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# Predicting prolific live streaming of child sexual abuse

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**Abstract |** Technologically enabled crime has proliferated in recent years. One such crime type is the live streaming of child sexual abuse (CSA). This study employs a machine learning approach to better understand the characteristics of Australians who engaged with known facilitators of CSA live streaming in the Philippines.

This model demonstrated notable success in identifying the individuals who would engage in a high number of transactions with known facilitators.

Individuals engaged in high-volume live streaming typically spent small amounts (under $55) at intervals of less than 20 days. Where prolific offenders had a criminal record, it was unlikely to consist of high-harm crime types, such as violent or sexual offences.

Live streaming of child sexual abuse (CSA) was first acknowledged in 2008 (de Leon 2013) but may have begun earlier (Kuhlmann & Aurén 2015). This is a unique offence type, in which offenders procure and view sexual abuse of children across the internet in real time, in exchange for money, often specifying the type of abuse (Açar 2017; Europol 2019). While the mode of offending results in substantial barriers to monitoring and prosecuting these individuals (Açar 2017), the trauma experienced by victims appears no different to less technologically enabled forms of abuse (Puffer et al. 2014). This is a technologically and financially enabled crime type (Europol 2019), using the internet for live streaming and financial transactions for procurement. Although some evidence has emerged (Brown, Napier & Smith 2020), there is a paucity of analytical research considering the characteristics of offenders or transactions. This research seeks to apply a supervised machine learning approach to consider the characteristics of offenders who live stream CSA in high volumes.

The types of technology used and the behaviours exhibited by offenders suggest that online sexual offending is a continually evolving crime type. The growth of mobile internet access and alternative types of finance has created a difficult environment to police (WeProtect Global Alliance 2019). Additionally, while the methods offenders use are relatively well understood, there appears to be limited understanding of antecedent behaviours among offenders (WeProtect Global Alliance 2019). However, the emergence of new technologies appears to have enabled live streaming of child abuse, which the Internet Watch Foundation (2018) considers to be an established and prolific form of online CSA.

The *Terminology guidelines for the protection of children from sexual exploitation and sexual abuse* recommend use of the term 'live streaming of child sexual abuse', which 'can be used without stigmatising and/or otherwise harming the child' (ECPAT International 2016: 47). Given CSA live streaming is a financially enabled crime, it is different to most other types of offline (contact) and online sexual offending. Although this type of offending occurs in multiple countries, it has been suggested that the Philippines in particular has emerged as a 'hub' for CSA live streaming (Europol 2019), due to the country's high rate of poverty, English language proficiency and high-speed internet connections (Kuhlmann & Aurén 2015; ECPAT International 2017). The high global demand for CSA live streaming (Terre des Hommes 2014), coupled with the poverty experienced in vulnerable countries such as the Philippines, creates a situation conducive to financially enabled crime. The financial element makes CSA live streaming different to, for example, child sexual abuse material (CSAM) offences, where images and videos are mostly shared freely on the internet or traded for other CSAM (Europol 2019). Similarly, a study that analysed the chat logs from 179 online grooming offenders (DeHart et al. 2017) classified only a small sub-group as 'buyers' of sex with children (13%, $n$=23), while most used manipulative tactics to gain what they wanted from child victims. Because CSA live streaming is usually accompanied by a financial transaction (Europol 2019), analysing these transactions is a key method for both detecting and understanding the offending behaviour.

To inform the disruption of crimes such as these, it is exceptionally important to understand the characteristics and behaviours of offenders. Current research into online child sexual offenders has focused on CSAM and online solicitation offenders. For example, offenders who engage with CSAM and solicit children online have been categorised as younger, with limited employment and, consequently, limited access to finance compared with the general population (Babchishin, Hanson & Hermann 2011). Additionally, offenders who specifically engage in the online solicitation of children have been categorised as highly manipulative and centrally focused on sexual arousal and gratification (Kloess et al. 2015). However, there is little understanding of the characteristics and behaviours of offenders who engage specifically in live streaming of CSA.

## Analysing child abuse and financial transactions

In recent times, machine learning (ML) analytics have provided an alternative method for considering complex datasets, with greater confidence than, for example, logistic regression (Couronné, Probst & Boulesteix 2018). Naturally occurring data generated in the process of undertaking daily activities, such as banking transactions, are often complex in structure as their purpose is not for research. For data such as these, the random forest is useful, as it is particularly good at interrogating non-linear interactions among variables (Berk 2013).

Recently, there has been a marked increase in the use of ML analytics in considering the two key areas of this research: child abuse and financial transactions. ML in association with text mining has proven to be a robust option for supporting identification of possible child abuse to assist practitioners (Amrit et al. 2017). Further, ML methods have been used to improve the triage decision making for reports of child abuse made to hotlines in the United States (Chouldechova et al. 2018). Analytics such as these are suggested to hold promise in supporting intervention programs and more accurately assessing risk as a means of preventing child maltreatment (Gillingham 2016).

Similarly, ML analytics are often applied to banking data, to identify and predict the key features of transaction behaviours. Supervised ML appears effective in interrogating transaction data to estimate the likelihood that a transaction was fraudulent, based on features such as the demographics of the individual, prior behaviours, and transaction history (Jullum et al. 2020). This research will consider the capacity of ML to identify the characteristics of individuals who engage in high-volume live streaming of CSA using banking transaction and criminal history data.

# Methodology

## Data

The Australian Transaction Reports and Analysis Centre (AUSTRAC) collects financial transaction data relating to individuals in Australia, primarily for the purpose of identifying financial crime. The Australian Criminal Intelligence Commission collects criminal history information relating to individuals who have come under notice for offending in Australia in the National Police Reference System. In 2018, the Philippine National Police and the Philippine National Bureau of Investigation provided the Australian Federal Police with a list of 118 individuals arrested for facilitating the sexual abuse of children. Using this information, AUSTRAC identified 299 Australia-based individuals who had made transactions with these known facilitators of child sexual abuse. At the time of data provision, some of these individuals had been arrested for child sexual offences, while others were under investigation. As such, there were individuals among these data who had not been charged with the live streaming of CSA at the time of analysis.

