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Abstract | The live streaming of child sexual abuse (CSA) is a technologically and financially enabled crime type which has proliferated in recent years. This study uses a machine learning approach to produce a proof of concept model for identifying the financial indicators associated with CSA live streaming.

This model was successful at identifying those who live streamed child sexual abuse, while making few errors in identifying those who did not.

Seven financial risk indicators were identified. Six risk indicators centred on the value of transactions, and one on the age of the individual making the transactions. These findings reveal an important opportunity to use financial transactions as an avenue for detecting and disrupting CSA live streaming.

Financial risk indicators of child sexual abuse live streaming: A proof of concept prediction model

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Live streaming of child sexual abuse (CSA) is a technologically facilitated crime characterised by the procurement and viewing of sexual abuse of children across the internet, in real time, in exchange for money (Açar 2017; Europol 2019). This crime type is often arranged and facilitated by a third party (Napier, Teunissen & Boxall 2021; Ramiro et al. 2019; Terre des Hommes 2013) and can feature an offender directing the abuse via the internet. The tech-enabled and online nature of CSA live streaming results in considerable barriers to monitoring by authorities, with little tangible evidence of the offence beyond a financial transaction and metadata (Açar 2017). Some evidence on the characteristics of financial transactions by CSA live streaming offenders has emerged (AUSTRAC 2022; Brown, Napier & Smith 2020; Cubitt, Napier & Brown 2023, 2021; Financial Action Task Force 2025; Gibraltar Financial Intelligence Unit nd). However, we do not yet know whether these transactions are meaningfully different from other financial transactions.

What is known about live streaming of child sexual abuse

CSA live streaming is also known as 'webcam child sex tourism/abuse' (Masri 2015; Puffer et al. 2014; Terre des Hommes 2013) and 'live-distance child abuse' (AUSTRAC 2019; EFC 2015). The Philippines has been identified as an epicentre of CSA live streaming offences (AUSTRAC 2019; ECPAT International 2017; Europol 2019; Puffer et al. 2014), facilitated by high-speed internet and good English language proficiency (Batha 2016; ECPAT International 2017; Puffer et al. 2014). A key factor in CSA live streaming offences is the interaction between those who procure the offences and those who facilitate them (Açar 2017; ECPAT International 2017; Europol 2019; Global Alliance against Child Sexual Abuse Online 2016). Facilitators of CSA live streaming are the recipients of financial transactions procuring the abuse, who then arrange the live streaming session on behalf of the offender. However, it is important to note that, in some instances, offenders also procure CSA live streams directly from victims (Napier, Teunissen & Boxall 2021).

There is little evidence that the live streaming of CSA is decreasing over time. Europol (2020a) reported an increase in sharing of child sexual abuse material (CSAM) on the darknet, including content classed as 'live streams' captured via webcam. A recent estimate suggested that, in 2022 alone, nearly one in every 100 Filipino children had experienced trafficking to produce CSAM, including CSA live streaming, and nearly three in every 1,000 adults had been involved in producing CSAM for profit (International Justice Mission 2023).

The financial element of child sexual abuse live streaming

Unlike some other forms of online sexual exploitation of children (DeHart et al. 2017; Napier et al. 2024), CSA live streaming typically involves a financial transaction. The technological and financial elements of CSA live streaming result in both challenges and opportunities for disruption by law enforcement. On the technological side, the evidence left by CSA live streaming offences is difficult to obtain—typically only resulting in streaming logs, chat logs and metadata (Açar 2017; ECPAT International 2017; Europol 2020b; Netclean 2019)—meaning the live streaming event is difficult to detect with this evidence alone. However, there appear to be additional detection opportunities on the financial side of live streaming offences. Police often rely on money transfers, call histories and chat logs for evidence during investigations (ECPAT International 2017), while early evidence has suggested that the characteristics of money transfers for procuring live streaming may be consistent enough to detect offending (Brown, Napier & Smith 2020; Cubitt, Napier & Brown 2023, 2021).

The present research uses a case-control design to consider the differences in the characteristics of financial transactions between those who make payments for live streaming of CSA and those who do not. We then analyse the financial characteristics of CSA live streaming to produce financial risk indicators. This research is oriented toward practice, so we undertake this analysis to understand whether these types of approaches could be useful in supporting disruption and intervention with perpetrators.

