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Prolonged school closure during the pandemic time in successive waves of COVID-19- vulnerability of children to sexual abuses – A case study in Tamil Nadu, India

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ABSTRACT

Objectives: The Tamil Nadu government mandated several stay-at-home orders, with restrictions of varying intensities, to contain the first two waves of the COVID-19 pandemic. This research investigates how such orders impacted child sexual abuse (CSA) by using counterfactual prediction to compare CSA statistics with those of other crimes. After adjusting for mobility, we investigate the relationship between situational factors and recorded levels of cases registered under the Protection of Children from Sexual Offences Act (POCSO). The situational factors include the victims' living environment, their access to relief agencies, and the competence and responsiveness of the police.

Methods: We adopt an auto-regressive neural network method to make a counterfactual forecast of CSA cases that represents a scenario without stay-at-home orders, relying on the eight-year daily count data of POCSO cases in Tamil Nadu. Using the insights from Google's COVID-19 Community Mobility Reports, we measure changes in mobility across various community spaces during the various phases of stay-at-home orders in both waves in 2020 and 2021.

Results: The steep falls in POCSO cases during strict stay-at-home periods, compared with the counterfactual estimates, were −72% (Cliff's delta −0.99) and −36% (Cliff's delta −0.65) during the first and second waves, respectively. However, in the post-lockdown phases, there were sharp increases of 68% (Cliff's delta 0.65) and 36% (Cliff's delta 0.56) in CSA cases during the first and second waves, with concomitantly quicker reporting of case registration.

Conclusions: Considering that the median delay in filing CSA complaints was above 30 days in the mild and post-intervention periods, the upsurge of cases in the more relaxed phases indicates increased occurrences of CSA during strict lockdowns. Overall, higher victimization numbers were observed during the prolonged lockdown-induced school closures. Our findings highlight the time gap between the incidents and their registration during the strict lockdown phases.

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Abbreviations

CSA	Child Sexual Abuse
FIR	First Information Report
MIP	Mild Intervention Period
POCSO	The Protection of Children from Sexual Offences Act 2012
Post-IP	Post Intervention Period
SAH	Stay at home
SIP	Strict Intervention Period

1. Introduction

The COVID-19 pandemic has impacted every conceivable aspect of human life. The disease has been ruthless and devastating, claiming the lives of over five million people in the last two years and pushing humanity to the brink of despair. The pandemic wrecked most countries' social and economic fabric, causing extensive unemployment and driving almost half a billion people into undernourishment and extreme poverty [1]. Governments worldwide implemented movement-restricting lockdown orders, ranging from strict intervention periods (SIP) to mild intervention periods (MIP), to contain the spread of the infection. The impact of these restrictions on criminal activities varies across different categories of offences, as well as geographical and demographic spaces. Property offences and violent crimes either decreased or stayed unaffected in most areas during this period [2].

However, an upsurge was reported in specific other crime categories in several regions. In particular, cybercrimes, economic offences, intimate partner violence, and child abuse exhibited an upward trend in most countries [3,4]. This study looks closely at one such crime category, child sexual abuse (CSA). First, we attempt to understand the broader context by studying the worldwide trends noticed in the maltreatment of children due to the impact of the COVID-19–induced lockdown. Next, we focus on analyzing the statistics and trends of CSA in Tamil Nadu, India, covering the pre-pandemic period and the various phases of stay-at-home orders in 2020 and 2021. The geographical and social context of the study makes it particularly significant because certain distinctive cultural and traditional practices and demographic factors, such as living in joint families and rural societies, continue to characterize India. For instance, cases of child marriage and persons involved in consensual sexual relationships with minor girls who promise to marry them are also registered as cases under the Protection of Children from Sexual Offences Act 2012 (POCSO). Three generations living under one roof, while prevalent in Indian households, is uncommon in most other countries. Due to movement restrictions and school closures over nearly two years, children were confined to a shared space with their immediate and sometimes extended family, making children and their spaces more vulnerable to abuse.

2. Literature review

A thorough literature survey reveals that while most regions worldwide reported sharp escalations in cases of child abuse and maltreatment, a few witnessed reductions in these offences. Studies seem to indicate that the declining trend was more due to the failure of the detection and reporting mechanisms of CSA rather than actual reductions in their occurrences. Aside from educational institutions, there is a multitude of other contextual factors that are responsible for the significant drop in recorded CSA levels. Advocacy groups, non-profit organizations, voluntary agencies, government agencies, and departments responsible for child welfare and protection are some of the formal mechanisms that help survivors of CSA file complaints. These institutions, along with law enforcement agencies and health and allied services, were preoccupied with pandemic-related work, which limited their ability to provide relief, rehabilitation, and legal assistance to such children. Educational institutions, which serve as critical community partners in detecting and reporting CSA instances, were closed, resulting in an erroneously supposed decline in child maltreatment cases [5]. Approximately 20% of the reported cases usually come from the designated persons in these educational institutions [6]. And when schools are not in session, cases of child maltreatment are more likely to go unnoticed and, by default, unreported [7]. While these researchers acknowledge that school closures might have been an effective strategy to halt the spread of the virus, they also recommend that policymakers consider the under-reporting of CSA when evaluating the cost-benefit analysis of reopening schools. Another study reported that Canadian healthcare workers who were actively involved in pandemic-related work were not given adequate education that could equip them to recognize and respond appropriately to cases of child maltreatment [8]. One study, based on a retrospective review (March 2017 to December 2020) of patients of all ages presented to a paediatric emergency trauma centre in the city of Orange, California, reported an increase in the frequencies of non-medical and medical neglect. However, the rates of physical abuse and sexual abuse showed declines [9].

There is sufficient literature that directly or indirectly signals an escalation of child maltreatment worldwide during pandemic-induced movement restrictions. A study in Kenya revealed that younger children were more likely to be abused by neighbours in private residences during the daytime than at night. It recommended alternative shelters and surveillance for these vulnerable children as schools were closed during the pandemic [10]. Another study in Kenya revealed that during the pandemic, children were more likely, when compared to adults, to be vulnerable to sexual assault by a single perpetrator rather than multiple perpetrators, during the daytime rather than night, and at private places rather than public, open spaces. Further, in terms of age, the victims were younger by four years compared to pre-pandemic figures. Most of these instances were amongst families with "low affluence and prior history of abuse" [11]. In a study of the Florida foster care system, researchers observed that contrary to earlier research findings of decreased reports of child maltreatment during the pandemic, there was a substantial increase in child maltreatment among white youths in foster care. However, there was some reduction in certain aspects of child maltreatment of Black youths [12].

Original research articles that use primary data to study the impact of the COVID-19 pandemic on CSA in India are almost non-existent in peer-reviewed journals. One study reported a massive spike of CSA reports in CHILDLINE calls based on newspaper and media sources. The reasons behind the recorded escalation are several, including offenders' frustration at being confined indoors, unemployment, poverty, and the mental health of poor parents [13]. A UNICEF case study indicated that the number of distress calls increased by 50% within ten days of the imposition of the lockdown [14]. The victims were generally from the underprivileged sections of society, and many offenders were committing incestuous acts. These occurred as the enforced lockdowns made children's homes and other living spaces susceptible to incidents of CSA.

India's sizeable child population is perceived as a nation severely afflicted by CSA [15,16]. This perception is based on data from before the COVID-19 pandemic when there was no additional stress or strain due to lockdown-induced lifestyle or movement restrictions declines. However, during the pandemic, humanity had to negotiate an unprecedented crisis, overwhelmed by the general unpredictability and uncertainty in various areas of life.