AUSTRAC provided transaction data relating to the 299 individuals to the Australian Institute of Criminology for analysis. However, prior to this, AUSTRAC provided the transaction data to the Australian Criminal Intelligence Commission so it could be linked to criminal history data in the National Police Reference System using names and dates of birth. This process resulted in a de-identified dataset of 256 individuals. (See Brown, Napier & Smith 2020 for the full data-matching methodology.)

Available data consisted of transactions processed between January 2006 and February 2019. Where demographic characteristics of individuals were unavailable, data were excluded from analysis. This resulted in a retained dataset of 207 individuals who had conducted at least one transaction with known facilitators of live streaming of CSA. These data included limited demographics, transaction details and criminal history.

Due to the nature of the data available, this is best considered a within-groups analysis. While it may have been beneficial to include a comparison dataset, these data were not available. Consequently, this analysis had a broad purpose: to consider whether, among a set of individuals known to have made financial transactions with facilitators of the live streaming of CSA, it was possible to identify those who would engage in the highest volume of transactions—and, more specifically, those individuals who would engage in 21 or more transactions with live streaming facilitators. This was the number of transactions made by the most prolific 10 percent of individuals whose data were available for analysis. Twenty-one individuals met these criteria, making between 21 and 141 transactions with live streaming facilitators. This group were referred to as the 'high-volume' group, with the remaining 186 individuals transacting in lower volumes.

While individual crime types were important in this analysis, the harm resulting from prior offences is emerging as a valuable measure of offending that accounts for the impact of offences rather than the volume (Ashby 2017). Specific to the Australian context, the Western Australian Crime Harm Index (WACHI) assigns a harm index weighted by the court penalties imposed (House & Neyroud 2018). The WACHI was developed based on the Australian and New Zealand Standard Offence Classification codes. Prior research in Australia has operationalised this harm index to measure the extent of harm among criminal groups (Morgan, Dowling & Voce 2020). Here, the WACHI is applied to the criminal history of individuals prior to their first live streaming transaction to provide an understanding of harm as a predictor of high-volume live streaming of CSA.

## Data limitations

There are several limitations to the data used in this research. While we can be certain that these transactions involved money being sent to known facilitators of live streaming of CSA, we cannot be certain that each transaction was intended for that purpose. It is possible that they may have been for other sexual purposes, such as live streaming of adult sexual content. It is, however, unlikely that these transactions were for contact offending or non-sexual purposes (Brown, Napier & Smith 2020). Additionally, the data considered here relate to a single law enforcement operation in the Philippines. It is unclear whether individuals in this dataset are representative of live streaming offenders more broadly.

Finally, the unit of analysis in this research consists of offences detected by police. This is an important limitation, as consideration must be given to sexual offences committed prior to the onset of live streaming among these offenders. There are evident barriers to the reporting of both child and adult sexual offences (Gruenfeld, Willis & Easton 2017; Smith et al. 2010), which have additional implications for the disclosure, reporting and prosecution of offences (Bunting 2014). Consequently, it must be noted that while the recorded criminal history of individuals in this sample comprehensively represents those on record, undetected offences among this sample are an inherent possibility.

## Analytical strategy

As previously noted, emerging evidence suggests that, particularly among complex datasets, the random forest algorithm performs notably better than logistic regression (Couronné, Probst & Boulesteix 2018). While it must be noted that there are a relatively small number of individuals in this dataset, data available for each individual were complex, with a relatively large number of covariates compared with the sample size, suggesting the importance of a non-parametric approach (Couronné, Probst & Boulesteix 2018). While the random forest algorithm has typically been used for large datasets, it appears to be an effective method for interrogating and making predictions from substantially smaller datasets than was available here (Choi & Ma 2020; Zhang & Wang 2009). In simple terms, the random forest model has been used for analysis here due to its proven ability to discern important effects among complex and limited data, with substantially greater success than more traditional analyses.

This analysis employs a receiver operating characteristic (ROC) curve to determine the robustness of the random forest model. The ROC curve assesses the rate at which the random forest successfully classified high-volume live streaming offenders in these data. The closer the ROC curve is to the 45-degree angle presented in Figure 2, the less accurate the random forest model. The robustness of the random forest model is given as the area under the ROC curve (AUROC). This metric has been computed for a logistic regression using the same parameters as the random forest, to demonstrate the comparative robustness of these models. The random forest model, presented in Figure 3, demonstrates which variables were most important in the rate of prediction of high-volume live streaming, provided by the ROC curve. The random forest is interpreted through the mean decrease Gini coefficient (MDG) (Hong, Xiaoling & Hua 2016). The Gini coefficient details the proportion of the model accounted for by each variable. The higher the MDG, the more important the variable in predicting high-volume live streaming.

To facilitate modelling, the sample were randomised, with 70 allocated to a training set, and the remaining 30 percent used as a test set to measure the trained model's accuracy. This 70–30 split was used due to the size and complexity of the dataset (Hyndman & Anthanasopoulos 2014). It allowed sufficient data to train the model and then test it. Analysis was performed using the 'randomForest', 'dplyr', 'pRoc', 'pdp' and 'ggplot2' packages of the statistical analysis software R. The model was trained on individuals who engaged in high-volume live streaming of CSA, and then exposed to the test set.

A confusion matrix was computed to determine the accuracy of the random forest predictions in the test set. The confusion matrix compares the predictions to observed outcomes—in this instance, whether or not an individual engaged in high-volume live streaming. This measures the rate of error in these predictions, thereby assessing the practical success of the model (Barnes & Hyatt 2012).

