researchers to identify would be the likelihood by said offender. For example, out of 100 convicted offenders who have committed sexual offences against children, how many are likely to repeat these crimes? The current thesis was able to provide additional support in line with prior research (DeLisi et al., 2019) that a current offender (who has been convicted of at least one more crime in the past) is much more likely to have committed that same crime in the past. Thus, the next step is to identify the prevalence of repeating that specific crime. Essentially, by analyzing these rates through a prospective lens, rather than through a retrospective lens, results valuable in contexts such as risk assessments may emerge.

Limitations

While the findings of this paper are valuable, there are several limitations that should be touched upon. First, as previously mentioned, there are drawbacks to using conviction data. It may reflect biases that exist within the criminal justice system more heavily than the true trends that exist within the region. For a conviction to occur, there are more steps within the criminal justice system that a charge must go through compared to simply a charge or arrest. This can be a positive if the court system exhibits less bias when compared to the arresting officers. However, this can be a negative if the court system exhibits more bias, or if the system as a whole (both police and the courts) is biased; the latter scenario would result in larger discrepancies between conviction data and what is actually happening at the offender level.

Furthermore, an argument can be made that an offender having been convicted of a crime makes them more visible to the police and the criminal justice system (particularly for committing the same offence that they were convicted of the first time) and this, in itself, increases their odds of being a chronic offender. While these limitations do exist with conviction data, there are limitations that exist for almost all types of crime data. In other words, ideal crime data does not exist. For example, offenders who have been charged or provided with warnings by the police on several occasions may be a more visible target when police are patrolling. Thus, using charge data on repeated offenders would run into similar issues as using conviction data. When attempting to identify trends amongst chronic offenders, the bias that police and the criminal justice system have against prior charged/convicted offenders cannot be isolated and excluded. Furthermore, all of these avenues of data (e.g., reported, solved, or recorded crime data) only capture a fraction of the crime that actually occurs. As with all crime data research, a large volume of crime is never known or processed by police (i.e., the dark figure of crime) and whether these incidents present with distinct trends cannot be deduced (de Castelbajac, 2014). That said, the likelihood that a crime will be reported to police has been shown to vary by crime type, with some crime types showing a higher likelihood to be reported than others (Tarling & Morris, 2010). In conclusion, although there are limitations associated with the use of crime data in research, interesting and useful findings can still emerge – the associated limitations should just be recognized.

It is also important to keep in mind that there may be a lack of generalizability with the findings in the current study. This research only used crime data from one (albeit, relatively large and diverse) region in Ontario, Canada over a span of 14 years. Therefore, the findings from this study cannot be assumed to be generalizable to all regions of Ontario, Canada, or beyond. More specifically, other regions may observe differences in the strength of some of these analyses (e.g., odds ratios) and in the exact clusters and trajectories identified. However, the general conclusion that specialization and versatility are not mutually exclusive appears to be a stable finding consistent with conclusions drawn in prior research (DeLisi et al., 2019; Francis et al., 2004; McGloin et al., 2009). As further touched upon in the previous section, the findings from this study should not be seen as conclusive evidence that offenders exhibit specific crime trends. Rather, it should be seen as evidence that an offender's prior behaviour can be a powerful indicator in predicting their future behaviour and furthermore, seen as a building block for future research to expand upon this concept.

Conclusion

The current study analyzed conviction data from the city of Hamilton, Ontario, Canada that spanned 14 years (i.e., from 2006 to 2019) and utilized logistic regression and latent transition analysis (LTA) to identify whether offenders are likely to repeat crimes that they had committed in the past. The logistic regression revealed that in almost all cases, offenders who have committed a specific crime type in the past are significantly more likely to commit the same crime type again in the future when compared to those who committed another type of crime in the past. The results from the LTA were less clear, which leads to two conclusions: (1) these trends are visible on the crime-specific, but not the aggregate, level, and (2) these trends suggest that an offender who commits a crime previously is more likely to commit that same crime in the future but not necessarily to the complete exclusion of other crime types. This former point suggests that while individual offenders or perpetrators of specific crimes may be more likely to repeat their crimes, these trends are difficult to parse out at any given point within the population when surveyed across all crime types.