Method

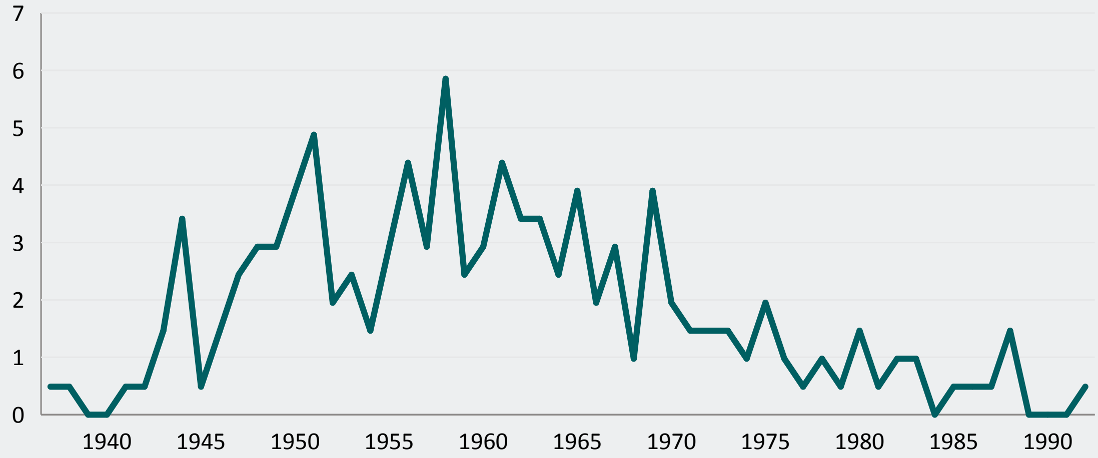
Data

To detect and prevent financial crime, the Australian Transaction Reports and Analysis Centre (AUSTRAC) collects financial transaction data relating to individuals in Australia. Separately, the Australian Criminal Intelligence Commission (ACIC) collects criminal history information relating to individuals who have come to police attention for offending in Australia. 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 CSA. AUSTRAC used this information to identify 299 Australia-based individuals who had made financial transactions with these known CSA facilitators. AUSTRAC provided the ACIC with information on the 2,714 transactions made by these Australia-based individuals, and the ACIC then linked the data with criminal history information using names and dates of birth, resulting in a deidentified dataset of 256 individuals. (See Brown, Napier & Smith 2020 for the full data-matching methodology.)

After the data were gathered and matched, the Australian Institute of Criminology took receipt of the data for analysis. These data consisted of transactions processed between January 2006 and February 2019, limited demographic information, and criminal histories. Consistent with prior research (Cubitt, Napier & Brown 2023, 2021), there were cases in which demographic data were not available and these were excluded from analysis prior to undertaking matching. AUSTRAC then provided a matched dataset of individuals who had not been identified for making a transaction for CSA live streaming, for comparison.

There were three pieces of information available to use in matching the comparison data: year of birth (see Figure 1), whether they had transferred money from Australia to the Philippines, and whether they had done so within the date range of the individuals who transacted with facilitators (January 2006 to February 2019). In instances where the data did not contain demographic details of members of the live streaming group, they were excluded from analysis as we were not able to match cases on their characteristics. A dataset of 10,007 individuals with the same date of birth distribution as the CSA live streaming sample, and who had transferred money from Australia to the Philippines between January 2006 and February 2019, were identified by AUSTRAC. The same procedure was then undertaken as with the CSA live streaming group, with the data linked to criminal histories by ACIC, before being provided in a de-identified format to the Australian Institute of Criminology. This process resulted in complete data for a total sample of 209 individuals who had transacted with facilitators of CSA live streaming, and a comparison group of 10,007 individuals, who had sent 288,587 transactions, none of which had been identified as going to facilitators of CSA.

Figure 1: Distribution of year of birth for those who transacted with facilitators of live streaming of child sexual abuse, and the matched comparison group (% of sample)



Note: The CSA live streaming group and the comparison group had the same age distribution due to the matching criteria
Source: Philippines CSA live stream financial transaction and comparison dataset

Measures

This research aimed to develop financial risk indicators identifying those who transact with facilitators of CSA live streaming. Importantly, there were several comparable variables across both groups, including the largest value sent in a single transaction, the smallest value sent in a single transaction, the total number of transactions processed, the average value of all transactions, the total value of all transactions, and the age of the individual at the time of their first transfer. These characteristics were included as independent variables for analysis, with the outcome variable whether an individual had transacted with a known facilitator of CSA live streaming. Each of these characteristics related only to transactions made from Australia to the Philippines, regardless of the payment service used to process the transaction. Every individual included for analysis had made at least one transaction sending money from Australia to the Philippines between January 2006 and February 2019.

Analytical approach

This research sought to develop a model capable of identifying individuals who were procuring CSA live streaming and individuals who were not, in a sample of more than 10,000 individuals, only using the details of their financial transactions. To do this, we computed a prediction model using machine learning methods, an analytical approach which is particularly good at making accurate predictions using very large and complex datasets. We first produced the machine learning model, known as the random forest, and we then measured how accurately that model performed at predicting which individuals did and did not transact with CSA live streaming facilitators. Next, given the performance of the model, we used post-hoc tests to identify the financial characteristics most useful in making good predictions, and present them as financial risk indicators. Full detail of the modelling procedure follows.

This was a very difficult classification task; the data were significantly imbalanced, with more than 10,000 cases who were not identified as transacting with CSA live streaming facilitators and 209 cases who were. It could have been possible to synthetically inflate the number of cases in the data who had transacted with a CSA live streaming facilitator, but for this research we preferred for the task to be analytically difficult as it better reflected the detection environment—there are many more people in banking data who do not pay to view CSA live streaming than do. To demonstrate the capacity of this modelling procedure to find a 'needle in a haystack', the data were retained as they were available, rather than being synthetically manipulated. This meant that randomisation needed to be effective. As a first step, data were randomised and partitioned into a 70 percent training set and a 30 percent test set. These splits were validated to ensure the distribution of CSA live streaming cases between the groups was correct. The random forest algorithm was trained on the larger set and the model was tested using the partitioned test set (Hyndman & Anthanasopoulos 2014).

A receiver operating characteristic (ROC) curve was used to determine the robustness of the random forest model. A ROC curve plots the true positive rate of classification, referred to as sensitivity (y-axis) compared with the false positive rate, equal to 100 minus the specificity (x-axis) at any threshold value. The area under the receiver operating characteristic (AUROC) curve was then calculated to provide an overall measure of performance, or model accuracy. As a validation exercise, we compared the AUROC for the random forest to the AUROC for a logistic regression model to measure whether the random forest outperformed the logistic regression. We then implemented a bootstrap test for statistical significance between ROC curves to determine whether the differences between the predictive accuracy of the models were statistically significant.