Post-hoc partial dependence plots (PDPs) were computed for independent variables (Zhao & Hastie 2019) to provide the effect within variables. PDPs demonstrate the association between particular characteristics within variables, and high-volume live streaming, controlling for all other variables. The logit value moving from point to point within variables identifies the points within the range of the variable with the strongest association with high-volume live streaming. For example, it shows the transaction value or time between transactions most associated with prolific live streaming. Where plotlines fall, the association with high-volume live streaming decreases, while increasing plotlines indicate a stronger association with high-volume live streaming.

# Results

## Summary statistics

The ages of individuals at the time of their first CSA live streaming transaction ranged from 20 to 76 years, but the mean age was 52 years. Individuals who engaged in high-volume live streaming were typically marginally older, with a mean age of 54 years at the time of their first transaction (range: 34–67 years). The mean number of transactions for the high-volume group was 53 (range: 21–141), while those in the low-volume group made a mean of three transactions (range: 1–18). Both groups of individuals spent relatively small amounts per transaction.

**Table 1: Transactions of low-volume and high-volume live streaming offenders**

| | Low-volume offenders (*n*=186) | High-volume offenders (*n*=21) |
|---|---|---|
| Age in years at first live streaming transaction (range) | 52.13 (20–76) | 54.64 (34–67) |
| Average number of transactions (range) | 3.39 (1–18) | 52.95 (21–141) |
| Median expenditure per transaction (range) | $45 (11–372) | $75 (16–335) |
| Median days between transactions (range)[a] | 15 (1–746) | 7 days (2–84) |

a: Only includes individuals who made two or more transactions

Source: Philippines CSA live stream financial transaction dataset

### *Criminal history*

Not all individuals had criminal histories featuring other types of criminal offending. Among the sample of 207 individuals engaged in live streaming of CSA, 98 (47%) had not come to the attention of the police for other types of criminal behaviour. Among the 21 individuals engaged in high-volume live streaming, 12 (57%) did not have a prior criminal history. High-volume streaming offenders who had a criminal history tended to begin offending later in life than low-volume offenders.

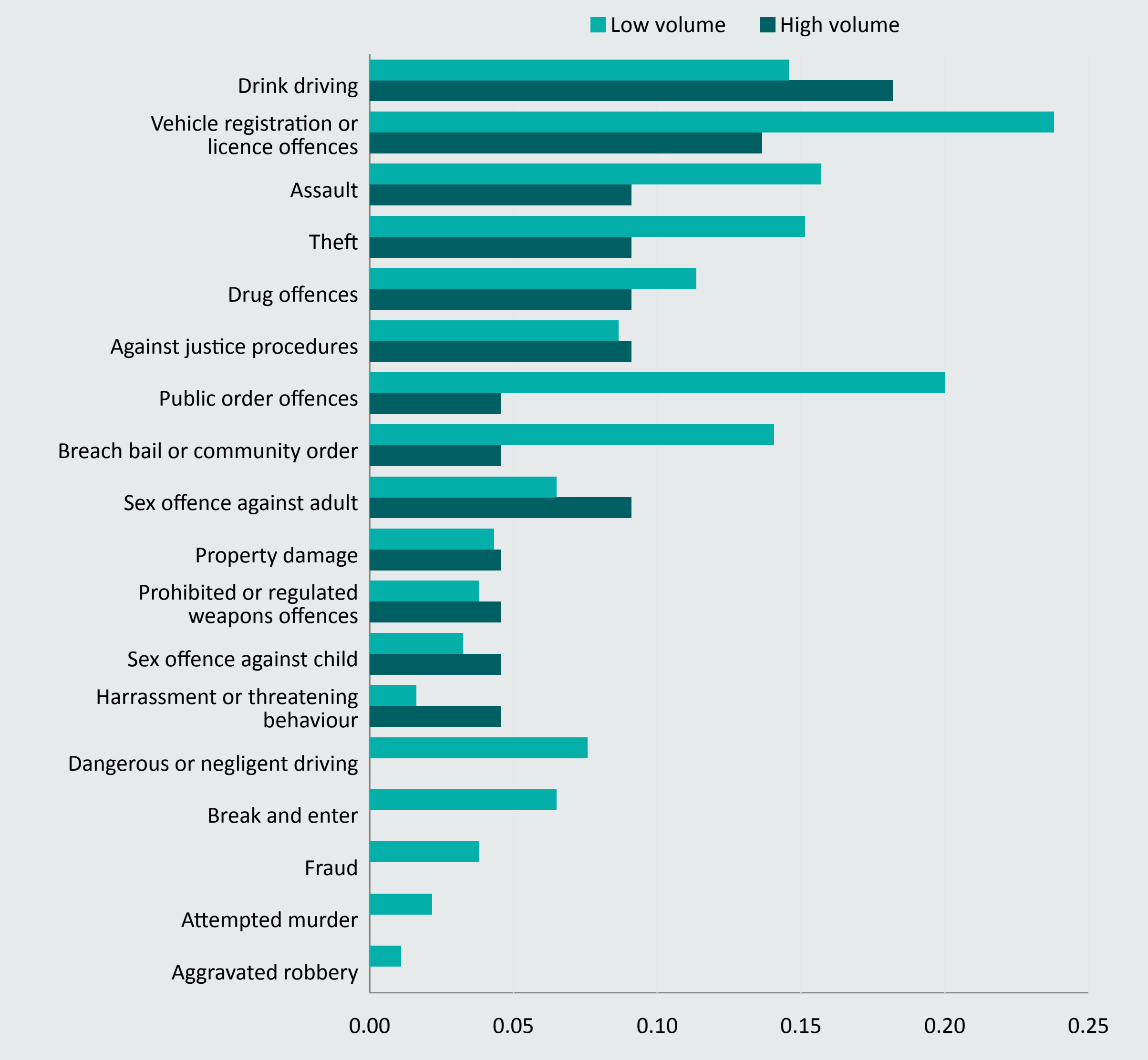
**Table 2: Criminal histories of low-volume and high-volume live streaming offenders**

