






ARTICLE

A Markov model to quantify the transitions in the psychological health of young adults in India during the COVID-19 pandemic

 Babita Goyal¹,  Alka Sabharwal^{2*} and  Lalit Mohan Joshi³

¹Department of Statistics, Ramjas College, University of Delhi, India

²Department of Statistics, Kirori Mal College, University of Delhi, India

³Department of Statistics, University of Delhi, India

*Corresponding author. Email: alkasabh@gmail.com

(Received: June 30, 2025; Revised: August 16, 2025; Accepted: September 07, 2025; Published: April 17, 2026)

Section editor: Gajendra Vishwakarma.

Abstract

A longitudinal data set where the system is characterized by its states in place of the values of the underlying random variables taken over time, can be modeled using a Markov model. In case of psychological data, the Markov models are beneficial as problems may progress or regress over time thus exhibiting the shift in the states of the system. These models, when applied to cohort studies may indicate at a general shift in the psychological health of the cohort under study. In a study regarding the psychological health of young adults in higher education in India during COVID-19 pandemic period, three independent surveys were conducted using the Strength and Difficulty Questionnaire (SDQ). 162 respondents were found to have been participated in all three surveys. A Markov chain model was used to study the transition of the respondents' psychological health over different phases of the pandemic duration in respect of the observed scores of the two components of SDQ viz, the 'Difficulty' score and the 'Impact' score; and the estimated 'Impact' scores obtained from the observed 'Difficulty' scores on application of the Quantile Regression and Quantile Regression Neural Network. For all the three data sets, the Markov model indicated at the prominent shift from a 'Normal' state to the 'Borderline' and the 'Abnormal' states of SDQ. Moreover, the stationary distributions showed significantly higher probabilities of being in the 'Borderline' and the 'Abnormal' states during the pandemic period than what is suggested by the psychological manuals in standard times.

Keywords: Difficulty scores, Impact scores, Markov chains, Strength and Difficulty Questionnaire, Stationary distribution.

1. Introduction

Psychological problems persist over time, and observations are to be taken repeatedly on the subjects of the study in order to assess the progression/regression of the problems. The data generated in the process, which is essentially longitudinal, can be effectively analyzed using transition models (Collins & Lanza, 2009). One of the characteristics of transition models is that the system is categorized into states, and the system, as observations are generated over time, is essentially identified as lying in one of the states among the mutually exclusive and exhaustive set of states. For such systems, the researcher is keen to determine not only the probability of the system lying in one of the states but also the

probability of the transition of the system from one state to another. Markov models are transition models where the probability of transition to any state is dependent only upon the previous state(s) the system was in, and the observations during the current time period, a property known as the Markov property. When the observations are generated at distinct and identifiable time points, the Markov model is called a Markov chain.

Markov models have been used widely in different spheres of experiments that generate longitudinal data, such as in fields of epidemiology, chronic disease, and the health sciences (Jackson, 2011; Kemeny & Snell, 1976). Duffy *et al.*, (1997) examined the progression of breast tumor using Markov model; Putter *et al.*, (2006) studied the breast cancer progression by estimating transition probabilities between different disease states using multi-state Markov model; Grover *et al.*, (2014) studied the progression of liver cirrhosis in the presence of various prognostic factors using multi-state Markov model; Srikanth, P. (2015) used these models to predict the natural progression of diabetic retinopathy; Goel *et al.*, (2018) used the model to predict the natural disease progression of type 2 diabetes based on hemoglobin A1c; Grover *et al.*, (2019) studied the progression of chronic kidney disease using multi-state Markov model; and McCarthy *et al.*, (2024) examined the progression of haemoglobin A1c levels in postpartum individuals with a history of gestational diabetes, using multistate Markov models. Speech recognition algorithms use Hidden Markov Models to predict spoken words based on observed sound signals (Rabiner, 1989). Recommendation systems use Markov chains to predict the next item a user is likely to purchase based on their previous purchases (Rendle *et al.*, 2010). Markov chain models are also used in public health, such as to model the spread of infectious diseases and predict the effectiveness of vaccination programs (Kwok, 2023). In a study by Claudio *et al.* (2023), a Markov chain model has been used to study the effect of intervention on the transitions between different states of mental health conditions.