This study investigates the impact of Tamil Nadu Government-mandated stay-at-home orders on counts of recorded CSA. To this end, our research utilizes actual data from police stations to assess the true impact of the pandemic on children who were sexually abused in Tamil Nadu. Considering the stay-at-home orders introduced to curb the spread of COVID-19 and their consequential changes to permitted mobility across different sectors is essential. Mobility in the residential sector is particularly crucial in the context of CSA, which is mainly committed inside children's homes. The study hypothesizes that mandated lockdowns that require people to remain indoors will result in an increase in child sexual abuse.

CSA crime trends in Tamil Nadu are analyzed using auto-regressive neural networks to predict the counterfactual daily count of CSA cases to determine causal inference. The study also investigates delays in registering offences at the state and district/city levels. The research highlights the wide gaps between the actual occurrence of CSA and the registration of the offence, especially during pandemic-induced lockdowns.

3. Data

Tamil Nadu is the sixth most populous of India's 28 states, with around 79 million people (almost double the population of California). It is spread over 130,000 sq. Km, equivalent to half the size of the United Kingdom. Tamil Nadu is the second most economically prosperous state in the country. It has 38 districts and seven cities, which are used as units for studying sub-population trends in CSA cases. People below 18 years of age constitute about 30% of the population. The estimated literacy rate of the state is around 87% as of 2021. Tamil Nadu is one of a few states to achieve a 100% net enrolment ratio in primary education. This ratio is the percentage of children enrolled in primary schools (standards 1 to 5) aged 6+ to 10+ [17].

The Tamil Nadu government's policy measures were primarily aimed at containing the rate of infection and fatality of the COVID-19 pandemic during the first two waves in 2020 and 2021. At the start of the pandemic, it enforced strict stay-at-home orders (a strict intervention period), during which there was a complete ban on vehicular and human movement. Certain exceptions were given to vehicles meant to supply essential commodities and services. Small windows of a few hours were also provided for the general public to purchase essential items. This was followed by more relaxed stay-at-home orders or a mild intervention period, which allowed people to access more services and open specific industries and institutions with minimal employees. These stay-at-home orders impacted mobility in different spheres of human activity to varying degrees.

3.1. Cross-sectional data of POCSO cases registered in districts/cities

In order to understand the nuances of this domain, it is imperative to look at the historical data that illuminates essential attributes of the crime. Data on the basic details of every crime registered under the POCSO Act 2013 and investigated from 2013 were collected from select districts and cities. This also enabled the researchers to understand extant urban-rural differences, if any. The attributes of the cases that have been studied include the age and gender of the perpetrator and the victim, whether the offender is known to the victim or not, the date, time, and place where the crime occurred, and the date of its report, in order to help ascertain the period of delay in reporting such crimes.

3.2. Crimes registered as First Information Report (FIR)-Time series data

The paper primarily relies on univariate time-series data for the state of Tamil Nadu. This pertains to the total cases registered daily under the Protection of Children from Sexual Offences Act, 2012 (POCSO) from January 1, 2013, to September 30, 2021, to analyze the impact of the closure of schools during the pandemic.

The univariate time series data is based on FIRs..[1] The police begin investigating a case only after an FIR is registered at a police

[1] First Information Report (FIR) is a written document prepared by the police when they receive information about the commission of a cognizable offence either from the victim or anyone else. It is a report of information that reaches the police for the first time; hence, it is known as a First Information Report (FIR). It sets the process of criminal justice in motion.

station. An FIR is a First Information Report, the document that forms the basis of an investigation. A complaint can be lodged online but may not be treated as an FIR. Most people lodge complaints at a police station in person to ensure prompt action. Our research focuses on CSA, the cases registered under the Protection of Children from Sexual Offences (POCSO) Act, 2012, form the central database of this study. This comprehensive law protects children from all kinds of sexual assault, sexual harassment, and pornography while ensuring the dignity and privacy of the child at every stage of the judicial process. As per the Act, a child is defined as a person below 18 years of age, and the penal provisions it outlines, including the death penalty, are designed as significant deterrents. The Act is gender-neutral, which has increased the scope of dealing with CSA. The expanded definition of sexual assault includes non-penetrative sexual assault and aggravated penetrative assault. It is important to note that the Act includes punishment for persons in positions of trust and authority, such as public servants, staff, employees of educational institutions, and police. It also includes provisions for mandatory reporting: a person who possesses knowledge of a child being sexually abused has a legal duty to report the offence, and failure to do so may invite imprisonment.

It is essential that a police officer, on receiving a complaint, makes immediate arrangements for the care and protection of the child, including medical treatment and placing the child in a shelter home if required. The child's medical examination has to be done with as little distress as possible in the presence of a person the child trusts. There are designated special courts for these offences, where in-camera trial proceedings are held without revealing the child's identity. Notably, in cases of aggravated forms of an offence committed by persons in authority, the offender may be sentenced to death.

As stated earlier, we classify the stay-at-home (SAH) orders issued by the Government in the years 2020 and 2021 into two categories: the strict intervention period (SIP), whose restrictions were severe and heavily impaired the mobility of people and vehicles, and the mild intervention period (MIP), which had some relaxations for select categories of people, goods, and services, and involved the gradual reopening of institutions. Stay-at-home orders were implemented differently during the first two waves. Schools remained shut during all phases of the lockdown between March 23, 2020, and October 30, 2021. However, higher secondary schools (from Grade 9 to Grade 12) were opened on September 1, 2021. The various phases of mandated stay-at-home orders are shown in Fig. 1.

3.3. *Mobility measured through Google Community Mobility Reports*

This study uses data from the Google Community Mobility Reports for two regions, namely, the state of Tamil Nadu and the city of Chennai, Tamil Nadu's capital and largest metropolitan area. The data's timespan covers the two pandemic years (2020 and 2021), which witnessed varying degrees of movement restrictions. There are six spatial domains, or categorized places, where the Google Community Mobility Report provides percentage changes in mobility from the baseline. These are Retail and Recreation, Parks, Transit Stations, Workplaces, Groceries and Pharmacies, and Residential. The data shows how the visitors to (or time spent in) the categorized places change compared to baseline days. A baseline day represents a *typical* value for that day of the week. The baseline day is the median value from the five weeks between January 3 and February 6, 2020 [18]. As we are interested in a comparative analysis of mobility in different periods, the lack of absolute numbers in terms of mobility does not pose a problem. Here again, we have univariate time-series data comprising a string of numbers, each of which is the percentage change in mobility from the baseline. We compute Cliff's delta as a measure of effect size to quantify the difference in mobility in the different comparison periods.

4. Method

Given the nature of time-series data, especially in child sexual abuse cases with enormous fluctuation in the daily count of crimes registered, an accurate forecasting model based on past observations has been a challenge to researchers and practitioners. While the decades-old conventional statistical tools have been reasonably accurate and consistent, the models become unstable, and their accuracy fails when encountering irregular and volatile data. Furthermore, most traditional forecasting methods provide only a point estimate of prediction, not a range of values with a confidence interval. In addition, the modeller has to intervene manually to specify the model's functional form and parameters.

To overcome these shortcomings, with the availability of computing power, we adopt an auto-regressive neural network to predict the daily count of CSA cases based on the model built with past data. We use an algorithm called DeepAR [19] that has met with tremendous success in various other fields, such as finance [20,21], supply chain management [22], speech recognition [23], language modelling [24] and generating text, video recognition and description [25].

In recent years, especially during the COVID-19 pandemic, the landscape of time-series forecasting in the various disciplines of social sciences has changed from conventional statistical methods to machine learning and deep learning techniques. These methods provide a range of predictions that raise the reliability level, and the model learns the parameters from a vast volume of data pertaining to past observations. The model does not assume the error term to be Gaussian and accommodates a wide range of continuous or discrete functions depending upon the nature of the input data.