| | Low-volume offenders (*n*=186) | High-volume offenders (*n*=21) |
|---|---|---|
| Age in years at first criminal charge (range)[a] | 30.22 (18–63) | 43.23 (18–67) |
| Mean number of criminal charges | 3.42 (0–51) | 2.05 (0–9) |

a: Only includes those with a criminal charge

Source: Philippines CSA live stream financial transaction dataset

**Figure 1: Average number of offences prior to live streaming among those with at least one criminal offence**




Source: Philippines CSA live stream financial transaction dataset

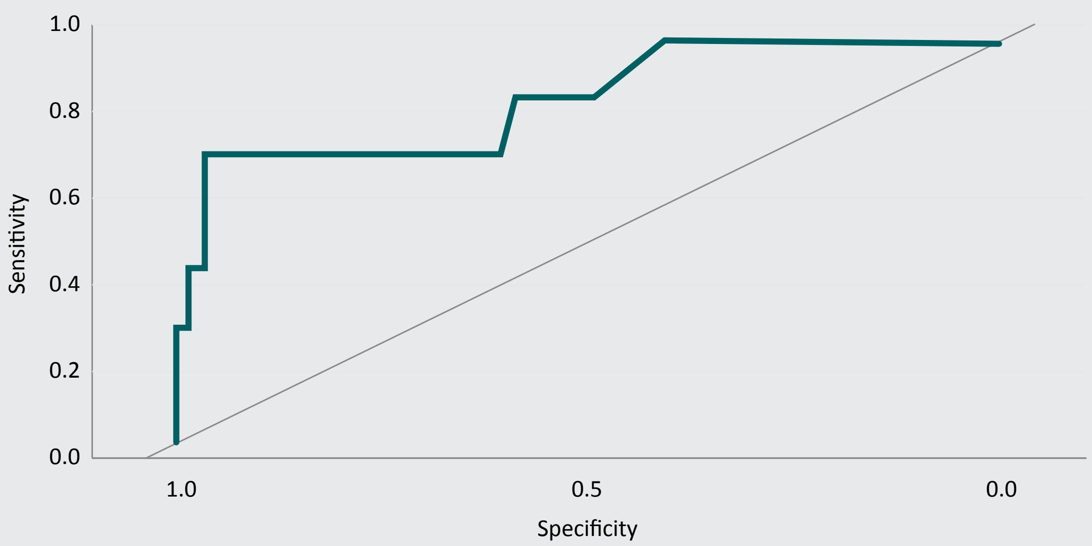
### *Prior sex offences*

Given the crime type under consideration here, it was important to examine whether these individuals had a history of prior sex offences. Among the sample of 207, 14 individuals had a history of recorded sexual offences against adults, of whom two went on to engage in high-volume live streaming. Seven individuals had a history of sexual offences against children, of whom one went on to engage in high-volume live streaming. It appears that, while this may be considered an analogous offence type, there was little interaction between prior sex offences and subsequent live streaming of CSA.

## Random forest analysis

The area under the ROC curve identified that this was a robust model with an AUROC of 0.852 (see Figure 2). The same data were then used to compute a logistic regression with the same intention, resulting in an AUROC of 0.607, supporting the contention that the random forest model was a more robust option for analysis of this complex dataset, despite the limited sample size.