This thesis was conducted to add to the debate between specialization and versatility and to pull practical information that could be applied to policy and corrections. It identified that specialization does exist but not to the exclusion of versatility, but rather, in tandem with it. Furthermore, it provided support for the use of some policies and regulations that exist to target chronic offenders (e.g., National Sex Offender Registry, mandatory minimum sentencing laws), but it questioned how effective the impact of these policies has been.

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Appendix A

Hypothetical Input Dataset for a Given Time-Interval

Offender ID	Theft under $5,000	Fraud under $5,000	Possession over $5,000	Utter threat	Obstruct justice	Level 1 assault	Operation while impaired
A	0	0	1	0	0	1	1
B	0	1	0	0	1	0	1
C	0	0	0	0	0	1	0
D	0	1	1	0	0	0	0
E	1	0	1	0	1	0	0
F	0	0	0	0	1	1	0
G	1	1	0	0	0	1	0
H	0	0	1	1	0	0	1
I	0	1	0	1	1	0	1
J	1	0	0	0	0	0	0
K	1	0	0	1	1	0	1

**Note. 1 denotes having been convicted of the crime during the time interval. 0 denotes not having been convicted.*

Appendix B

ProcLTA (SAS) Code to Conduct LTA for Male Sample

```
proc lta data = data;
      title2 "MALES - 4 class LTA (baseline), 335 items";
      nstatus 4;
      ntimes 5;
      items mischief_property_T1 harm_neglect_animal_T1 threat_T1
one_assault_T1  assault_T1 fail_attend_court_T1 weapon_assault_T1
traffick_abduct_confine_T1 sex_offense_child_T1 possess_child_porn_T1
procure_sex_T1 indecent_act_T1 theft_traffic_other_T1 sex_a_T1
fail_comply_probation_T1 breach_probation_T1 possess_weapon_T1
robbery_theft_T1 robbery_violence_T1 crim_harassment_T1 computer_sex_child_T1
robbery_weapon_T1 robbery_intent_T1 fail_reattend_court_T1 imitate_firearm_T1
theft_under_T1 dang_operation_T1 be_commit_T1 agg_assault_T1
acc_attempt_murder_T1 officer_assault_T1 unlawful_dwell_T1 disobey_court_T1
trespass_entry_T1 disguise_T1 operation_impair_T1 robbery_gen_T1 be_intent_T1
possess_firearm_T1 arson_explosives_T1 officer_obstruct_T1 fraud_T1
fail_stop_remain_T1 disturbance_T1 obs_justice_pub_mischief_T1 drive_disq_T1
possession_under_T1 burlgary_tools_T1 vehicle_theft_T1 possession_over_T1
theft_over_T1 fail_undertake_bail_T1 fraud_under_T1 theft_under_other_T1
mischief_person_T1 theft_credit_T1 fraud_over_T1 refuse_sample_T1
be_attempt_T1 comm_benefit_prostitution_T1 counterfeit_mark_T1 forgery_T1
prop_crime_under_T1 ident_fraud_T1 prop_crime_over_T1 ident_theft_T1
resist_officer_T1

mischief_property_T2 harm_neglect_animal_T2 threat_T2 one_assault_T2
assault_T2 fail_attend_court_T2 weapon_assault_T2 traffick_abduct_confine_T2
sex_offense_child_T2 possess_child_porn_T2 procure_sex_T2 indecent_act_T2
theft_traffic_other_T2 sex_a_T2 fail_comply_probation_T2 breach_probation_T2
possess_weapon_T2 robbery_theft_T2 robbery_violence_T2 crim_harassment_T2
computer_sex_child_T2 robbery_weapon_T2 robbery_intent_T2