To find the most robust modelling approach, hyperparameters of the random forest model were tuned to optimise iterations and variables randomly considered at each split. When optimising the random forest, model performance will typically plateau as the ntree parameter (number of trees) reaches several hundred iterations (Couronné, Probst & Boulesteix 2018). In the present research, model performance was optimal at ntree=5,000, with five features randomly selected at each split. We then reported the out-of-bag error estimate, which describes the aggregate error of the random forest on the training set (Schonlau & Zou 2020). The random forest is interpreted through the mean decrease Gini coefficient (Hong, Xiaoling & Hua 2016), which provides the proportion of the model accounted for by each variable. The higher the mean decrease Gini, the more important the variable in predicting CSA live streaming. A confusion matrix was then computed to determine the accuracy of the random forest predictions in the test set. The confusion matrix compares the predictions to observed outcomes to measure the performance of the trained model on the test set, providing a metric of how often the model successfully or unsuccessfully made predictions (Barnes & Hyatt 2012).

Finally, post-hoc partial dependence plots (PDPs) were computed for independent variables (Zhao & Hastie 2021) to provide the effect within variables. PDPs show the association between particular characteristics within variables, and CSA live streaming. The y-axis of PDPs represents the logit value associated with different points within the range of a variable, identifying where the relationship with CSA live streaming transactions is strongest (at the highest point in the plots) and weakest (at the lowest point in the plots).

Analysis was performed using the 'randomForest', 'dplyr', 'pRoc', 'pdp' and 'ggplot2' packages of the statistical analysis software R Studio. The model was trained on individuals who procured live streaming of CSA.

Limitations

While we can be certain that these transactions involved money being sent to known facilitators of CSA live streaming, we cannot be sure 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, given the receivers of money were arrested for facilitating the sexual exploitation of children (Brown, Napier & Smith 2020). Additionally, the data considered here relate to a single law enforcement operation in the Philippines, making this a type of within-groups analysis. It is unclear whether individuals in this dataset, and therefore the resulting findings, are representative of live streaming offenders more broadly. While those in the comparison group were not detected transacting with facilitators of CSA live streaming, it is possible that they interacted with facilitators who were not detected. Finally, while we matched the comparison data on available variables, there were limitations to our ability to match beyond the three factors used. Additional demographic characteristics relating to CSA live streaming offenders would likely have improved the accuracy of matching, but given the volume of data it is unlikely that this would have meaningfully influenced the findings.

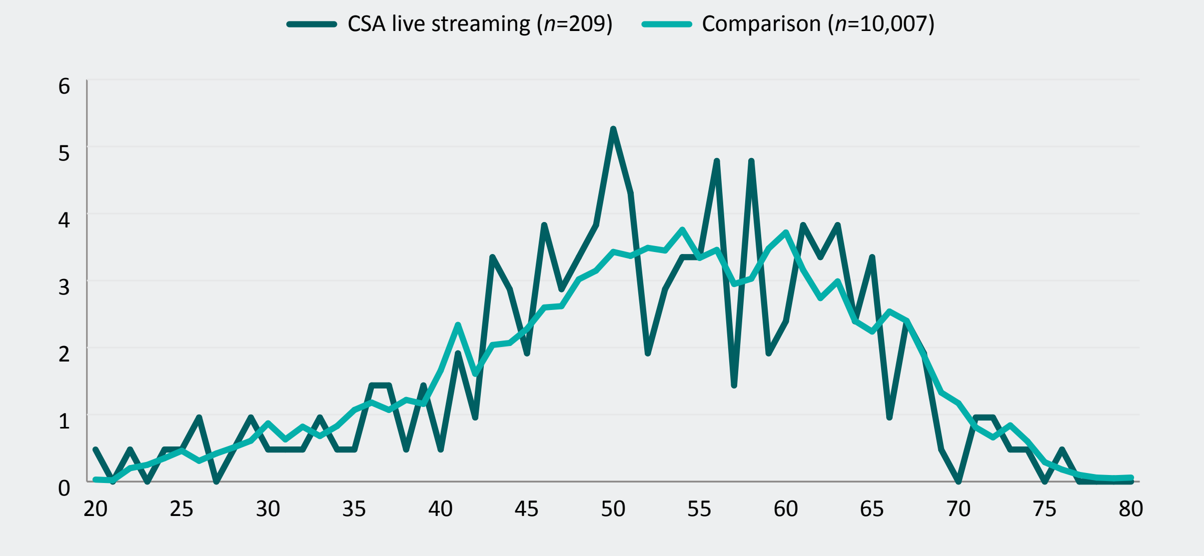
The results presented here are intended as a proof of concept for how financial transactions can be analysed to identify CSA live streaming offenders. However, given the noted limitations, as we progress further from the date of data collection, their usefulness as operationalisable risk indicators may be limited.

Results

We first compared the available summary statistics for the group who had transacted with a facilitator of CSA live streaming, and the comparison group. Notably, the age distribution of the onset of transactions was similar for both groups (Figure 2). In other words, whether or not these individuals were transmitting money from Australia to the Philippines to procure live streaming of CSA, the proportions of the sample who began transacting at each age were similar.

It is important to note that, due to the matching criteria used to develop these samples, more than half of each group were born between 1937 and 1960, meaning they were between the ages of 46 and 69 years old at the beginning of the observation period. Since the observation period spanned 13 years, these individuals would have been between 59 and 82 years old at the end of it. The matching criteria therefore likely influenced the onset age of transactions among both groups to be older, and the onset opportunity to be within the 13 years from their age in January 2006. However, this does not dictate that the aggregate onset age for the two groups must be similar. It is therefore noteworthy that the average age at which individuals processed the first transaction to a live streaming facilitator was 52.2 years, while among the comparison group the average age of first transaction from Australia to the Philippines was 52.7 years.