4.1. *Auto-regressive recurrent neural network—DeepAR*

Let Z_{it} represent the t^{th} sample of the time series we aim to forecast, and $z_{t_1:t_2}$ be the series $z_{t_1}, \cdots, z_{t_2}$. The problem of forecasting is that of predicting $z_{t_{0+1}:T}$, given $z_{0:t_0}$ and any ancillary information $x_{0:T}$ that may be available.

The DeepAR model decomposes the *a posteriori* probability $P(z_{t_{0+1}:T} | z_{0:t_0}, x_{0:T})$ as

Fig. 1. Title: Stay-at-home orders timeline
Description: Timeline of various stay-at-home orders during both waves of COVID-19 in Tamil Nadu in 2020 and 2021. SIP: Strict Intervention Period; MIP: Mild Intervention Period; Post-IP: Post-Intervention Period.

$$P\left(z_{t_0:T}\middle|z_{0:\tau-1}, x_{0:T}\right) = \prod_{t=t_0+1}^{T} P(z_t|z_{0:t-1}, x_{0:T}), \tag{1}$$

and characterizes the individual terms on the right-hand side of Equation (1) as a parametric distribution:

$$P(z_t|z_{0:t-1}, x_{0:T}) \approx P(z_t; \theta_t). \tag{2}$$

The individual samples z_t are thus assumed to be drawn from the distribution $P(z;\theta_t)$, i.e. $z_t \sim P(z;\theta_t)$, as shown in Equation (2). Expressly, for counts data (such as for our crimes data), DeepAR assumes $P(z;\theta_t)$ to be a negative binomial distribution,

$$P(z;\theta_t) = \frac{\Gamma\left(z+\frac{1}{\alpha_t}\right)}{\Gamma(z+1)\Gamma\left(\frac{1}{\alpha_t}\right)}\left(\frac{1}{1+\alpha_t\mu_t}\right)^{\frac{1}{\alpha_t}}\left(\frac{\alpha_t\mu_t}{1+\alpha_t\mu_t}\right)^{z}, \tag{3}$$

In Equation (3), $\theta_t = [\alpha_t, \mu_t]$ is the scale parameter and mean of the predicted distribution of z_t, and $\Gamma(.)$ is the Gamma function. The DeepAR model models the series $\theta_0, \theta_1\cdots$ by a recurrent neural network (RNN).

An RNN is a class of artificial neural networks designed to model series data. It captures temporal dependencies in the series by introducing a recurrently computed latent variable, h_t. In the DeepAR model $\boldsymbol{h}_t$ is computed autoregressively as

$$h_t = h(h_{t-1}, [z_{t-l_1}, z_{t-l_2}, \cdots, z_{t-l_K}], x_t; \Theta) \tag{4}$$

where $z_{t-l_1}, z_{t-l_2}, \cdots, z_{t-l_K}$ represent K past samples from the series at lags $l_1, l_2, \cdots, l_K$ from the current instant t, and Θ represents the parameters of the network. Recurrence is obtained through the dependence of $\boldsymbol{h}_t$ on $\boldsymbol{h}_{t-1}$, and captures the larger temporal trends of θ_t. Autoregression is obtained through the dependence on z_{t-l_k}, and captures dependence on the *specific* past samples observed. The initial values $z_{-j}, j > 0$ and $\boldsymbol{h}_{-1}$ are generally set to 0.

θ_t is computed from $\boldsymbol{h}_t$ as

$$\theta_t = \log(1+\exp(h_t W_\theta + b_\theta)). \tag{5}$$

In the DeepAR model $h(\boldsymbol{h}_{t-1}, [z_{t-l_1}, z_{t-l_2}, \cdots, z_{t-l_K}], x_t;\ \Theta)$ is implemented as a multi-layer *long short-term memory* (LSTM) network

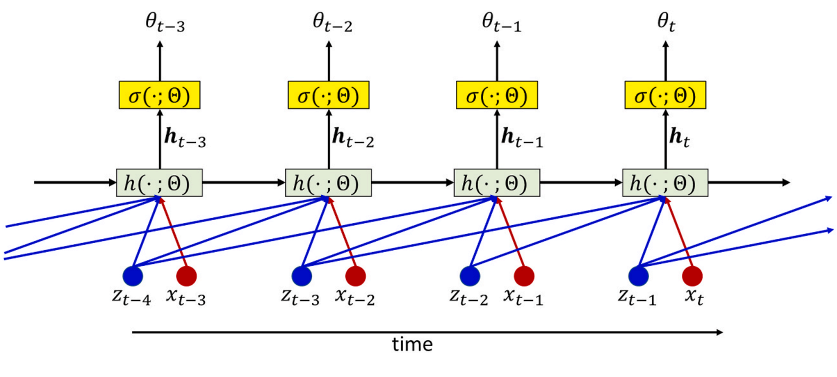

Fig. 2. Title: The DeepAR model
Description: The blue dots represent observations, and the red dots represent covariates. $h(\cdot;\ \Theta)$ represents the recurrent function of Equation (4). In this example, the model employs three autoregressive lags: $z_{t-1},\ z_{t-2}$, and z_{t-3}. $\sigma(\cdot;\ \Theta)$ represents the parameter estimation function of Equation (5). The model parameters Θ are learned to minimize the negative log-likelihood of the observation sequence given by Equation (6).

(Hochreiter & Schmidhuber, 1997). $\boldsymbol{W}_\theta$ and $\boldsymbol{b}_\theta$ too are part of the network parameters Θ. Fig. 2 below illustrates the model discussed.

4.1.1. Training the model

The model parameters Θ are estimated by optimizing a likelihood criterion. Given a set of training sequences $\{(z^n_{0:T_n}, x^n_{0:T_n}), n = 0, \cdots, N-1\}$ (here and below, n indexes the training instance, and N is the total number of training instances), we define a *loss* $\mathscr{L}(\Theta)$ as the negative log-likelihood

$$\mathscr{L}(\Theta) = -\sum_{n=0}^{N-1}\sum_{t=0}^{T_n-1}\log P\left(z^n_t;\theta^n_t\right). \tag{6}$$

To estimate Θ in Equation (6), $\mathscr{L}(\Theta)$ is minimized with respect to Θ through mini-batch gradient descent, the derivatives for which are computed using the backpropagation algorithm. The reader is directed to Hochreiter and Schmidhuber (1997) and Greff et al. (2017) for details on LSTMs and the backpropagation algorithm.

4.1.2. Forecasting

Forecasting is performed through ancestral sampling. Given a *conditioning* sequence $z_{0:t_0}$ (and the associated covariates $x_{0:t_0}$), Equation (4) is used to compute h_{t_0}. Subsequently, $z_{t_0+1:T}$ are obtained by sequentially sampling the distribution $P(z;\theta_t)$. In order to make robust predictions, we actually generate a number of samples from the distribution and set the actual predicted value to the median:

$$z_{t,i} \sim P(z;\theta_t), i = 0 : N-1;$$

$$z_t = median\left(z_{t,0}, \cdots, z_{t,N-1}\right), \tag{7}$$

In Equation (7), θ_t is computed using Equations (4) and (5), and N represents the number of samples drawn at each time. Fig. 3 illustrates this process. The N samples drawn from the distribution are also used to calculate the quantiles needed to estimate the confidence interval at each time step of the prediction period. For example, to estimate the 95% confidence interval (used in the study), 0.025 and 0.975 quantiles are calculated, and the interval formed by them represents the required confidence interval.