fail_reattend_court_T2 imitate_firearm_T2 theft_under_T2 dang_operation_T2
be_commit_T2 agg_assault_T2 acc_attempt_murder_T2 officer_assault_T2
unlawful_dwell_T2 disobey_court_T2 trespass_entry_T2 disguise_T2
operation_impair_T2 robbery_gen_T2 be_intent_T2 possess_firearm_T2
arson_explosives_T2 officer_obstruct_T2 fraud_T2 fail_stop_remain_T2
disturbance_T2 obs_justice_pub_mischief_T2 drive_disq_T2 possession_under_T2
burlgary_tools_T2 vehicle_theft_T2 possession_over_T2 theft_over_T2
fail_undertake_bail_T2 fraud_under_T2 theft_under_other_T2 mischief_person_T2
theft_credit_T2 fraud_over_T2 refuse_sample_T2 be_attempt_T2
comm_benefit_prostitution_T2 counterfeit_mark_T2 forgery_T2
prop_crime_under_T2 ident_fraud_T2 prop_crime_over_T2 ident_theft_T2
resist_officer_T2

mischief_property_T3 harm_neglect_animal_T3 threat_T3 one_assault_T3
assault_T3 fail_attend_court_T3 weapon_assault_T3 traffick_abduct_confine_T3
sex_offense_child_T3 possess_child_porn_T3 procure_sex_T3 indecent_act_T3
theft_traffic_other_T3 sex_a_T3 fail_comply_probation_T3 breach_probation_T3
possess_weapon_T3 robbery_theft_T3 robbery_violence_T3 crim_harassment_T3
computer_sex_child_T3 robbery_weapon_T3 robbery_intent_T3
fail_reattend_court_T3 imitate_firearm_T3 theft_under_T3 dang_operation_T3
be_commit_T3 agg_assault_T3 acc_attempt_murder_T3 officer_assault_T3
unlawful_dwell_T3 disobey_court_T3 trespass_entry_T3 disguise_T3
operation_impair_T3 robbery_gen_T3 be_intent_T3 possess_firearm_T3
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arson_explosives_T3 officer_obstruct_T3 fraud_T3 fail_stop_remain_T3
disturbance_T3 obs_justice_pub_mischief_T3 drive_disq_T3 possession_under_T3
burlgary_tools_T3 vehicle_theft_T3 possession_over_T3 theft_over_T3
fail_undertake_bail_T3 fraud_under_T3 theft_under_other_T3 mischief_person_T3
theft_credit_T3 fraud_over_T3 refuse_sample_T3 be_attempt_T3
comm_benefit_prostitution_T3 counterfeit_mark_T3 forgery_T3
prop_crime_under_T3 ident_fraud_T3 prop_crime_over_T3 ident_theft_T3
resist_officer_T3

mischief_property_T4 harm_neglect_animal_T4 threat_T4 one_assault_T4
assault_T4 fail_attend_court_T4 weapon_assault_T4 traffick_abduct_confine_T4
sex_offense_child_T4 possess_child_porn_T4 procure_sex_T4 indecent_act_T4
theft_traffic_other_T4 sex_a_T4 fail_comply_probation_T4 breach_probation_T4
possess_weapon_T4 robbery_theft_T4 robbery_violence_T4 crim_harassment_T4
computer_sex_child_T4 robbery_weapon_T4 robbery_intent_T4
fail_reattend_court_T4 imitate_firearm_T4 theft_under_T4 dang_operation_T4
be_commit_T4 agg_assault_T4 acc_attempt_murder_T4 officer_assault_T4
unlawful_dwell_T4 disobey_court_T4 trespass_entry_T4 disguise_T4
operation_impair_T4 robbery_gen_T4 be_intent_T4 possess_firearm_T4
arson_explosives_T4 officer_obstruct_T4 fraud_T4 fail_stop_remain_T4
disturbance_T4 obs_justice_pub_mischief_T4 drive_disq_T4 possession_under_T4
burlgary_tools_T4 vehicle_theft_T4 possession_over_T4 theft_over_T4