**Figure 2: ROC curve for random forest model trained on high-volume live streaming offenders**

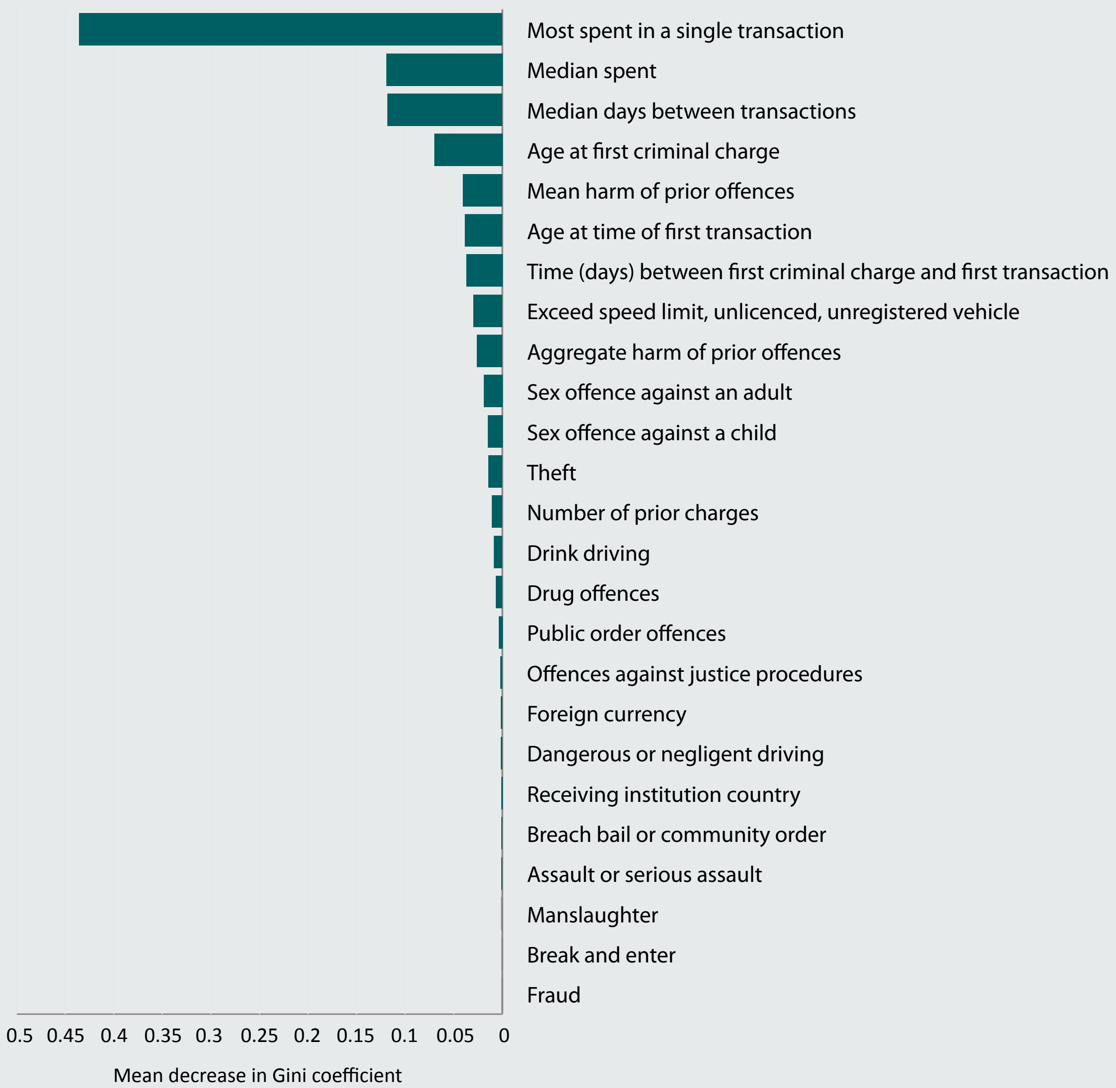



Note: ROC=receiver operating characteristic

Source: Philippines CSA live stream financial transaction dataset

Random forest results (Figure 3) identified the most important variables in the computation of this model. The most important three variables related to transaction data, including the most spent in a single transaction, the median spent across transactions and the median days between transactions. Demographic details of offenders were marginally less important. While the age of onset of criminal behaviour was noteworthy, the age at the time of first transaction did not feature a noteworthy MDG coefficient. Finally, the mean harm of prior offences bears some consideration, while the specific type of prior offences was not a good measure with which to identify high-volume live streaming offenders. This supported the notion that a history of sex offending against either adults or children was not a good means by which to identify those at risk of live streaming CSA. No criminal history variable was particularly useful in predicting high-volume live streaming offenders. Rather, transaction data proved most useful.

**Figure 3: Variable importance associated with high-volume live streaming**




Source: Philippines CSA live stream financial transaction dataset

## Confusion matrix

To explore the predictive accuracy of the random forest model, a confusion matrix was produced for the test set. Table 3 identifies where the random forest correctly classified high-volume live streaming offenders, and where it failed. Given the limited sample available, and despite the prior success of random forest models among small samples, this was a difficult task. However, the model performed relatively well in classifying high-volume offenders among a small sample. It is also important that the model demonstrated some success in identifying those who would not engage in high-volume offending. This model was considered to perform well, but caution should be exercised, given the small sample size.

**Table 3: Confusion matrix for predicting high-volume live streaming offenders**

| | True low-volume offender | True high-volume offender | Classification error |
|---|---|---|---|
| Predicted low-volume offender | 59 | 2 | 5% |
| Predicted high-volume offender | 2 | 6 | 25% |
| Classification error | 5% | 25% | 69 |

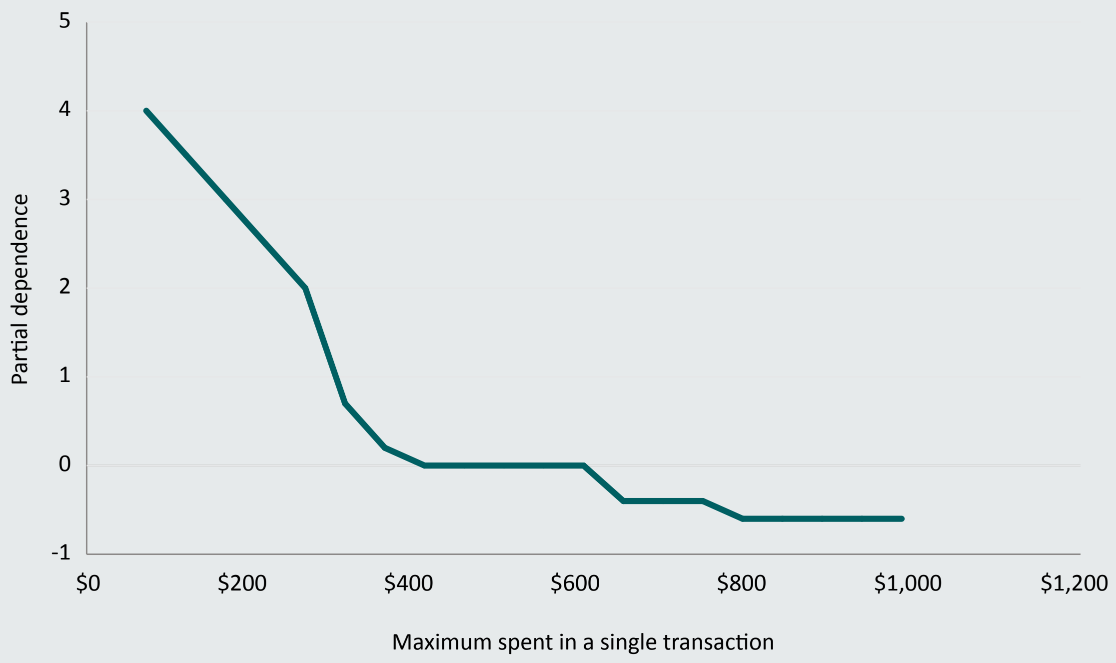
## Partial dependence

Partial dependence plots were computed for five noteworthy variables. Among some variables, such as age at onset of criminal offending, the change is relatively minor, suggesting that the likelihood of high-volume live streaming was similar across the majority of age groups. However, among some PDPs there was substantial change, suggesting that there were specific points at which high-volume live streaming was substantially more likely than at others. The section below outlines the relationship between high-volume live streaming and each of these variables.