Once the time series forecast for the pandemic-induced lockdown period has been predicted, it is compared with the actual/observed time series. The difference between the two time series is the causal impact of the enforced restrictive orders during the pandemic. In order to quantify the impact, the two-time series distributions are checked for normality using the Shapiro test. In the likelihood that the distribution is non-normal, the Wilcoxon test is conducted to determine the presence of a statistically significant difference between the two-time series. The effect size of the difference is computed using Cliff's delta, a non-parametric measure, instead of Cohen's d, as the former is a robust and appropriate measure for when normality assumptions are not met.

An appropriate error metric is required to evaluate the forecast accuracy of the DeepAR model using popular forecast techniques such as the Auto-regressive Integrated Moving Average (ARIMA) method, the Holt-Winters method, and state-of-the-art models like the generalized additive model (GAM) and the Bayesian structural time-series (BSTS) model. This study employs the Weighted Mean Absolute Percentage Error (WMAPE) to check the prediction accuracy of 19 different types of crime series as it is unit-free and easily interpretable.

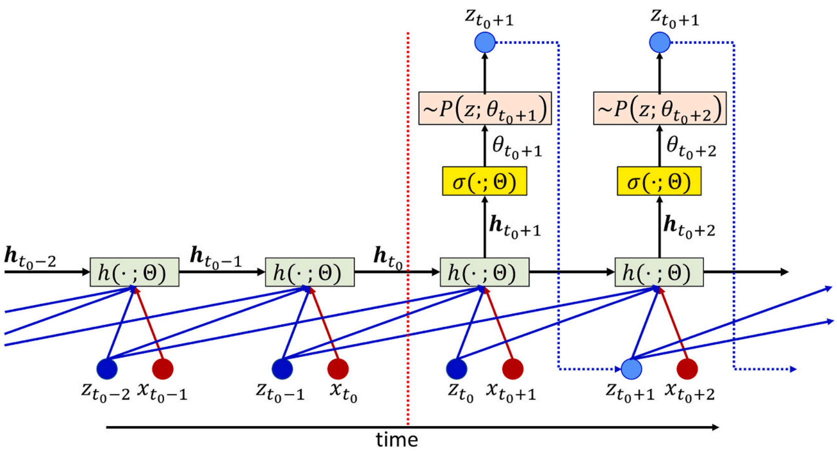

Fig. 3. Title: Forecasting with DeepAR model
Description: The dotted red line separates the conditioning observations (shown by the dark blue dots) and the predicted observations (shown by the light-blue dots). $\sim P(z;\theta_t)$ represents the sampling process of Equation (7).

4.1.3. Experiments

The dataset used in this study contains state- and district-level data for Tamil Nadu ranging from January 1, 2013, to September 30, 2021, with day-wise frequency. For district-level data, weekly-frequency data was used instead of daily-frequency data to avoid non-zero values in the time series, which would have made it difficult for the model to fit the training data and could subsequently led to poor forecasts. The data from January 1, 2013, to December 31, 2019, was designated as training data for the prediction models. The models were validated with data from January 1, 2020, to March 22, 2020. The forecast period was from March 23, 2020, to September 30, 2021, covering the COVID-19–induced lockdown periods.

We employ the DeepAR model described in Section 4.1 for forecasting. The prediction function $h(\boldsymbol{h}_{t-1}, [z_{t-l_1}, z_{t-l_2}, \cdots, z_{t-l_K}], \boldsymbol{x}_t;\ \Theta)$ is a three-layer LSTM network. To predict daily data, the set of lags $l_1, \cdots, l_K$ used are $\{l_1, \cdots, l_K\} = \{1, 2, 3, 4, 5, 6, 7, 8, 13, 14, 15, 20, 21, 22, 27, 28, 29, 30, 31, 56, 84, 363, 364, 365, 727, 728, 729, 1091, 1092, 1093\}$. Lags from 1 to 8 are considered to account for the influence of past weeks' observation; 13 to 15, 20 to 22 and 27 to 29 are considered for weekly seasonality. 30, 31, 56 and 84 are considered to account for monthly seasonality. The rest of the lags are considered for yearly seasonality. Hence the model captures all the seasonal effects present in the time series. For the weekly district-wise data, we considered $\{l_1, \cdots, l_K\} = \{1, 2, 3, 4, 8, 12, 52, 104, 156\}$. In all cases, the covariate x_t only comprised the time from the origin of the sequence.

The model was trained on the training data. In order to train the model on the daily series, we randomly drew segments of 639 samples for which the prediction likelihood was computed. To each segment, we also included an initial "warm-up" of 7 samples (resulting in a total segment length of 646) over which the likelihood is not computed. For the weekly data, the random segment lengths were set to 84, with a warm-up of 7 weeks, for a total length of 91. The choice of length in both cases was based on the number of days/weeks between January 1, 2020, and September 30, 2021, as this is the period over which our final analysis is performed. In all cases, a total of 800 such segments covering the entire training period were drawn for each phase of training.

For forecasting, the entire data from January 1, 2020, until September 30, 2021, was considered. In order to make daily predictions, the seven days from December 25, 2019, until December 31, 2019, were used as the preliminary conditioning period. For the weekly data, the seven weeks prior to January 1, 2020, were considered the conditioning period. The period from January 1, 2020, to March 22, 2020, was used as *validation* data. The evaluation data was from March 23, 2020, to September 30, 2021. The procedure from Section 4.1.2 was used for forecasting, with $N = 100$ samples drawn at each forecast time to make the predictions.

Before training the model, it is imperative that several hyperparameters that define the RNN model structure be specified. Hyper-parameters like the number of hidden layers and the number of cells in each layer were tuned to jointly achieve a minimum loss value in the training and validation set. Following are the hyperparameters (with their ranges) of the DeepAR model tuned in the study:

Likelihood function = Negative Binomial; Epochs = 1 to 300; Patience = 10 to 40; Decay factor = 0.2 to 0.9; Learning rate = 1e-3 to 1e-20.

The hyperparameters, with their default values, which were not tuned in the study, are:

Batch size = 16; Number of hidden layers/cells in each layer = 3/80.

The learning rate parameter can be adjusted to avoid under-fitting or over-fitting the time series by controlling the training process. The patience parameter indicates the number of steps needed to wait before early stopping, and the decay factor reduces the learning rate parameter. This model is implemented using the GluonTS package in Python.

To quantify the impact of stay-at-home orders on instances of CSA, we not only compute the percentage difference of the mean between the predicted and observed daily counts of POCSO cases but also measure the effect size in the distribution to accurately capture the impact. Initially, we check for normality assumptions for these distributions, following which we compute Cliff's delta, a more robust measure of effect size for non-normal distributions [26].

5. Results

5.1. Analysis of cross-sectional data

It is not surprising to note that across districts and cities, the perpetrators of most cases were known to their victims. In fact, around 80% of recorded offences were committed by immediate family members, relatives, friends, or neighbours within closed premises. Rural and urban areas show no differences in terms of the profiles of offenders and victims. However, there is a noticeable difference in the reporting of crimes. During the pre-lockdown period (January 1, 2010, to March 22, 2020), there were long delays in filing the complaints by the victims or their guardians, which is unlike the reporting trend of most other crimes. CSA, like other offences such as violent crimes, property crimes, and traffic violations, suffers from under-reporting and non-reporting. However, there is a significant difference in the time it takes to report CSA offences versus other crimes. For other offences such as property crimes, general violent crimes, road traffic crashes, and cybercrimes, the delay in filing complaints is a few hours at the most, whereas, in cases of CSA, delays are in the order of a few days or weeks. While most cases were reported in the first few days after the offence was committed, a few cases were reported after a considerable delay, which ranged from several weeks to months. These few cases skew the distribution. Therefore, for this study, we use median delay rather than mean.