In psychological studies, questionnaires are used to assess the mental health of the respondents. When the same questionnaire is administered repeatedly over different periods, it gives an excellent picture of the transitions in mental health into various distinct states as identified by the questionnaire manuals. If the questionnaire(s) are administered to a group of respondents, the researcher can estimate the general shift in the mental health of the cohort that is being represented by the group of respondents (Cipresso *et al.*, 2023).

In order to obtain the relationships between the variables involved in any statistical investigation, one of the commonly used techniques is regression modeling. While the classical regression models assume the data to be distributed uniformly around the mean, the condition may not always be true in real-life data where skewness is a common feature of the data. In such situations, a more representative measure of the central tendency is the median or in more generally, a quantile. One of the models that can be used in case of skewed data is a Quantile regression (QR) model, which estimates the unknown parameters across different percentiles, making it more robust to extreme values and is more flexible, as it doesn't need to follow strict assumptions about data distribution and can be used for predictions involving multiple factors within linear or simple nonlinear models (Huang *et al.*, 2017; Koenker *et al.*, 2005; Koenker, 2005). However, the model has to be run for every quantile individually. An improvement in this area is the Quantile Regression Neural Network (QRNN). This nonlinear, nonparametric approach makes use of neural networks for nonlinear data and can choose the best representative quantile among a set of various quantiles (Taylor, 2000; Zhang, 2003). In a study by Merlo *et al.* (2022), a QRNN model

was applied for multivariate longitudinal data to jointly estimate the quantiles of a univariate conditional distribution of a multivariate response, accounting for dependencies between the outcomes based on SDQ data for 5342 children.

In this study, we have applied a Markov chain model to the data collected through three surveys using the Strength and Difficulty Questionnaire (SDQ) during COVID-19 times, administered to young adults studying in higher educational institutions across India. The objective of the study was to assess the changes in the psychological health of young adults across different phases of this period. The states of the system were identified as ‘Normal’, ‘Borderline’, and ‘Abnormal’, which are according to the specifications of the SDQ manual (Goodman, 1999). In another study on the same data, the authors have fitted a Quantile regression (QR) and Quantile Regression Neural Network (QRNN) in tandem to obtain a data-based relationship between the two components of SDQ, namely the ‘Difficulty’ score through the four difficulty scales, namely the ‘Hyperactivity-inattention’, the ‘Peer problem’, the ‘Conduct problem’, and the ‘Emotional symptoms’, and the ‘Impact’ score. The regression model thus obtained was able to predict the ‘Impact’ score using the scores of the four components of difficulty score scales’ (Sabharwal *et al.*, 2024b). In this study, the authors used the Markov chain model to estimate

- (i) the transition probabilities from one state of observed SDQ scores to another over time
- (ii) the transition probabilities from one state of estimated ‘Impact’ scores using QR and QRNN models, to another over time
- (iii) stationary probabilities and hence the proportions of young adults in either of the three states in the long term.

To the best of our knowledge, this is the first study to understand the transitions from one psychological state to another in the case of a data-based model. Further, the stationary long-term proportions corroborated the earlier claims of the authors that the standard proportions of the healthy times in the three states do not work well in problem times (Sabharwal *et al.*, 2023; Goyal *et al.*, 2023; Sabharwal *et al.*, 2024a).

2. Materials and Methods

2.1 Material

During the time of the COVID-19 pandemic, the data were collected through three surveys, conducted in online and offline modes on young adults studying in different colleges and educational institutes across India, using the SDQ 17+ extended version. The first survey was conducted in May–June 2020 and had 1020 responses; the second survey was conducted in October 2020–February 2021 and had 743 responses; and the third survey was conducted in January–February 2022 and had 934 responses (Goyal *et al.*, 2023). A total of 162 respondents had been found to have participated in all three surveys. The data from these 162 responses have been used for this study. The SDQ scores were categorized according to the standard classification of cut-off points in the SDQ manual (Goodman, 1999). Table 1 below presents the demographic and socio-economic details, such as age, gender, family income, educational background, area, and COVID status of the respondents in all three surveys, and 162 respondents common to all three surveys.