fail_undertake_bail_T4 fraud_under_T4 theft_under_other_T4 mischief_person_T4
theft_credit_T4 fraud_over_T4 refuse_sample_T4 be_attempt_T4
comm_benefit_prostitution_T4 counterfeit_mark_T4 forgery_T4
prop_crime_under_T4 ident_fraud_T4 prop_crime_over_T4 ident_theft_T4
resist_officer_T4

mischief_property_T5 harm_neglect_animal_T5 threat_T5 one_assault_T5
assault_T5 fail_attend_court_T5 weapon_assault_T5 traffick_abduct_confine_T5
sex_offense_child_T5 possess_child_porn_T5 procure_sex_T5 indecent_act_T5
theft_traffic_other_T5 sex_a_T5 fail_comply_probation_T5 breach_probation_T5
possess_weapon_T5 robbery_theft_T5 robbery_violence_T5 crim_harassment_T5
computer_sex_child_T5 robbery_weapon_T5 robbery_intent_T5
fail_reattend_court_T5 imitate_firearm_T5 theft_under_T5 dang_operation_T5
be_commit_T5 agg_assault_T5 acc_attempt_murder_T5 officer_assault_T5
unlawful_dwell_T5 disobey_court_T5 trespass_entry_T5 disguise_T5
operation_impair_T5 robbery_gen_T5 be_intent_T5 possess_firearm_T5
arson_explosives_T5 officer_obstruct_T5 fraud_T5 fail_stop_remain_T5
disturbance_T5 obs_justice_pub_mischief_T5 drive_disq_T5 possession_under_T5
burlgary_tools_T5 vehicle_theft_T5 possession_over_T5 theft_over_T5
fail_undertake_bail_T5 fraud_under_T5 theft_under_other_T5 mischief_person_T5
theft_credit_T5 fraud_over_T5 refuse_sample_T5 be_attempt_T5
comm_benefit_prostitution_T5 counterfeit_mark_T5 forgery_T5
prop_crime_under_T5 ident_fraud_T5 prop_crime_over_T5 ident_theft_T5
resist_officer_T5;
      categories 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2;
      seed 861551;
run;
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Appendix C

Logistic Regression Odds Ratios for Male Offender Sample

	PAST																
FINAL	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**	**O**	**P**	**Q**
A. Level 1 assault	1.91 (***)	0.25 (***)	0.84	1.66 (***)	0.21 (***)	0.06 (***)	0.35 (***)	0.98	0.095 (*)	< .01	0.35 (**)	0.08 (*)	1.02	0.30 (*)	0.18 (***)	0.92	0.67
B. Theft under $5,000	0.62 (***)	9.03 (***)	0.92	0.50 (***)	0.60 (**)	0.63 (*)	0.84	0.76	1.27	1.40	0.67	0.88	0.62	0.58 (*)	0.17 (***)	0.09 (*)	0.47
C. Mischief (property)	1.67 (***)	0.64 (**)	2.71 (***)	0.98	0.74	0.73	0.87	1.82 (***)	0.68	0.71	1.31	0.76	1.10	0.59	0.22 (**)	< .01	0.65
D. Utter threat	1.39 (*)	0.27 (***)	1.27	2.02 (***)	0.56	0.16 (**)	0.52	1.73 (**)	< .01	0.30	0.23 (*)	0.19	0.57	0.16	0.43	< .01	0.83
E. B&E commit	0.76	0.7	0.90	0.81	13.30 (***)	0.94	1.06	0.67	0.95	1.92 (*)	1.25	1.16	1.96 (*)	0.48	0.64	0.85	0.56
F. Operation while impaired	0.86	0.17 (***)	0.74	0.57 (**)	0.23 (***)	6.97 (***)	0.37 (***)	0.3 (***)	0.28 (*)	0.30 (**)	0.43 (*)	0.13 (**)	1.33	1.41	0.13 (***)	0.30 (*)	0.38 (*)
G. Possess weapon	0.74	0.77	1.20	1.77 (**)	0.98	0.75	5.09 (***)	1.18	1.59	1.06	1.83 (*)	0.83	1.52	1.16	6.59 (***)	0.59	0.37
H. Weapon assault	1.36	0.24	0.76 (**)	1.51	0.32	0.16	0.53	3.39 (***)	0.54	< .01	3.24 (**)	< .01	0.83	1.07	< .01	< .01	0.61