As stated above, the delay in filing complaints for other offences is in the order of hours. In contrast, the median delay length for the cases of CSA registered in Tamil Nadu during the pre-pandemic period was six days. During the stay-at-home orders, this delay differed substantially in most districts and cities. When mobility was severely hampered during SIP-2020, it is reasonable to presume that the victims faced delays in accessing the police stations to formally register their complaints of sexual offences. It is, however, germane to note that the removal of movement restrictions in 2020 turned out to be a decisive facilitator for victims of CSA, who lodged their complaints with greater ease. It can be inferred that the offences committed during periods of severe restrictions could not be reported until the restrictions were removed. The most marked difference was noticed during the second wave (in 2021), during the mild and post-intervention periods. The median delay in the state increased from 6 days in the pre-pandemic period to 40 days and 14 days in the mild intervention and post-intervention phases of the second wave, respectively. Overall, during the various pandemic-induced restrictive periods, the delay in reporting considerably increased when compared with the pre-pandemic period (see Table 1).

In all phases of lockdowns in both COVID-19 waves, cities fared better in the reception of victims of CSA, as the delay in registration of FIRs against the offenders was substantially lower in cities than in rural districts. There is no sizeable variation noticed in the age group of the victims. Across all districts, it is seen that the vulnerable age group of these victims are in the range of 14–16 years; similarly, the age profile of the offenders is in the 25–30 year range.

The descriptive statistical analysis of the trends for the various districts and cities points out that the delay in registering CSA complaints in police stations has always been present, with no substantial differences among districts and cities during the pre-pandemic years. As the number of cases in one district or city was very few, forecast methods to predict counterfactuals for causal analysis were not done.

5.2. Analysis of time series data

An initial comparison gives a broad indication of how the pandemic has increased children's vulnerability to sexual abuse. We do not take into account the effects of trend, seasonality, and holiday on the time-series data of the daily count of POCSO Act cases in Tamil Nadu, either in the pre-pandemic interval (between January 1, 2013, and March 22, 2020) or the pandemic years (between March 23, 2020, and December 31, 2021).

Before the pandemic, the mean, median, and mode number of daily cases of POCSO were 4, 3, and 0, respectively, which increased during the pandemic years to 12.9, 12, and 16, respectively. The substantial impact can be seen in Fig. 4 below, which gives the distribution of the cases during the relevant periods.

5.3. Impact of lockdown on POCSO cases: time-series analysis

Table 2 presents a remarkable reduction in the recorded level of POCSO cases during SIP-2020, with Cliff's delta of −0.99 and a 72% decline when pitted against the counterfactual. Though of lesser magnitude, the same trend was noticed during the second wave, as the decline in SIP-2021 was 36%, with Cliff's delta of −0.65. However, increasing trends were observed in both the first and second waves when the curbs were removed, as Post-IP-2020 and Post-IP-2021 reported case increases of 68% (Cliff's delta 0.68) and 36% (Cliff's delta 0.56), respectively. There was a noticeable difference between the two waves during mild intervention periods. While the actual and predicted values were the same for the first wave, in the second wave, the two phases of MIP-One-2021 and MIP-Two-2021 reported a 35% (Cliff's delta - 0.43) and 44% (Cliff's delta −0.42) escalation in actual cases, respectively (when compared with predicted cases). It is also important to note that there were no movement restrictions in the period between the waning of the first wave and the onset of the second wave of the pandemic when life briefly returned to normalcy. In this scenario, it is expected that the actual and predicted daily count of cases would remain the same. However, there was a sustained higher registration of these offences when compared with forecasted values (see Fig. 5).

5.4. Differential pandemic severity and fatality rates, and mobility during two waves

The COVID-19 pandemic saw several virus variants and mutations, each with its own rate of transmission and severity of infection. The spread of the virus across Tamil Nadu was vastly different between 2020 and 2021. The first wave in 2020 had significantly lower infection rates, spread, severity and fatalities than the second wave in 2021. Fig. 6 (below) clearly shows that infection and fatality rates were 4–5 times higher in the second wave than in the first. The average daily number of infections in Tamil Nadu during the first

Table 1
The median length of delay in filing complaints of child sexual abuse offences by victims in various phases of stay-at-home orders is expressed in days. The figures in the bracket are the total number of cases.
SIP: Strict Intervention Period; MIP: Mild Intervention Period; Post-IP: Post-Intervention Period; Pre-IP: Pre-Intervention Period (January 1, 2013, to March 22, 2020).

Delay in Registration (Days)							
District	Pre-IP	SIP-2020	MIP-2020	Post-IP-2020	SIP-2021	MIP-2021	Post-IP-2021
State	6	5	3	5	6	40	14
Chennai City	2	14	4.5	2	2	0.5	1
Coimbatore City	1.50	1	1	1	0	2	1
Salem City	3	1	3	2	1	1	1
Madurai	2	6	16	4	11.5	7	3
Trichy	31.5	5.5	31	6	6	1	5
Vellore	2	1	60	1	3	0	2
Tirunelveli	1	6	1	1.5	2	2.5	1
Tirupur	3	65	2	2	128	7	9
Thanjavur	5	107	6	34.5	32.5	4	5

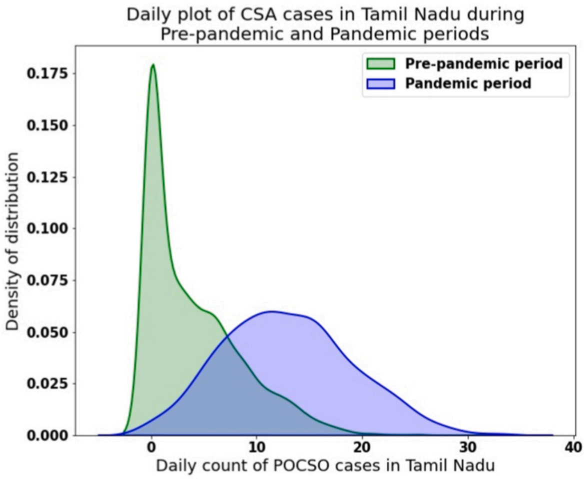

Fig. 4. Title: Density distribution of child sexual abuse cases during the last eight years
Description: Distribution of daily count of POCSO cases in Tamil Nadu during pre-pandemic and pandemic-induced lockdown periods. The X-axis shows the daily count of cases of CSA, and the Y-axis gives the density of the distribution.

Table 2
Actual/Predicted daily count of POCSO cases in Tamil Nadu with percentage change and difference measured by effect size (Cliff's delta)
SIP: Strict Intervention Period; MIP: Mild Intervention Period; Post-IP: Post-Intervention Period; Pre-IP: Pre-Intervention Period (January 1, 2013, to March 22, 2020).

	Actual	Predicted Mean (C·I.)	% Change	Cliff's delta
Pre-IP	11	10.84 (3.94, 20.9)	1.46	−0.03 (-0.21, 0.19)
SIP-2020	3.08	10.95 (4.47, 18.14)	−71.88	−0.99 (-0.97, −0.94)
MIP-2020	10.45	10.53 (4.61, 18.13)	−0.75	−0.09 (-0.29, 0.15)
Post-IP-2020	13.66	8.14 (1.86, 16.93)	67.86	0.65 (0.41, 0.72)
Pre-IP-2021	13.37	10.56 (5.08, 16)	26.6	0.39 (0.08, 0.59)
MIP-One-2021	15.5	11.48 (5.08, 19.34)	35.07	0.43 (0.13, 0.66)
SIP-2021	7.2	11.27 (5.3, 17.84)	−36.13	−0.65 (-0.85, −0.19)
MIP-Two-2021	14.09	9.76 (5.46, 15.5)	44.37	0.42 (0.15, 0.62)
Post-IP-2021	13.33	9.81 (2.75, 18.9)	35.95	0.56 (0.26, 0.65)