Table 1. Demographic and socio-economic details of respondents

Variable		Survey 1 (1020) (%)	Survey 2 (743) (%)	Survey 3 (934) (%)	Common respondents (162) (%)
Gender	Female	54.79	48.45	56.10	56.59
	Male	45.21	51.55	43.90	43.41
Age	Below 20 years	50.05	44.42	52.78	45.74
	Above 20 years	49.95	55.58	47.22	54.26
Education background	UG	55.05	54.42	73.66	85.27
	PG/Higher	44.95	45.58	26.34	14.73
Family Income	Less than 5 lakh per annum	-	38.63	73.45	55.81
	More than 5 lakh per annum	-	61.37	26.55	44.19
COVID status	COVID	-	11.44	42.93	43.41
	Non-COVID	-	88.56	57.07	56.59
Area	Urban	-	-	69.27	73.64
	Rural	-	-	30.73	26.36

The family income, COVID status, and geographic were not considered in the first survey, as the effect of COVID-19 was not very visible and the lockdown was being used as a preventive measure at that time. Also effect of lockdown, which was imposed in late March 2020, did not start appearing in the months of May-June 2020. The geographic region was not considered in the second survey although the family income and the COVID status were considered.

2.2 Methods

2.2.1 Markov Chains

A Markov chain is a sequence of random variables $\{X_t, t \in T\}$ observed at times $t \in T$, T being an index set, such that (Norris, 1998)

$$P(X_{t+k} = j | X_0 = i_0, X_1 = i_1, \dots, X_t = i) = P(X_{t+k} = j | X_t = i) = p_{ij}^{(k)}; k \geq 1 \quad (1)$$

where $p_{ij}^{(k)} \forall i, j \in S; k \geq 1$ is called k -step transition probability. The collection of the transition probabilities for all possible pairs of states forms a Transition Probability Matrix (TPM), given by

$$P^{(k)} = \left(p_{ij}^{(k)} \right) = \begin{array}{c} \text{States} \\ \begin{array}{c} 1 \\ 2 \\ \vdots \\ n \end{array} \end{array} \begin{array}{c} 1 \quad 2 \quad \dots \quad n \\ \left[\begin{array}{cccc} p_{11}^{(k)} & p_{12}^{(k)} & \dots & p_{1n}^{(k)} \\ p_{21}^{(k)} & p_{22}^{(k)} & \dots & p_{2n}^{(k)} \\ \vdots & \vdots & \vdots & \vdots \\ p_{n1}^{(k)} & p_{n2}^{(k)} & \vdots & p_{nn}^{(k)} \end{array} \right] \end{array} \quad (2)$$

where $P^{(k)}$ is a square matrix with non-negative elements, S is the state space of the chain, and $\sum_j p_{ij}^{(k)} = 1, \forall i \in S$. If every state can be reached from every state of the chain, i.e., if $p_{ij}^{(k)} > 0 \forall i, j \in S; k \geq 1$, then the chain is said to be irreducible.

Following Medhi (2017), Kumar (2022), and Kemeny & Snell (1976), a stationary distribution of a Markov chain is a probability vector $\mathbf{v} = (v_1, v_2, v_3, \dots, v_p)$ satisfies the condition.

$$\mathbf{v} = \mathbf{vP}^T \text{ with } \sum_i v_i = 1, v_i \geq 0 \forall i \in S \tag{3}$$

2.2.2 Quantile Regression (QR) and Quantile Regression Neural Network (QRNN)

Any multiple regression model with k predictors can be written as

$$Y = X\beta_{qk} + \varepsilon \tag{4}$$

where Y is $(n \times 1)$ matrix of the response variable, X is an $(n \times (k+1))$ matrix of the predictor variables (including the intercept), β_{qk} is a $((k+1) \times 1)$ matrix of the regression coefficients to be estimated and ε is a $(n \times 1)$ matrix of the error.