Figure 2: Age of onset of transactions among those who transacted with facilitators of CSA live streaming, and the matched comparison group (%)



Source: Philippines CSA live stream financial transaction and comparison dataset

There were five transaction characteristics available for analysis in each group (Table 1). The average transaction value for procuring CSA live streaming was notably smaller than the average transaction value among the comparison group (A$113 vs A$737). On average, the CSA live streaming group made 12 transactions, while the comparison group made 29. The largest (A$236 vs A$2,072) and smallest (A$54 vs A$385) amounts spent in a single transaction tended to be smaller among the CSA live streaming group. Finally, the aggregate value of all transactions tended to be smaller among the CSA live streaming group than the comparison group (A$2,870 vs A$16,143).

Table 1: Average financial transaction characteristics

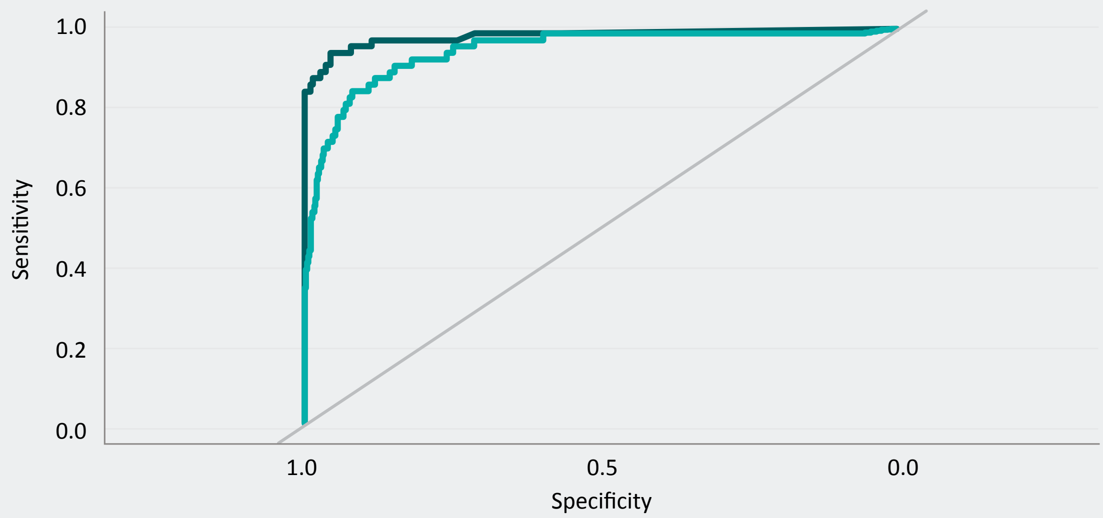
	CSA live streaming (*n*=209)	Comparison (*n*=10,007)
Transaction value (A$) (range)	113 (12–6,745)	737 (4–211,016)
Number of transactions (range)	12 (1–479)	29 (1–1,382)
Most spent in a single transaction (A$) (range)	236 (12–9,975)	2,072 (4–349,991)
Least spent in a single transaction (A$) (range)	54 (1–1,306)	385 (1–211,016)
Collective total of all transactions (A$) (range)	2,870 (12–119,151)	16,143 (4–5,330,469)

Source: Philippines CSA live stream financial transaction and comparison dataset

Random forest

The AUROC of 0.976 identified that this was a robust model (see Figure 3). The same data were then used to compute a logistic regression, resulting in an AUROC of 0.937. A bootstrap test for statistical significance between ROC curves found that the random forest returned a significantly greater rate of prediction than the logistic regression ($p<0.001$). Of note, we also undertook the same modelling procedure with linked criminal histories for each group included, but the additional data produced only marginally improved accuracy.

Figure 3: ROC curve for random forest (dark green) and logistic regression (bright green)



Note: Random forest AUROC=0.976; logistic regression AUROC=0.937

Source: Philippines CSA live stream financial transaction and comparison dataset

The random forest returned an out-of-bag error estimate of 1.31 percent; a confusion matrix was then produced to consider the distribution of prediction accuracy (Table 2). The aggregate classification error closely mirrored the out-of-bag estimate, at 0.13 percent. The rate of false positives was 22.73 percent, while the model had a false negative rate of 0.01 percent. Further, the model failed to predict only 0.003 percent of true negatives, and the error rate for true positives was 46.03 percent. This finding suggests that around half of those identified by the modelling procedure as transacting with facilitators of CSA live streaming were not.

It is important to note that the sample of CSA live streaming offenders accounted for 2.06 percent of the total sample considered. As a result, if a naïve estimate were to be made that every individual in the total sample did *not* transact with a facilitator of CSA live streaming, it would result in a classification error of 2.06 percent. In other words, such a guess would accurately predict everyone who did not transact with a facilitator of CSA live streaming, and fail to predict everyone who did. It is therefore pivotal that our model significantly outperformed this naïve estimate, producing an aggregate classification error of 0.13 percent. While our model accurately predicted which individuals transacted with facilitators of CSA live streaming a substantial proportion of the time, it almost always correctly predicted which individuals did not transact with facilitators.