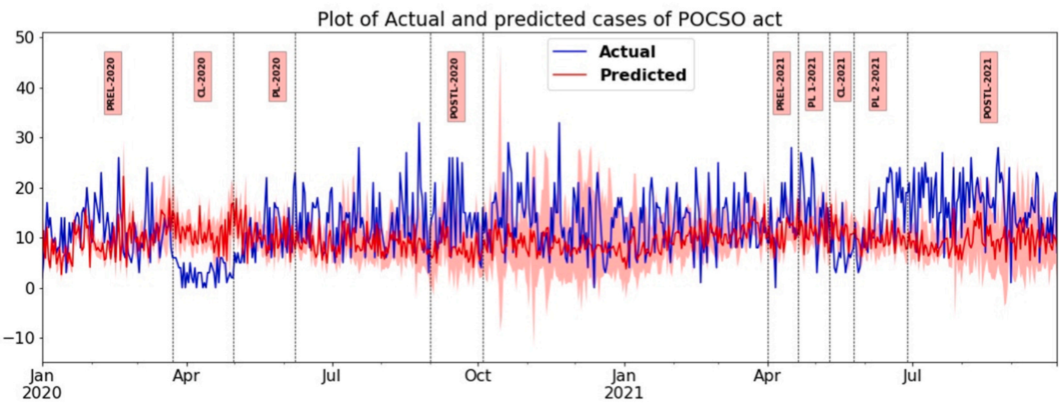

Fig. 5. Title: Actual and forecast daily count of child sexual abuse cases
Description: Distribution of daily count of POCSO cases in Tamil Nadu during pre-pandemic and pandemic-induced lockdown periods. The X-axis shows the daily count of cases of child sexual abuse, and the Y-axis gives the density of the distribution.
CL: complete lockdown; PL: Partial lockdown; Post-L: Post lockdown.

and second waves was 2403 and 12,265, and similarly, the number of daily deaths was 34 and 153, respectively. This explains why the second wave was so lethal and overwhelmed hospitals and other health infrastructure, which faced a deluge of infected people daily. Furthermore, the second wave had a wider geographical spread, reaching and severely affecting life even in remote corners of the state.

In contrast, the first wave was more centred in and around urban cities.

In general, mobility restrictions were noticed more in wave one, during all the phases of stay-at-home orders, than in their corresponding phases in wave two. Moreover, within each wave, the change in mobility was more marked during the strict intervention period than during the mild intervention period, along the expected lines. As expected, there was a considerable percentage increase from the baseline value of mobility for residential neighbourhoods, as stay-at-home orders ensured people remained indoors. The Residential sector is the only place that witnessed a contrary trend of increased mobility during the lockdown phases, with a higher increase in mobility when the restrictions were more severe. There was a steep percentage decline in mobility in all other spheres of activities, i.e. Retail and Recreation, Grocery and Pharmacy, Parks, Transit Stations, and Workplaces. Mobility in residential areas is of concern to this study, as CSA cases predominantly occur inside homes. The highest percentage increases in mobility in this sector were 32.1% during SIP-2020 and 31.1% in SIP-2021, and the lowest increase of 9% was post-IP-2021. The transition from a strict intervention period to a mild intervention period in both waves translated into a relative decrease in mobility in the residential sector.

6. Discussion

6.1. Research findings

Publicly-available literature on and knowledge of CSA occurrences in India represents only the tip of the iceberg [27]. A vast majority of CSA stays submerged, invisible in data and records. This reinforces the false belief of low or non-existent levels of CSA. This denial is one of the foremost hurdles to be overcome while addressing this grave issue. Children who disclose the abuse they suffered are likely to be silenced by elders in the family through cajoling or threats. The few children who manage to speak out about their abuse are often eventually forced to retract their claims. Unfortunately, this often leads the child to believe that it is better to come to terms with the unpleasant experience by ignoring it rather than go through the excruciating ordeal of explaining it to people who willfully refuse to acknowledge the existence of the problem. There are also instances where children lack the awareness to comprehend the offence perpetrated on them and are rebuked for prevaricating when attempting to explicitly explain their experiences. In cases of alleged abuse in institutional centres, including juvenile homes, under-reporting or non-reporting is more acute, as the majority of abusers are not related to their victims [28].

Going by the First Information Reports filed by complainants over the years, occurrences of CSA are usually observed in five places most commonly inhabited by both the victims and offender. Accordingly, the broad categories of CSA are abuse 1) within the family, 2)

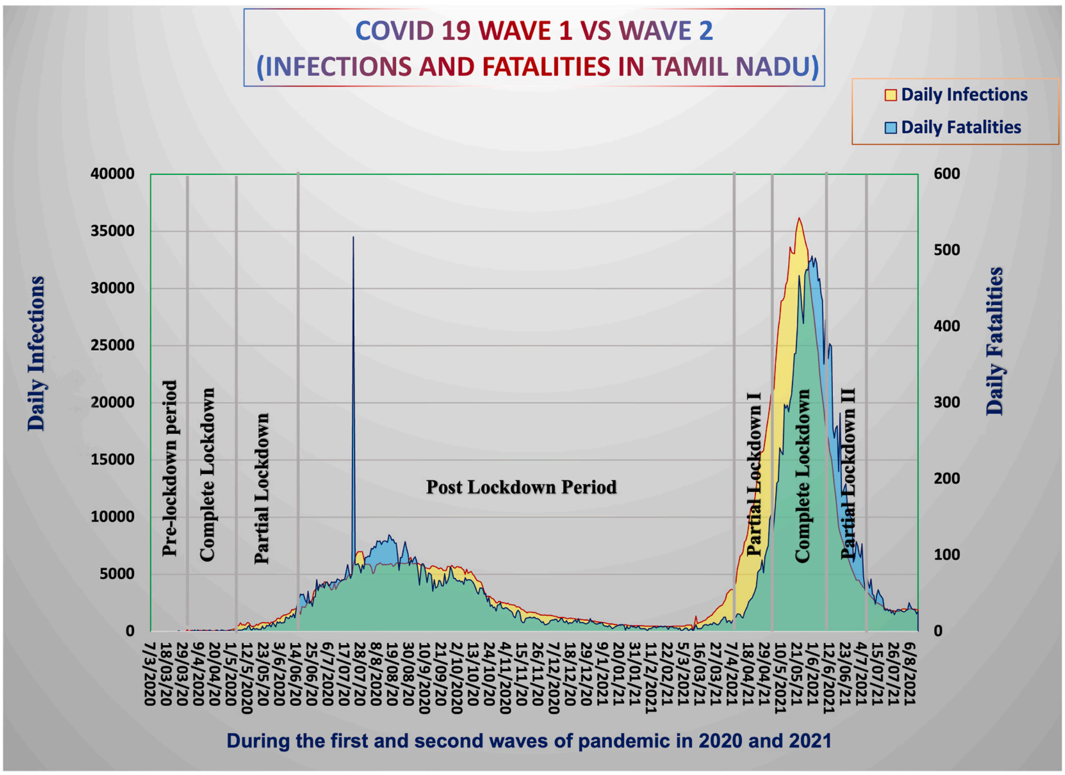

Fig. 6. Title: Plots of infection and fatality during both waves in Tamil Nadu
Description: Graph of the daily number of infections (Y-axis–left in thousands) and fatalities (Y-axis–right) during the first two waves of the pandemic (X-axis day timeline).

within the community, 3) in educational settings, 4) in institutional centres, and 5) at the workplace [29]. In the first category, where the abuse occurs within the family, the perpetrators are those responsible for protecting the child. Offenders include older siblings, fathers, uncles, and aunts. The second setting involves abuse within the community. The offenders are usually closely related to the child, including family, friends, secular and religious headmen, drivers, and security guards. Some offenders indirectly wield control over the child through the parents, such as landlords, village elders, and employers of the child's parents. The third category involves a large group of children living in a shared space as students, either in schools or hostels. The fourth category includes institutional centres such as destitute children's homes, orphanages, and correctional schools. The final physical space where abuse occurs in the workplace. Although child labour is banned and prohibited by law, it is common for children to be informally employed in households, farmlands, and cottage industries. During the lockdowns, most of these places were closed, and the children were predominantly confined to their residences, exposing themselves to perpetrators from the family or community. This partially explains the drastic fall in cases during the SIP-2020 and the SIP-2021, as some categories of spaces were not contributing to CSA reporting.