I. Prop. crime under $5,000	0.58 (*)	1.44	0.79	0.85	1.69 (*)	1.18	1.91 (**)	1.23	5.29 (***)	1.10	1.14	2.16 (*)	1.37	0.89	1.11	0.75	0.48
J. Possession under $5,000	0.40 (**)	1.44	0.53	0.80	1.01	0.11 (*)	0.82	0.57	< .01	6.99 (***)	< .01	0.23	1.10	2.87 (**)	0.24	0.69	1.23
K. Robbery (general)	0.28 (**)	0.50	0.12 (*)	1.32	0.59	< .01	0.34	0.71	< .01	1.02	35.24 (***)	< .01	2.21	0.85	0.42	< .01	1.49

	PAST																
FINAL	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**	**O**	**P**	**Q**
L. Fraud under $5,000	0.71	0.76	1.17	0.53	0.35	0.70	0.26	0.62	2.52 (*)	1.44	0.72	29.61 (***)	0.61	0.74	< .01	1.25	< .01
M. Assault (other)	1.61	0.17	0.56	0.92	0.52	< .01	0.33	1.46	< .01	< .01	1.71	< .01	1.82	< .01	0.73	< .01	1.34
N. Dangerous operation of a vehicle	0.61	0.39 (**)	0.43 (*)	0.82	2.26 (*)	1.80	0.46	1.11	0.81	1.73	0.50	< .01	1.08	13.85 (***)	0.45	< .01	0.61
O. Possess firearm	0.47 (*)	0.18 (**)	0.17 (**)	1.19	0.38	0.21 (*)	4.53 (***)	0.31	0.51	0.73	0.74	< .01	0.09 (*)	2.14	22.41 (***)	< .01	0.64
P. Sex offence, child	0.17 (*)	< .01	< .01	0.11	< .01	< .01	< .01	< .01	< .01	< .01	< .01	< .01	< .01	< .01	< .01	108.28 (***)	3.06
Q. Sexual assault	0.70	< .01	< .01	0.41	< .01	< .01	< .01	1.03	< .01	< .01	< .01	< .01	0.40	< .01	< .01	3.46 (*)	65.06 (***)

**Note. Cells coloured in grey denote odds ratios that are significant and positive.*

* *p* < .05, ** *p* < .01, *** *p* < .001

Appendix D

Logistic Regression Odds Ratios for Female Offender Sample

	PAST									
FINAL	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**
A. Theft under $5,000	9.36 (***)	0.45 (***)	0.23 (**)	0.54	0.16 (**)	0.68	0.67	0.53	0.62	0.28
B. Level 1 assault	0.16 (***)	2.69 (***)	3.06 (**)	< .01	< .01	1.74	0.52	0.32	< .01	1.24
C. Mischief	0.33 (**)	2.16 (**)	3.35 (***)	< .01	0.83	1.16	1.42	< .01	1.04	1.36
D. Fraud under $5,000	1.06	0.26	0.52	16.27 (***)	0.43	0.86	1.15	3.89 (**)	0.35	0.38
E. Operation while impaired	0.18 (***)	0.62	0.39	0.09 (*)	18.93 (***)	0.32	1.39	0.19	0.24	0.47
F. B & E	0.46	0.57	1.39	1.07	0.85	7.95 (***)	2.26	< .01	1.83	0.85
G. Weapon assault	0.20	2.97 (*)	1.58	< .01	< .01	< .01	3.18 (*)	< .01	< .01	5.34*
H. Forge/ counterfeit	0.49	0.34	0.50	2.27	< .01	0.31	< .01	7.67 (***)	< .01	0.49
I. Communicate/ benefit from prostitution	0.07 (*)	0.30	< .01	< .01	1.04	0.65	< .01	< .01	71.73 (***)	< .01
J. Utter threat	< .01	3.96 (**)	0.80	< .01	< .01	< .01	1.42	< .01	4.54	8.31 (***)

**Note.* *Cells coloured in grey denote odds ratios that are significant and positive.*
* *p < .05, ** p < .01, ** p < .001*

Appendix E

LTA Item Response Probabilities at T1 for Males

Item	Cluster 1	Cluster 2	Cluster 3	Cluster 4
	62.38%	15.61%	17.57%	4.45%
Mischief, damaging property	0.27%	8.75%	16.29%	2.41%
Bodily harm, neglect, manslaughter, animal abuse	0.00%	0.00%	0.29%	0.26%
Utter threat	0.15%	3.08%	16.23%	0.37%
Level 1 assault	1.17%	6.64%	41.08%	4.76%
Assault (other)	0.32%	1.42%	4.67%	0.00%
Failure to attend court	0.00%	26.84%	27.51%	10.24%
Assault w/ a weapon	0.11%	3.75%	8.37%	0.50%