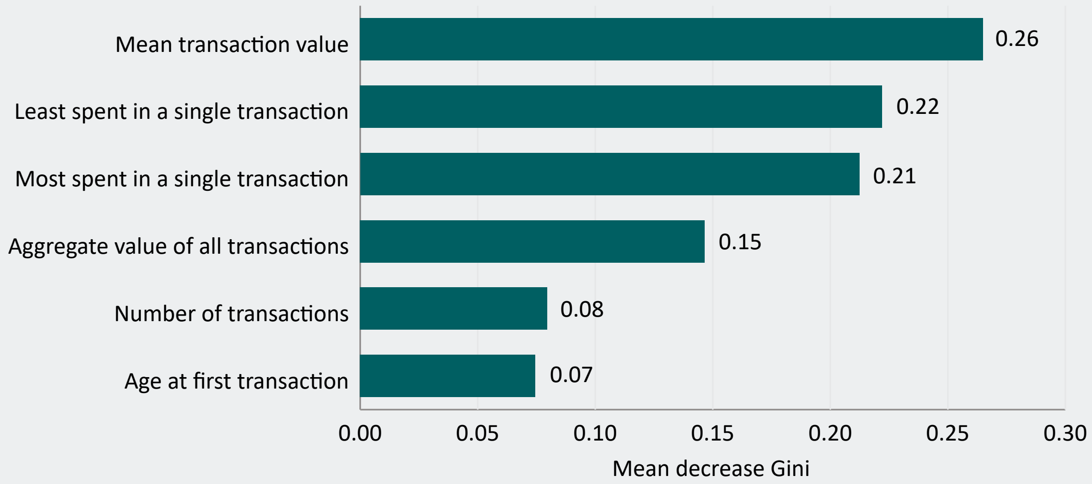
Table 2: Confusion matrix for random forest model trained on individuals who transacted with facilitators of live streaming of child sexual abuse

		Actual CSA live streaming offender?		Classification errors
		No	Yes	
Predicted CSA live streaming offender (*n*)	No	2,992	29	0.010%
	Yes	10	34	22.727%
Classification errors		0.003%	46.031%	0.127%

Source: Philippines CSA live stream financial transaction and comparison dataset

Of the six variables used in the modelling process, the five relating to transaction values contributed the greatest power to the predictive model (see Figure 4). The mean transaction value of each individual within these data, the least spent in a single transaction, and the most spent in a single transaction, were the three most important pieces of information in making these predictions. Next most important was the aggregate value of all transactions, while the raw number of transactions made from Australia to the Philippines, and the age of an individual at the time of their first transaction were least important to the predictive power of the model.

Figure 4: Variable importance associated with live streaming of child sexual abuse



Source: Philippines CSA live stream financial transaction and comparison dataset

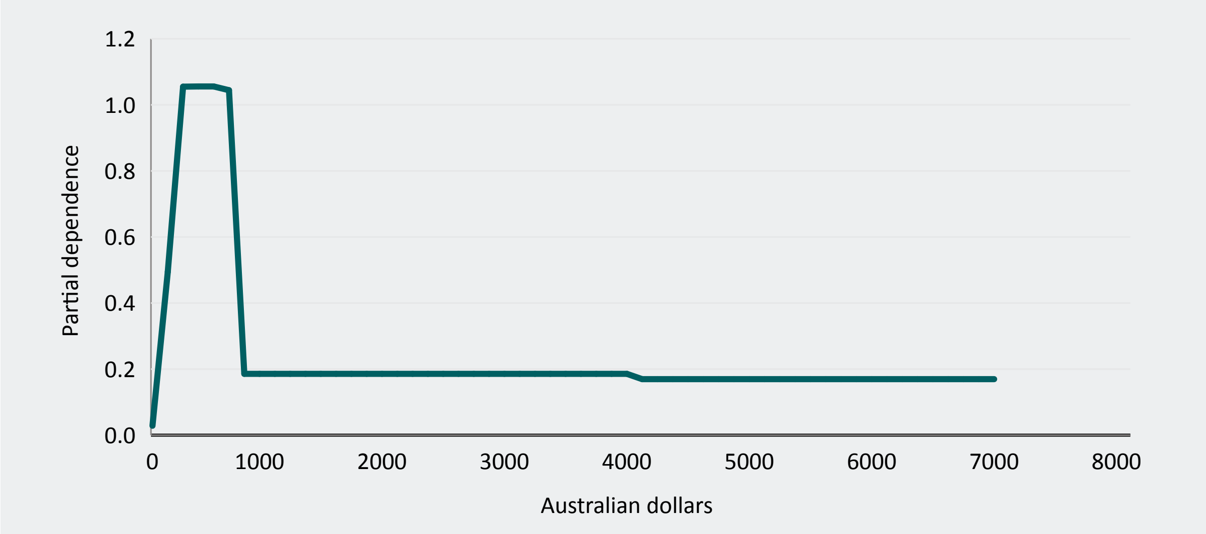
Partial dependence

We then computed PDPs to find the association with CSA live streaming transactions within each individual variable. In Figures 5 to 10, the point at which the chart peaks demonstrates the strongest relationship with CSA live streaming transactions, or the point of greatest risk, and the lowest point of each chart represents the point at which the interaction is weakest.

Average value of transactions

The average transaction value was the most important variable in the classification rate produced by the random forest. That is, it contributed the largest amount of predictive power in identifying who did and who did not transact with CSA live streaming facilitators. A PDP was computed to identify the point within this variable most associated with individuals who transacted with CSA live streaming facilitators. Figure 5 suggested that individuals with an average transaction value of between A$300 and A$600 across all of their transactions were most associated with CSA live streaming.