We endeavour to explain the unprecedented fall in POCSO cases during SIP-2020 and the moderate decline during SIP-2021 using the routine activities approach of Cohen and Felson (1979) using mobility. During the strict intervention periods of the first and second waves, unprecedented and stringent restrictions were imposed to reduce mobility in an attempt to contain the spread of COVID-19. The percentage changes in mobility in SIP-2020 and SIP-2021 were −80% and −60% for Retail and Recreation, −39% and −40% in Parks, −62% and −48% in Transit Stations, −52% and −22% for Groceries and Pharmacy, and −64% and −45% in Workplaces, respectively. These changes are indeed quite historical. Restricted mobility substantially reduced the interactions between potential offenders (strangers) and victims. Further, there was increased guardianship at home because of the substantial increase in mobility in the Residential sector (by 32.1% and 30.1% during SIP-2020 and SIP-2021, respectively). High residential mobility also entails an increase in the number of hours people spend at home. It can be argued that the prolonged presence of people inside a residence, including possible offenders, would enhance the possibility of interaction between offender and victim. This closer interaction augments the probability of the temporal and spatial convergence of the three elements: potential offender, target victim, and absence of guardian. Therefore, more offences are predicted during the strict intervention periods as per Routine Activity Theory (RAT). However, the actual reported cases of CSA during the strict intervention periods were drastically lower than the counterfactual predicted counts. Fig. 7 clearly indicates the inverse relationship between mobility in residential areas and change in registered CSA counts with counterfactuals for all the phases except in the last phase of the post-intervention period in 2021. As discussed, lower CSA figures might not be the ground truth because of the factors influencing the non-reporting of complaints. Moreover, the stay-at-home orders severely curtailed people's movement and limited the victims' access to recourse and remedies from the agencies supposed to provide relief. This is supported by the evidence of escalated levels of actual cases when pitted against the counterfactual in the mild and post-intervention periods by 35% (ES 0.43) in MIP-One-2021, 44% (ES 0.42) in MIP-Two-2021, and 36% (ES 0.56) in Post-IP-2021. The mean delay in registration of cases during the post-intervention period increased manifold to 40 days, compared to the mean delay of 6

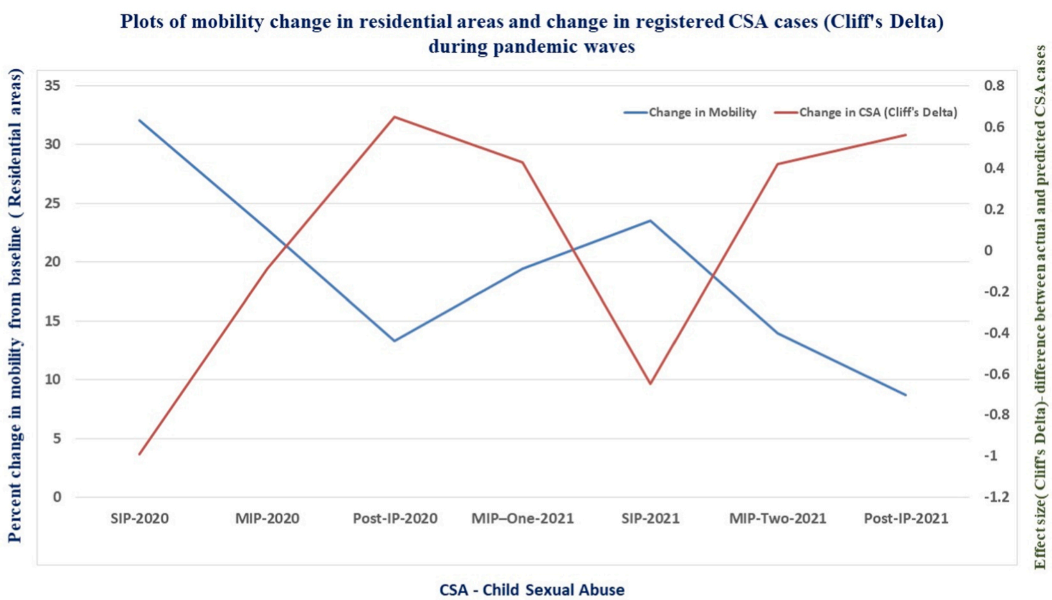

Fig. 7. Title: Mobility and its effect on child sexual abuse cases in Tamil Nadu
Description: Plots of mobility and effect size difference in actual and predicted child sexual abuse cases in the different phases of stay-at-home orders in Tamil Nadu
X-axis: The various stages of lockdown in discrete intervals.
Y-axis–left: The mean percentage change in mobility from baseline in the residential sector
Y-axis–right: The effect size (Cliff's delta)—the difference between the actual and predicted daily count of registered cases of child sexual abuse.

days before the pandemic. Secondly, a steep fall in cases was recorded during the strict intervention periods. These empirical findings highlight the victims' inability to access the relief and rehabilitation centres meant for CSA victims, thereby resulting in the decline of CSA cases reported during the strict intervention periods.

The reality of under-reporting and non-reporting can be indirectly inferred from the upsurge during the post-intervention periods, especially when the delay in filing the complaint is considered. The recorded data support the presumption that the cases reported during post-lockdowns refer to offences that occurred during the lockdowns' restricted periods.

Like other crimes, CSA is no exception to a strong history of under-reporting and non-reporting by victims. This problem is not unique to Tamil Nadu or India; it is prevalent worldwide to varying degrees [30,31]. Furthermore, sometimes CSA cases are never reported [32,33]. The numerous reasons for underreporting or non-reporting are explained in brief below. The most important ones that uniquely characterize and distinguish India (Tamil Nadu) are discussed first.

The joint family tradition and strong familial hierarchy in India prescribe that children should be unquestionably obedient to their elders. This expectation is an enabler when it comes to crime towards children. It serves as a deterrent for the victim even to voice, let alone formally report, the incidence of sexual abuse to anyone, within the family or outside. India's average family household ranges from five to six members as against two or three members in Western nations. Often, three to four generations live under one roof in Africa and Asia, which is not common in other cultures [34]. This tradition of co-residence, which is deeply hierarchical, also hinders the free reporting of victimization. Incidents of CSA are often shrouded in secrecy. Where every older family member is privy to the offence and is an active conspirator in silencing the victim, this tendency exists at every level of the societal structure, reinforcing and perpetuating the culture of denial surrounding CSA. This scenario became exacerbated during pandemic-induced stay-at-home periods when family loyalty dynamics get further strengthened as a result of constant proximity and interaction over months of confinement and the shared suffering of the manifold difficulties and uncertainties brought forth by the pandemic.

Primary and secondary schools in Tamil Nadu were closed for most of the pandemic's first two waves, from March 23, 2020, to September 1, 2021. When schools are not in session and stay physically closed for students, many instances of child maltreatment go unnoticed or unreported [7]. They also suggest that school closures may contain the pandemic; however, policymakers should consider the under-reporting of child maltreatment when evaluating the cost-benefit analysis of school reopening. Another unfortunate fallout of prolonged school closures is the sudden cessation of awareness and sensitization programs aimed at protecting children from predators. A dramatic decline in child abuse and neglect hotlines in more than half a dozen states of Colorado, Missouri, Texas, Illinois, and Florida, which is attributed to school closures [35]. Around two-thirds of these hotline calls were from educators and legal systems.