### *Most spent in a single transaction*

The most spent in a single transaction was an important predictor of high-volume live streaming. Where the most spent in a single transaction was less than $200, the association with high-volume live streaming was strong. Where the most spent in a single transaction was above $300, the association declined substantially. Where the maximum amount spent in a single transaction was greater than $600, individuals were unlikely to engage in high-volume live streaming. Evidently, among this sample, the higher the maximum amount spent in a single transaction, the less likely an individual was to engage in prolific CSA live streaming.

**Figure 4: Partial dependence plot for most spent in a single transaction and high-volume live streaming**

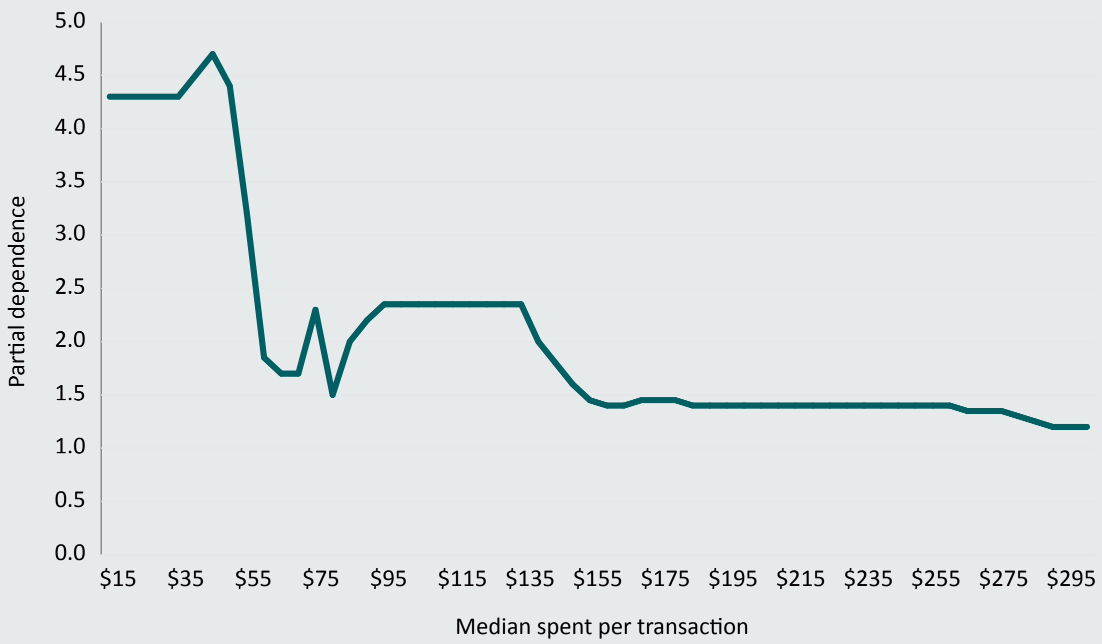



Source: Philippines CSA live stream financial transaction dataset

### *Median spent per transaction*

To further interrogate this effect, it was important to consider the median amount spent per transaction. Figure 5 supports the notion identified in Figure 4, that individuals engaged in prolific live streaming of CSA tended to spend less on each occasion. The association with high-volume live streaming was strongest where the median amount spent per transaction was below $55. Above this value, the relationship between prolific live streaming and median amount spent weakened. However, this effect had a long taper, indicating that the association largely plateaued, remaining relatively constant after this point.

**Figure 5: Partial dependence plot for median spent per transaction and high-volume live streaming**

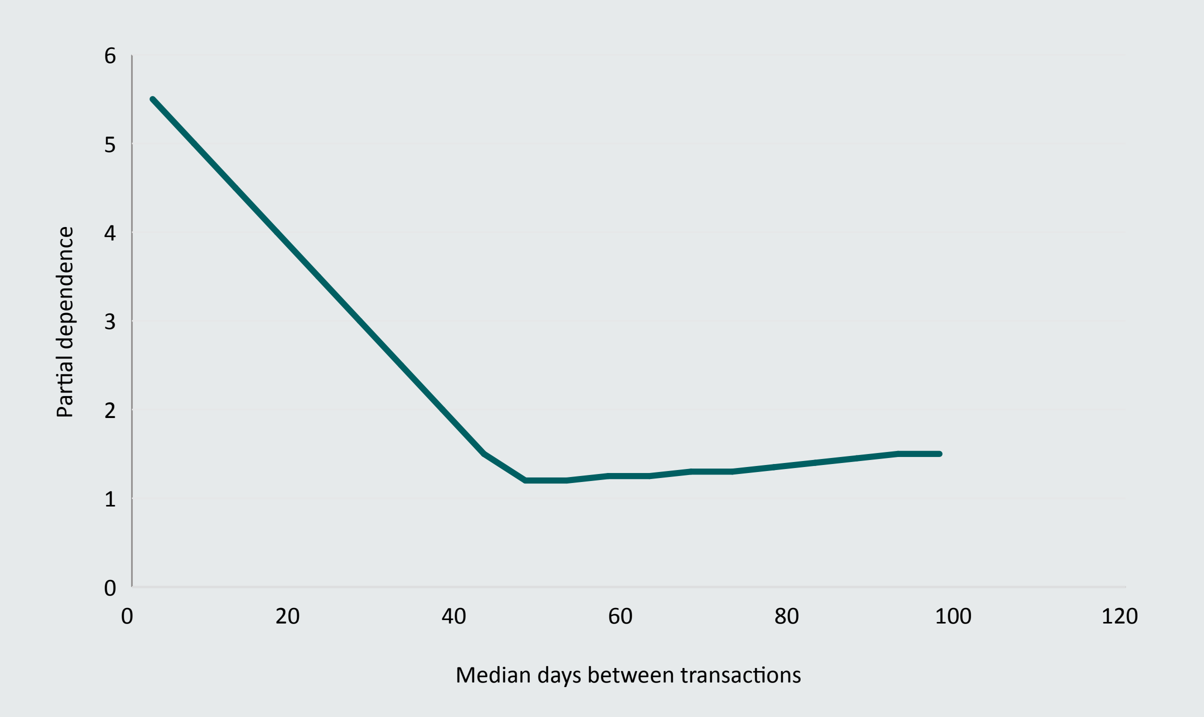



Source: Philippines CSA live stream financial transaction dataset

### *Median time between transactions*

The PDP for median time between transactions suggested that, while more prolific live streaming was associated with comparatively small expenditure per transaction, it was also associated with a short time frame between transactions. As may be intuitive, Figure 6 suggests that the shorter the time between transactions, the greater the association with high-volume live streaming.