Figure 5: Average transaction value associated with live streaming of child sexual abuse (A$)

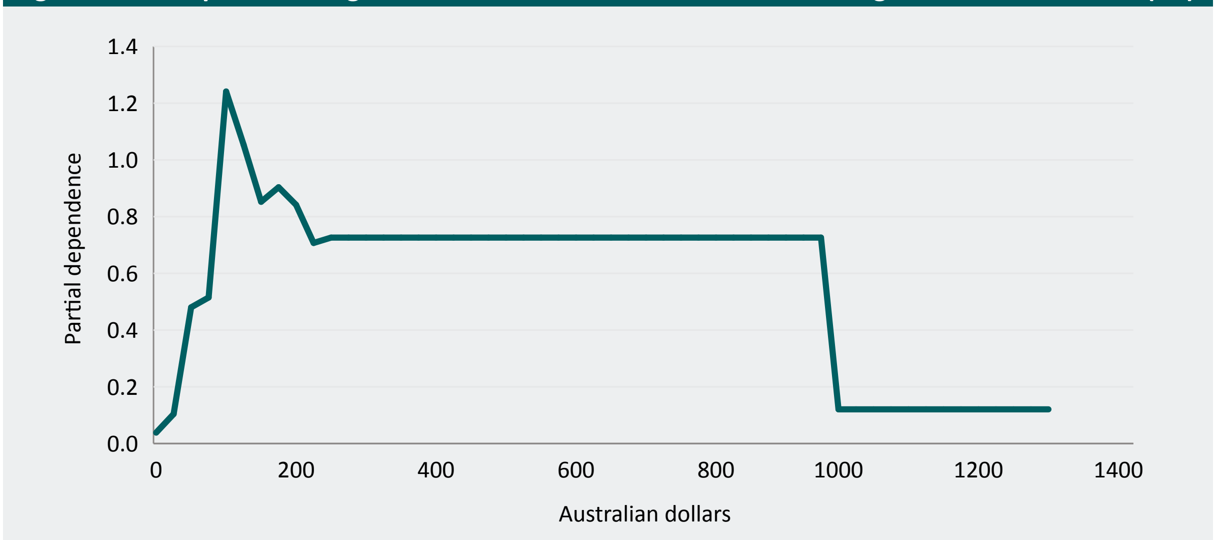


Source: Philippines CSA live stream financial transaction and comparison dataset

The smallest and largest transactions

For each individual in these data, we analysed the smallest and largest transactions. Figure 6 reflects the relationship between smallest amount sent and whether an individual transacted with a facilitator of CSA live streaming. The smallest transaction having a value between A$50 and A$200 held the strongest association with an individual transacting with a facilitator, but it is important to note that this variable featured a long tail, with some degree of relationship up to A$950.

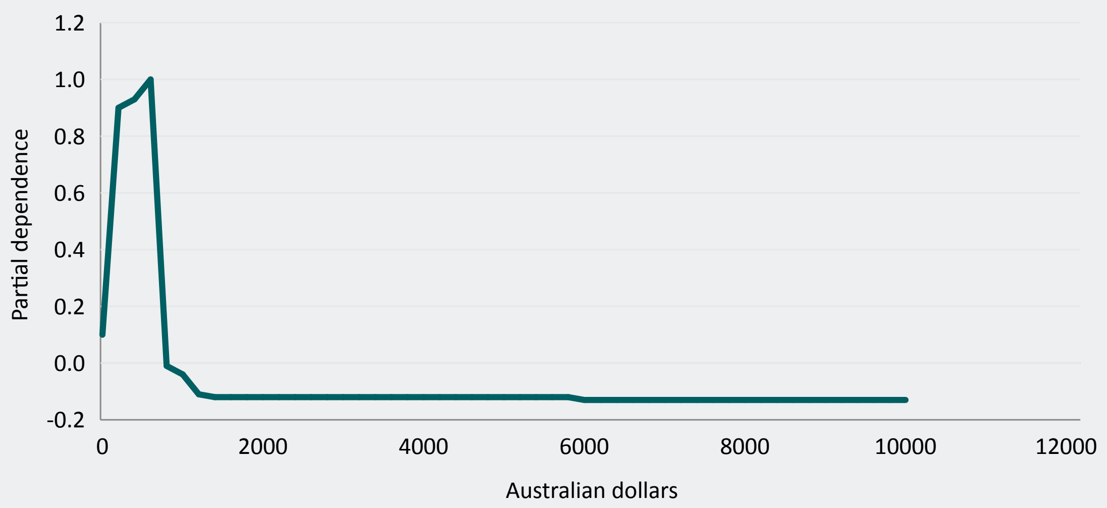
Figure 6: Least spent in a single transaction associated with live streaming of child sexual abuse (A$)



Source: Philippines CSA live stream financial transaction and comparison dataset

Taking the value of the largest amount sent to the Philippines by each individual in the data, we then computed a PDP investigating its association with transacting with facilitators of CSA live streaming (Figure 7). Compared with the findings for the minimum spent, this variable indicated a smaller range with an identifiable association. The relationship was strongest when the largest transaction value was between A$200 and A$600. Importantly, after this point the relationship was inverse, meaning that those who made at least one transaction worth at least A$1,000 were less likely to be procuring CSA live streaming.

Figure 7: Most spent in a single transaction associated with live streaming of child sexual abuse (A$)