According to historical data gathered from specific districts and cities in Tamil Nadu, approximately 80% of perpetrators were family members, close relatives, or neighbours known to the victims. The strict implementation of the lockdown during both waves increased the presence of people in their homes, with residential zones reporting an increase of 39% and 28% during the complete lockdown phases of wave one and wave two, respectively. Tamil Nadu is the only state with 100% enrollment in elementary and secondary schools. As schools remained closed during lockdowns, children were confined to their homes. The evidence presented thus far strongly suggests that the offences were most likely intrafamilial in nature. The sharp increase in CSA reports during the partial lockdown and post-lockdown phases, when restrictions were eased, is also indicative of conditions more conducive to reporting such incidents. The vast majority of literature indicates that intra-familial child sexual abuse is harmful to the child's long-term functioning and that CSA has invariably resulted in long-term outcomes. Ray (1996), Briggs, F. (1995a), Coid et al. (2001), and Johnson (2004) identified over a dozen serious psychological consequences of CSA.

The devastating effect of the pandemic was not restricted to public health and the frontline warriors fighting the pandemic but spread to trade, economies, and businesses across the world. Tamil Nadu was no exception and witnessed an unprecedented rise in unemployment rates during both waves. Alarming unemployment rates of 49.8%, 33.2% and 12.2% during April, May, and June 2020 disrupted the lives of millions of people. The second wave also registered a high unemployment rate of 28.0% and 8.3% in May and June [36]. Researchers have long established strong evidence-based connections between unemployment and child maltreatment, including CSA, based on pre-COVID-19 data. A 1% increase in unemployment translates into at least a 0.50 per 1000 children increase in child maltreatment and suggests the lagging effect of this on maltreatment over the following year [37]. A very similar effect was discerned in our research when the unemployment rate was at its nadir in April 2020, which showed an increased number of cases of CSA in June, July, and August 2021. A recent study during the pandemic also arrived at similar findings: an increase of 1% unemployment rate was found to be associated with excess calls for police services by 0.15–0.17 per 10,000 children in the first year of COVID-19 [38]. Hence, the authors of this paper accept a sustained connection between unemployment rates and CSA, especially during the various phases of stay-at-home orders.

Some studies [39–41] reveal that stress and poverty are potent contributors to CSA. Unfortunately, the COVID-19 pandemic exacerbated both psychological stress and economic strain [42]. The authors address the issues of CSA, as mentioned above, from both immediate and past perspectives through the explanation offered by the general strain theory. This theory focuses on the consequences of negative emotions such as anger, frustration, and resentment on subsequent human behaviour. The effects observed could either be attributed to past situations or immediate circumstances or primarily cumulative factors such as loss of livelihood and severe economic hardship. Furthermore, in the context of the pandemic-induced months-long lockdowns, close proximity and enhanced interaction between the victim and the offender (who is likely to be a parent, relative or sibling) can potentially increase intra-family stress that can culminate in the crime of sexual abuse.

6.2. Limitations of the research

In addition to descriptive statistical analysis, a counterfactual analysis is used to assess the impact of the pandemic on recorded CSA levels. Changes in mobility are to be expected during times of crisis, such as pandemics. A counterfactual prediction of the daily counts of CSA is made based on historical data, which is a univariate time series. This figure represents the expected daily median CSA count, having assumed the absence of a global pandemic. The pandemic's impact is measured by comparing the actual daily counts of CSA registered during the pandemic with the predicted number. A possible critique is that the study assumes that the population growth, newer state laws, the changing role of law enforcement, and other related institutions remain similar or changes at the same rate to pre-pandemic periods. However, the prediction or forecast takes into account these variations, which could have manifested as seasonal, trending upward or downward, or holiday-related. Because these factors existed prior to, during, and after the crisis, they had no bearing on our conclusions or the conclusions drawn from our causal impact analysis.

Regarding the investigation method, DeepAR is a complex model with many parameters that must be trained. This makes the model difficult to interpret andcomputationally expensive to train. Forecasting with a DeepAR model trained on small datasets may result in overfitting, resulting in poor forecasts. This may not directly apply to this study as models built have been and tested on unseen data. The validation errors have been minimal.

Instead of the current univariate time series, multidimensional data would enrich the analysis. Another source of independent data, such as the details of distress calls received at the state emergency call centre, could be helpful for validation. Furthermore, while this study is purely quantitative in nature, a mixed approach involving some qualitative studies, such as one-on-one interviews with victims and focus groups, could be considered for future research.

7. Conclusions

Unlike other crimes, the average delay in registering a CSA case can extend up to several days, even before the pandemic, primarily due to the prevalent social mindset that chooses to turn a blind eye to a crime that may upset the sanctity of a hierarchy-based societal order. When severe restrictions were imposed as part of the strict stay-at-home orders during the first two waves of the pandemic, this delay in registration increased manifold in Tamil Nadu, highlighting the hindrances victims may have faced while attempting to file complaints.

A sharp fall in CSA crimes during strict stay-at-home orders and a steep incline in these cases in mild and post-intervention phases were noticed, especially during the second wave. Another critical aspect of these phases was that the median delay in registering CSA offences increased to around 40 days compared to the pre-lockdown interval of 6 days. These findings highlight that though Tamil Nadu witnessed elevated levels of CSA occurrences during the post-lockdown phases of the pandemic, these offences were not reported or registered immediately but only later. Thus, it is possible for these offences to have been committed during the strict and mild intervention periods, which had highly increased probabilities of a potential offender having access to a target in the absence of their guardian in line with RAT. These cases were reported only when situational factors enabled the victims to lodge complaints, i.e. during the post-lockdown phases. In aggregate terms, the mean daily count of cases was only four during the pre-pandemic period (January 1, 2013, to March 22, 2020) as against the tripled figure of 13 during the pandemic phases (March 23, 2020, to December 31, 2021). The prolonged closure of schools in 2020 and 2021 also explains the increasing trends of CSA during lockdown periods and the inordinately delayed reporting of such incidents. The absence of crucial educators who identified, recognized, and reported the CSA cases explains the reduced number of instances reported during strict lockdowns. Children were cut off from the awareness programs and safety protocols organized by teachers and counsellors, which further exposed them and made them vulnerable to predators.

Before the COVID-19 pandemic, 80% of offenders were known to their victims. However, during the pandemic, the lockdown measures mandated by the Government increased people's presence inside their homes, and prolonged school closures exacerbated the plight of children subject to sexual abuse. The pandemic-induced lockdowns increased the occurrences of CSA, the nature and complexity of which became more intrafamilial, preventing victims from coming forward openly. Furthermore, the closure of schools removed an avenue for students to express their abuse. Overall, this has serious long-term negative consequences for the victims.

Our research findings highlight the need for an alternative mechanism to support and enable the victims of CSA, increasing their accessibility to relief and rehabilitation centres during similar periods of crisis. The pandemic-induced restrictive orders had no significant differential impact on CSA figures in urban and rural areas; however, cities fared better in the reception of victims, as they reported considerably lower time delays in reporting the crimes. The duration of the delay, the ages of the offender and victim, and closed spaces as a place of occurrence remained almost identical across the various districts and cities examined in this study.

Author contribution statement

Kandaswamy Paramasivan: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Bhiksha Raj: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Nandan Sudarsanam: Conceived and designed the experiments; Analyzed and interpreted the data.

Rahul Subburaj: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

The authors do not have permission to share data.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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