**Figure 6: Partial dependence plot for median time between transactions and high-volume live streaming**

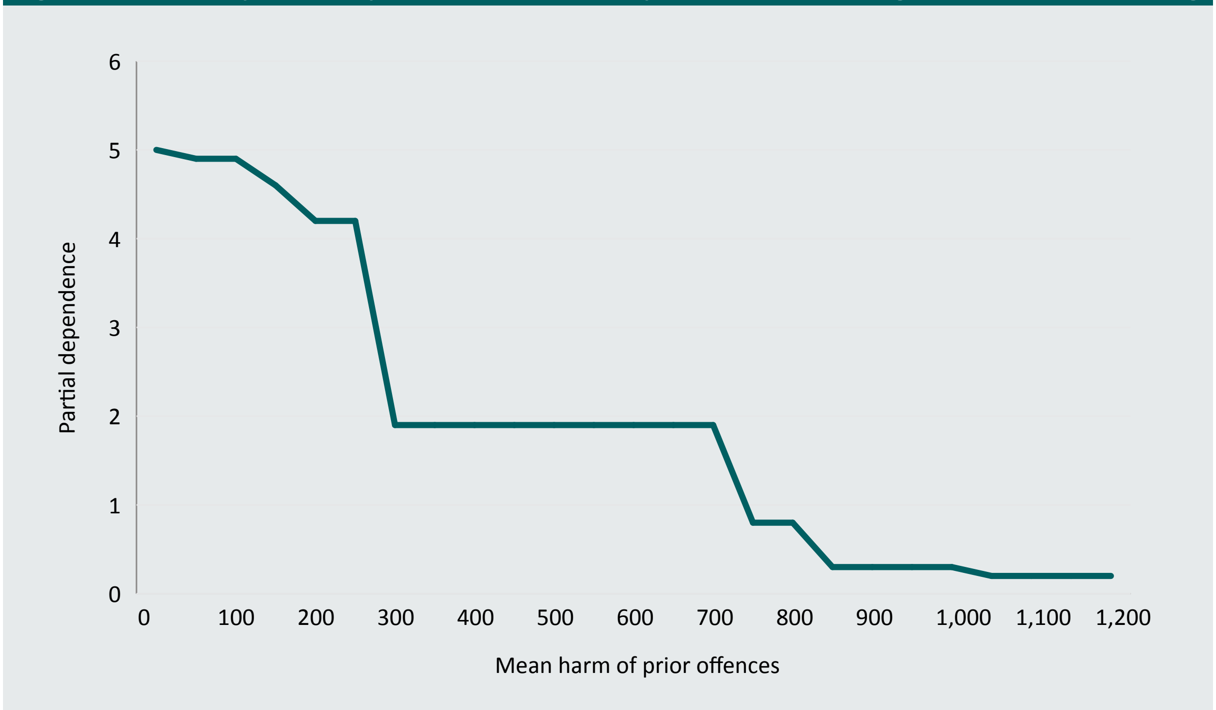



Source: Philippines CSA live stream financial transaction dataset

### *Mean harm of prior criminal offences*

The criminal histories of individuals were important to consider. This analysis employed variables identifying the harm resulting from prior offences, as well as the age of onset of detected criminal offending. While neither of these variables were particularly strong predictors, they demonstrated some interaction with prolific live streaming. Figure 7 suggests that high-volume live streaming was most associated with individuals who did not have a history of detected high-harm offending. Rather, individuals for whom the mean harm per offence was relatively low were more likely to engage in prolific live streaming. This finding supports the notion that the individuals in this sample were unlikely to have committed a prior sex offence; however, as Figure 1 suggests, they were also unlikely to have engaged in violent offences. Prior high-harm offences were weakly associated with subsequent prolific live streaming of CSA.

**Figure 7: Partial dependence plot for mean harm of prior offences and high-volume live streaming**




Source: Philippines CSA live stream financial transaction dataset

### *Age at onset of criminal offending*

Finally, the age of onset of criminal offending appears to have little association with high-volume live streaming. The likelihood of prolific live streaming was relatively even up to around 50 years of age, at which point it declined substantially. The criminal history of individuals appears to give little insight into their likelihood of prolific live streaming. However, Figures 7 and 8 suggest that a history of low-harm offences prior to 50 years of age had some predictive value, but was typically outperformed by transaction variables.

**Figure 8: Partial dependence plot for age at onset of criminal offending and high-volume live streaming**


Source: Philippines CSA live stream financial transaction dataset

## Discussion

These findings provide a relatively clear view of individuals who engage in high-volume live streaming. It was particularly important that the three variables most useful in predicting prolific live streaming were characteristics of financial transactions.

## Transaction variables

Brown, Napier and Smith (2020) noted that, among those who made more than one transaction, the time between transactions declined. This assertion was supported here. Not only did high-volume offenders make transactions for CSA live streaming roughly twice as often as low-volume offenders, but the closer together these transactions were the higher the likelihood that the individual was engaging in high-volume live streaming. Additionally, where the maximum amount spent on a single transaction was less than $250, there was strong interaction with high-volume live streaming. The smaller the value of that maximum expenditure, the stronger this interaction was. This finding was supplemented by the finding relating to the median expenditure per transaction (Figure 5). The likelihood of high-volume live streaming was highest where individual transactions were $55 or less.