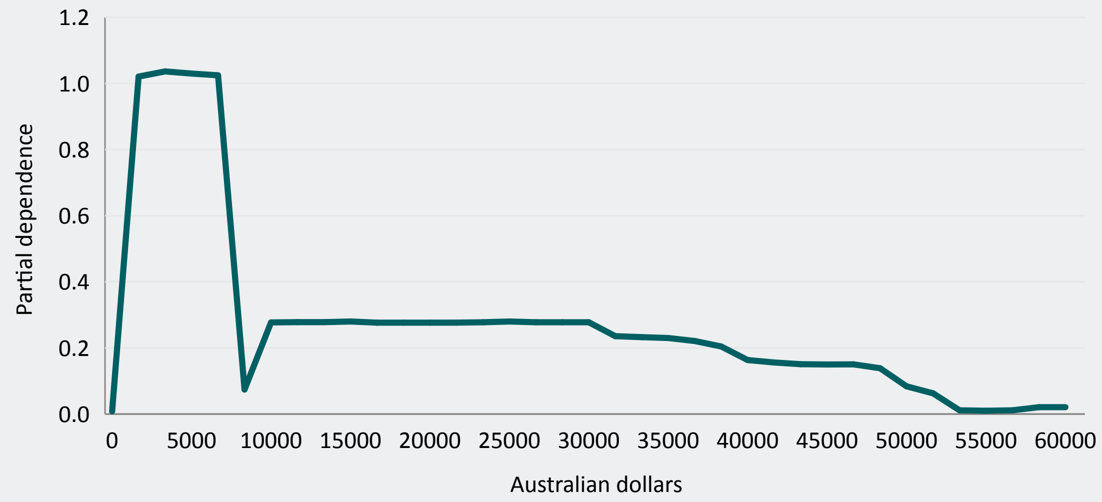


Source: Philippines CSA live stream financial transaction and comparison dataset

Total value of all transactions

A PDP was then produced reflecting the relationship between the total value of all transactions made by each individual in these data, and transacting with a facilitator of CSA live streaming (Figure 8). This relationship was strongest among individuals who had, in total, sent between A$2,000 and A$6,000 from Australia to the Philippines. Importantly, among those who sent more than A$10,000, the relationship was weak; these individuals were unlikely to be transacting with facilitators of CSA live streaming.

Figure 8: Total amount of money sent associated with live streaming of child sexual abuse (A$)

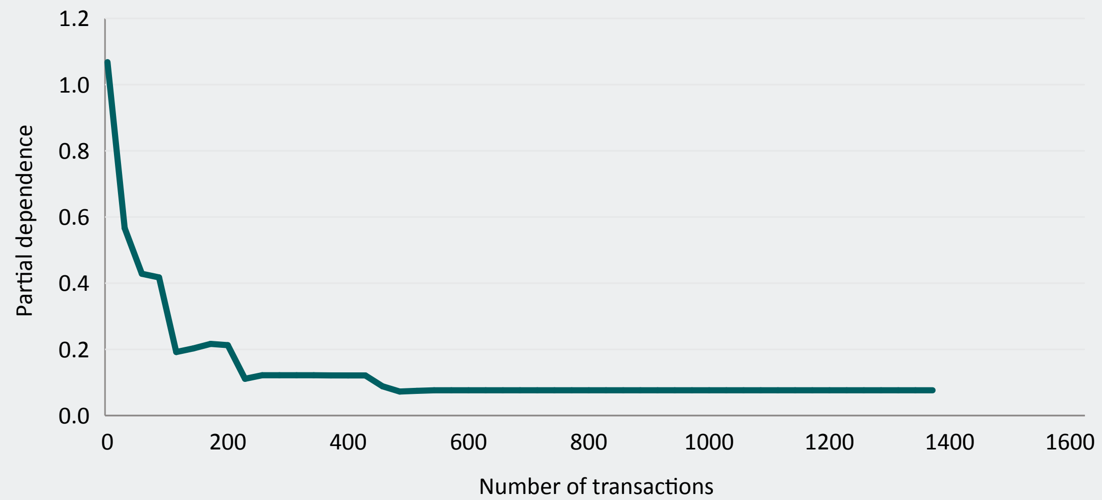


Source: Philippines CSA live stream financial transaction and comparison dataset

Number of transactions

The relationship between the raw number of transactions made and transacting with a facilitator of CSA live streaming was then considered. Figure 9 suggests that individuals who made fewer transactions were more likely to be transacting with a facilitator of CSA live streaming. In particular, those who processed fewer than 30 transactions were most likely to do so, and this interaction diminished as the number of transactions increased. Ultimately, those who had sent money from Australia to the Philippines more than 90 times were notably less likely to be transacting with a facilitator of CSA live streaming.

Figure 9: Number of transactions associated with live streaming of child sexual abuse

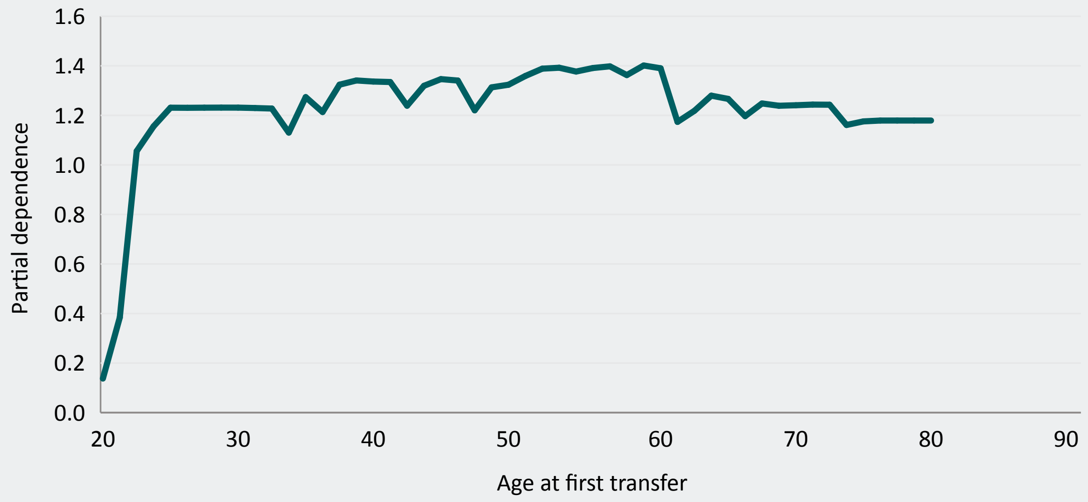


Source: Philippines CSA live stream financial transaction and comparison dataset

Age at the time of first transaction

The final variable included in the model was the age at which an individual made their first transaction. This variable contributed the least power to the classification model and, on producing the PDP in Figure 10, it was clear this was because a range of ages held a relationship with transacting with a facilitator of CSA live streaming. However, it was clear that people under the age of 25 were unlikely to be transacting with facilitators, and those most likely were between the ages of 50 and 60.