Traffick, abduct, or confine	0.00%	0.26%	1.19%	0.00%
Child sex offense	0.53%	0.00%	0.22%	0.31%
(Possession, production, distribution of) child pornography	0.12%	0.00%	0.21%	0.00%
Procuring sexual services	0.13%	0.00%	0.14%	0.00%
Indecent act	0.09%	0.16%	0.73%	0.00%
Theft, traffic (other)	0.12%	0.53%	0.00%	0.00%
Sexual assault	0.20%	0.09%	1.11%	0.00%
Failure to comply with probation	0.00%	35.05%	33.58%	4.58%
Breach probation	0.12%	19.79%	14.18%	0.77%
Possession of a weapon	0.23%	8.99%	3.06%	0.54%
Robbery, theft	0.16%	3.34%	0.69%	0.00%
Robbery, violent	0.12%	3.19%	0.31%	0.00%
Criminal harassment	0.00%	0.12%	4.93%	0.00%
Computer sex offense with someone < 18	0.08%	0.00%	0.08%	0.00%
Robbery with a weapon	0.11%	5.03%	0.61%	0.00%
Robbery, intent	0.00%	1.67%	0.64%	0.00%
Failure to reattend court	0.00%	16.15%	8.11%	5.78%
Imitate firearm	0.01%	1.67%	0.09%	0.00%
Theft under (other)	0.94%	34.07%	8.31%	0.39%
Dangerous operation (vehicle)	0.00%	5.87%	1.14%	5.84%
Break & enter - commit	0.36%	12.22%	2.11%	0.48%
Aggravated assault	0.06%	0.96%	1.01%	0.00%
Accessory to murder / attempted murder	0.09%	0.47%	0.13%	0.54%
Assault against a peace officer	0.03%	3.41%	3.62%	1.17%
Unlawfully in dwelling house	0.03%	1.07%	2.18%	0.36%
Disobey court order	0.00%	0.41%	3.18%	0.00%
Forcible entry & trespass	0.01%	1.02%	1.47%	0.14%

Item	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**
Disguise with intent	0.00%	1.00%	0.00%	0.00%
Operation (vehicle) while impaired	0.00%	1.88%	2.11%	62.01%
Robbery (general)	0.02%	0.00%	0.06%	0.00%
Break & enter - intent	0.09%	3.76%	0.89%	0.00%
Possession of a firearm	0.38%	4.72%	0.69%	0.00%
Arson / explosives	0.08%	0.12%	0.56%	0.00%
Obstruct a peace officer	0.06%	9.14%	3.52%	0.00%
Fraud	0.06%	0.96%	0.53%	0.00%
Failure to stop / remain	0.00%	1.37%	0.00%	8.08%
Disturbance	0.03%	0.56%	1.18%	0.00%
Obstruct justice / public mischief	0.06%	0.81%	0.59%	0.30%
Driving while disqualified	0.00%	3.89%	0.32%	14.89%
Possession under $5,000	0.28%	16.61%	1.21%	0.99%
Possession of burglary tools	0.00%	4.01%	0.00%	0.00%
Vehicle theft	0.00%	3.54%	0.20%	0.64%
Possession over $5,000	0.12%	4.52%	0.00%	0.72%
Theft over $5,000	0.07%	2.16%	0.00%	0.87%
Failure to comply with undertaking/recognizance/bail	0.02%	0.93%	0.76%	0.00%
Fraud under $5,000	0.19%	4.58%	0.74%	0.36%
Theft under $5,000	0.00%	0.96%	0.33%	0.00%
Mischief, interfering with a person	0.04%	0.15%	0.18%	0.34%
Theft of credit card and/or data	0.03%	2.95%	0.22%	0.30%
Fraud over $5,000	0.15%	2.01%	0.06%	0.00%
Refuse to provide a breath sample	0.00%	0.14%	0.13%	10.91%
Break & enter - attempt	0.02%	0.64%	0.16%	0.42%
Communicating / materially benefitting from prostitution	0.09%	0.00%	0.69%	0.00%
Counterfeit mark	0.01%	0.93%	0.04%	0.00%
Forgery	0.07%	3.73%	0.29%	0.00%
Property obtained through crime under $5,000	0.04%	0.79%	0.27%	0.00%
Identity fraud	0.01%	1.21%	0.14%	0.00%
Property obtained through crime over $5,000	0.01%	0.41%	0.00%	0.00%
Identity theft	0.00%	0.00%	0.00%	0.00%