When viewed in totality, it appears that high-volume offenders typically made frequent low-value transactions and were unlikely to spend more than $250 in any single transaction. Among a different group of online sex offenders, Babchishin, Hanson and Hermann (2011) noted a lack of access to employment and finances. While this is a marginally different group, this may go some way to explaining the limited financial outlay among prolific CSA live streaming offenders. However, given the frequency of these low-cost transactions, it is possible that this is a strategy offenders use to avoid detection.

## Criminal history variables

As Brown, Napier and Smith (2020) pointed out, the offending histories of individuals in this sample are roughly analogous to those of online CSAM offenders. The proportion of individuals who had a history of sexual offences (against children or adults) was higher among the prolific live streaming offenders than among the low-volume group. It would be beneficial to explore the potential link between high-volume CSA live streaming and contact sexual offending with a larger sample. While the extent of offending among both groups was relatively low, there was some suggestion that low-harm offences may precede high-volume live streaming. There was a moderate interaction between the mean harm of prior offences and the likelihood of high-volume live streaming. The stronger association was with a history of low-harm offending. This may partially be accounted for by under-reporting and the difficulty of prosecuting high-harm offences, particularly sex offences (ECPAT International 2018).

Seto, Hanson and Babchishin (2011) identified that the rate of contact sexual offending by CSAM offenders recorded in criminal justice data was substantially below the rate of self-reported contact offending among CSAM offenders. Given the rate of prior offending among CSA live streaming offenders is similar to the rate of contact sex offending among CSAM offenders (Seto, Hanson & Babchishin 2011), there is some suggestion that there was undetected high-harm offending. Regardless, while individual crime types were not associated with high-volume live streaming, a history of low-harm offending appears to have limited predictive value.

## Onset of offending

While the demographic characteristics of offenders did not have a strong association with prolific live streaming, the characteristics of these individuals were noteworthy. While the age at first live streaming transaction was relatively similar for low- and high-volume offenders in this sample, the age at onset of criminal behaviour was not. Although analysis suggested that criminal history was not particularly associated with prolific live streaming among those with a criminal history, high-volume offenders tended to begin criminal behaviour later than low-volume offenders, and tended to commit fewer offences. Previous research has suggested that live streaming offenders tend to be older than those who commit other CSAM offences (eg possession or distribution of images/videos; Brown, Napier & Smith 2020), but the age of onset for offences prior to live streaming was similar to that of online and contact sex offenders identified by Babchishin, Hanson and Hermann (2011). This initial evidence suggests that, where individuals in this sample had engaged in prior criminal behaviour, it likely began at around the same age as the typical onset of offending among online or contact sex offenders.

## Implications for law enforcement and financial institutions

In November 2019, AUSTRAC took legal action against Westpac Bank for failing to monitor $11b worth of suspicious transactions, including money sent to the Philippines suspected to be for child sexual abuse (Butler 2019). Enhanced technologies have resulted in new forms of child exploitation, and it is clear that financial transactions are attached to some of these—in particular, CSA live streaming. Financial institutions will require increasingly sophisticated methods to identify suspicious transactions. The findings from this paper are a crucial first step in assisting institutions to identify suspicious transactions. For example, evidence here would suggest transactions for small amounts (below $55), sent frequently (around 7 days apart, certainly less than 20) to the Philippines or other countries identified as vulnerable to child exploitation could be flagged for further investigation by law enforcement.

However, it should be noted that any system used to identify suspicious transactions will need improved accuracy. The present research is largely a scoping study to consider the potential of machine learning to identify prolific live streaming offenders. The potential impact of false positives among this field of work is substantial, and may lead to the ineffective use of law enforcement resources and psychosocial harm to those incorrectly targeted. While these approaches have promise, analyses such as these should be applied to a larger dataset, with the intention of reducing false-positive rates, before they can be taken up by law enforcement.

### Limitations

This research is best considered to be a within-group analysis of individuals who pay for CSA live streaming. These findings are not generalisable to all transactions processed by financial institutions. To establish this capability an additional analysis featuring a control sample is necessary. However, as a scoping study considering how well prolific live streaming behaviours could be identified, this analysis performed well and produced useful insight. While findings here only relate to individuals who engage in high-volume live streaming of CSA, there is potential to employ a control group of individuals who engage in live streaming more broadly.

Further, findings here relate to the data originating among the group of facilitators arrested in the Philippines. Given this data source, there may be inherent biases in these data that relate to the specific services provided by these facilitators. Analytically, collinearity, in which predictor variables are highly correlated, thereby reducing the reliability of findings, are important to note among naturally occurring data. While the random forest is uniquely placed to account for collinearity through bootstrap aggregation, and steps were taken prior to analysis to consider collinear variables, it should be noted that collinearity among naturally occurring data cannot be ruled out entirely.

Finally, data on the severity of offending were not available for this analysis. The metric employed for analysis was the volume of offending, but the nature of the offences is unknown. It is possible that offenders spending more per transaction were procuring more severe abuse. Further research is needed on the relationship between cost and severity of abuse.

## Conclusion

This study considered whether machine learning analytics could offer insight into the transaction and offending behaviours of prolific live streamers of CSA. This is an emerging body of work in which the characteristics of offenders are largely unknown. The frequency and monetary value of transactions among these individuals are particularly important and have implications for identifying these crimes among financial transactions data. Offenders did not appear to have engaged in violent offending; rather, a history of low-harm offending was common, although the under-reporting of sexual offences among children and adults is an important consideration. Findings here may contribute to a better understanding of and ability to identify offenders who pay to watch the abuse of children via live stream, but further analyses of this type employing a control group could substantially contribute to this area of work.

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