Figure 10: Age at onset of CSA live streaming transactions (years)



Source: Philippines CSA live stream financial transaction and comparison dataset

Discussion

This study undertook a 'needle in a haystack' task, using a machine learning approach to develop a proof of concept model for identifying CSA live streaming offenders, with considerable success. It is important to note that a model that naïvely predicted, or guessed, that not one of the 10,216 individuals in our sample was a CSA live streaming offender would fail to predict the outcome only 2.06 percent of the time. The present model significantly outperformed this naïve prediction, producing an aggregate error rate of only 0.13 percent. While this model was extremely good at identifying individuals who did not transact with facilitators of CSA live streaming, it also performed well at identifying those who did.

When designing interventions, it is pivotal that the model performs at least as well at identifying those who are unlikely to be transacting with facilitators as those who are. The present model only failed at this task in 0.003 percent of cases. While it was designed as a proof of concept, this finding suggests that, if such an approach were to be implemented as a part of a detection or intervention exercise, only a small number of people who did not require the intervention could be expected to receive it.

This research isolated a series of characteristics indicative of an individual transacting with a facilitator of CSA live streaming. Importantly, this type of modelling does not intend to reflect the patterns within the financial transactions used to procure CSA live streaming as explored by Brown, Napier and Smith (2020). Rather, it finds the factors that collectively predict the largest proportion of CSA live streaming offenders possible. Table 3 consolidates these findings into financial risk indicators. None of these indicators should function independently of the others, but collectively they indicate a high probability of CSA live streaming. Our analysis suggests that individuals who send money from accounts in Australia to the Philippines and whose transactions meet the specifications in Table 3 represent a risk of procuring CSA live streaming.

Table 3: Financial risk indicators for individuals transacting with facilitators of child sexual abuse live streaming
Average transaction value per individual of less than A$600
Smallest transaction value per individual between A$50 and A$200
Largest transaction value per individual between A$200 and A$600
Very unlikely to make individual transactions worth A$1,000 or more
Total value of transactions per individual between A$2,000 and A$6,000
Very likely to process fewer than 30 transactions
Very unlikely to be 25 or under at the time of first transaction, most likely to be between the ages of 50 and 65

Note: 'Transaction' refers to money sent from Australia to the Philippines

It is important to reiterate that, when the factors listed in Table 3 co-occur, the likelihood of CSA live streaming is considerable. For example, the average transaction value for live streaming offenders is known to be relatively low (Brown, Napier & Smith 2020), a finding also reflected in Table 1 and Figure 4. As a standalone measure, average transaction values could only assist to predict a small number of CSA live streaming cases (see Figure 3). However, when cases were assessed as meeting the sequence of indicators in Table 3 in totality, the likelihood of successfully predicting CSA live streaming was high. Furthermore, intelligence-based law enforcement reports may yield individual indicators for CSA live streaming transactions that differ to those presented here, given the present type of modelling is rarely used in this context. However, AUSTRAC (2022) reported that CSA live streaming transactions are usually less than A$500, which is similar to the average transaction value presented in Table 3.

Implications and limitations

As a proof of concept, this model performed exceptionally well, providing evidence that it may be possible to predict CSA live streaming offenders using financial transactions data. It is possible that, in collaboration with law enforcement and regulatory agencies, a model such as this could be developed to detect suspicious transactions for further investigation. When cases met the risk criteria, investigations could be supported by existing financial intelligence holdings and, where appropriate, could lead to downstream intervention with offenders. This type of approach could also be used for real-time monitoring of suspicious transactions, assisting in identification, referral and investigation procedures. The performance of this proof of concept model supports consideration as an approach to assist the detection and triage of cases.

However, there are also several limitations to this research. While the model demonstrated success in making predictions, the data were current up to 2019. It is possible that the CSA live streaming environment has changed in the intervening time, meaning our model is less useful. For this reason, we suggest that it is a proof of concept rather than an implementable procedure. If this model were to be implemented, it must first be either validated or reproduced with contemporary data. Further, while the model very rarely predicts that someone has procured live streaming of CSA when they did not (in just 0.003% of cases), it only successfully identifies 54 percent of offenders. For every individual found to be procuring live streaming of CSA, the model misses another such individual. Put another way, the model successfully finds about half the needles in the haystack.

Finally, while our research focuses on the Philippines, CSA live streaming is not restricted solely to this region. Rather, any country which experiences elevated rates of poverty coinciding with high-speed internet appears to be vulnerable to facilitation of CSA live streaming. It is possible that the characteristics of these offences occurring in other parts of the world could be different to those we have observed. Separately, the increasing potential use of cryptocurrency to procure CSA live streaming offences is noteworthy. We do not yet know if the financial values observed in this study translate to instances where cryptocurrency is used to procure offences. While we are unable to make this assessment using the present data, future research should seek to understand the role of cryptocurrency in supporting these offences, and whether the type of currency influences the trends in procuring offences.

Conclusion

Risk indicators may hold important potential as a tool for identifying high-risk individuals and cases which need further investigation to determine if CSA live streaming has occurred. Our findings suggest this may be possible, with very few false positives—avoiding misidentification of those who are not involved in this type of offending. This proof of concept model offers support for an approach to targeting individuals who have previously operated with a significant degree of impunity, ultimately reducing some of the harm caused to children through live streamed CSA.

Acknowledgements

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