Resist peace officer	0.00%	0.00%	0.00%	0.00%

Appendix F

LTA Item Response Probabilities at T1 for Females

Item	Cluster 1	Cluster 2
	26.69%	73.31%
Assault (other)	1.12%	0.49%
Level 1 assault	12.95%	1.38%
Assaulting an officer	3.14%	0.34%
Operation while impaired	2.46%	2.01%
Assault with a weapon	4.60%	0.41%
Robbery	2.95%	0.56%
Sex offense	1.95%	0.11%
Refuse demand/resist arrest	1.44%	0.96%
Weapon/firearm	1.62%	0.15%
Threat	3.41%	0.47%
Obstruct officer	7.84%	0.05%
Harass/disturb	2.25%	0.00%
Failure to comply	42.49%	0.00%
Dangerous driving/driving while prohibited	1.25%	0.21%
Fail to comply with court order	41.26%	0.00%
Possession under $5,000	7.24%	0.11%
Theft under $5,000	24.98%	2.36%
Fail to reattend court	28.76%	0.02%
Break & enter	4.96%	0.05%
Mischief	7.50%	0.69%
Theft (other)	2.07%	0.29%
Arson / other	1.31%	0.12%
Fraud over $5,000	0.76%	1.06%
Breach probation	29.21%	0.00%
Fraud under $5,000	4.33%	0.88%
Communicate/ benefit from prostitution	14.30%	0.00%
Forgery / counterfeit	2.92%	0.87%
Vehicle theft	2.25%	0.00%
Credit (data) theft	3.00%	0.32%
Fail to stop and remain	0.99%	0.38%
Possession over $5,000	1.43%	0.00%
Fraud / obstructing justice	3.16%	0.34%
Identity theft	0.00%	0.00%
Obtain property under $5,000	0.00%	0.00%

Appendix G(i)

Transition Probabilities for Males (T1 to T2)

	Time 2			
Time 1	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster 1	65.98%	19.19%	9.40%	5.43%
Cluster 2	57.68%	2.04%	39.95%	0.34%
Cluster 3	51.22%	41.61%	5.20%	1.96%
Cluster 4	62.97%	10.53%	1.23%	25.27%

Appendix G(ii)

Transition Probabilities for Males (T2 to T3)

	Time 3			
Time 2	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster 1	64.81%	17.08%	6.10%	12.01%
Cluster 2	62.79%	33.24%	2.95%	1.02%
Cluster 3	53.16%	4.11%	35.99%	6.74%
Cluster 4	69.23%	3.19%	1.28%	26.31%

Appendix G(iii)

Transition Probabilities for Males (T3 to T4)

	Time 4			
Time 3	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster 1	67.13%	15.62%	3.31%	13.94%
Cluster 2	65.35%	30.45%	2.72%	1.48%
Cluster 3	37.88%	9.58%	35.72%	16.82%
Cluster 4	72.48%	6.67%	3.40%	17.45%

Appendix G(iv)

Transition Probabilities for Males (T4 to T5)

	Time 4			
Time 3	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster 1	81.35%	11.87%	3.93%	2.85%
Cluster 2	64.69%	34.35%	0.14%	0.82%
Cluster 3	28.06%	22.90%	49.04%	0.00%
Cluster 4	75.17%	7.04%	16.29%	1.49%

Appendix H(i)

Transition Probabilities for Females (T1 to T2)

	Time 2	
Time 1	Cluster 1	Cluster 2
Cluster 1	43.41%	56.59%
Cluster 2	20.99%	79.01%

Appendix H(ii)

Transition Probabilities for Females (T2 to T3)

	Time 3	
Time 2	Cluster 1	Cluster 2
Cluster 1	34.25%	65.75%
Cluster 2	27.19%	72.81%

Appendix H(iii)

Transition Probabilities for Females (T3 to T4)

	Time 4	
Time 3	Cluster 1	Cluster 2
Cluster 1	28.63%	71.37%
Cluster 2	23.45%	76.55%

Appendix H(iv)

Transition Probabilities for Females (T4 to T5)

	Time 5	
Time 4	Cluster 1	Cluster 2
Cluster 1	38.99%	61.01%
Cluster 2	19.19%	80.81%