2.2.2.1 Quantile Regression (QR)

A Quantile Regression (QR) model uses an asymmetric weighting system of data, with weights being in proportion to the distance of the observation from the data-specific quantile for the estimation (Forooqi, 2019).

To obtain the estimates, the sum of absolute errors, $\sum_{i=1}^n |\varepsilon_{qi}|$ is minimized subject to asymmetric penalties $q(0 < q < 1)$ for under-prediction and $(1-q)$ for over-prediction so that the objective function to be minimized is

$$Q(\beta_q) = \min \left[q \sum_{i:Y_i \geq X_{i\beta}} |\varepsilon_{qi}| + (1-q) \sum_{i:Y_i < X_{i\beta}} |\varepsilon_{qi}| \right] \tag{5}$$

where, $\varepsilon_{qi} = Y_i - (\beta_{q0} + \sum_{i=1}^k X_{qi}\beta_{qi})$

The $X_{qi}\beta_{qi}$ is the linear predictor obtained by multiplying the i^{th} row of X with regression coefficients β under the q^{th} quantile.

2.2.2.2 Quantile Regression Neural Network (QRNN)

A QRNN model with one hidden node, given predictors, $X_i(t)$ and response variable, $Y(t)$ provides an estimate of the conditional q^{th} quantile $\hat{Y}_q(t)$, as

$$\hat{Y}_q(t) = f \left(\sum_{j=1}^J o_j(t) + W_j^{(0)} + a^{(0)} \right) \tag{6}$$

where $W_{ij}^{(h)}$, and $a_j^{(h)}$ are the weight, and bias of the hidden layer respectively. $o_i(t)$ is the output of at a hidden layer node j given by (Cannon, 2011),

$$o_i(t) = \tanh\left(\sum_{i=1}^I X_i(t)W_{ij}^{(h)} + a_j^{(h)}\right). \quad (7)$$

The details of QR and QRNN models can be seen in (Sabharwal et al., 2024b)

2.2.2.3 Goodness of Fit test for QR and QRNN model

The likelihood ratio (LR) test measures the difference in the absolute deviations of null model and the full model as a proportion of null model at the q^{th} quantile (Koenker et al., 1999). i.e.,

$$LR = \frac{2(\tilde{Z}(q) - \hat{Z}(q))}{q(1-q)\{f_{eq}(0)\}^{-1}} \sim \chi^2_{(t)} \quad (8)$$

where $\{f_{eq}(0)\}^{-1}$, the reciprocal of the density function evaluated at the quantile of interest, is called the sparsity function; and is considered a nuisance parameter (Koenker et al., 1999).

$$\tilde{Z}(q) = \sum_{i=1}^n |Y_i - \beta_0|; \text{ and}$$

$$\hat{Z}(q) = \sum_{i=1}^n |Y_i - (\beta_0 + \beta_1 X_{i1} + \dots + \beta_t X_{it})|;$$

and t is the difference between the number of predictors in full model and null model.

3 Results

The data for this study was collected from a series of three surveys collected during COVID-19 lockdown period, using SDQ 17+ extended version, conducted on young adults studying in different colleges and educational institutes across India. A total of 162 respondents, who were found to have participated in all three surveys, constituted the data for this study. Table 2 provides the mean, median, mode, and standard deviation scores of these respondents for all three surveys.

Table 2. Descriptive statistics of the 162 respondents’ data variables: Hyperactivity-inattention symptoms, Emotional symptoms, Conduct problems, Peer problems, Difficulty score, and Impact score

Variable	Survey	Mean	Median	Mode	Std.
Hyperactivity Inattention symptoms	Survey1	5.178	5	5	1.400
	Survey2	3.736	4	3	2.059
	Survey3	4.248	5	5	1.948
Emotional Symptoms	Survey1	3.875	4	4	2.388
	Survey2	3.728	4	3	2.474
	Survey3	4.875	5	5	2.704
Conduct problem	Survey1	2.224	2	1	1.547
	Survey2	2.837	3	3	1.204
	Survey3	3.294	3	3	1.588
Peer Problem	Survey1	4.620	5	4	1.387
	Survey2	2.829	3	2	1.908
	Survey3	3.139	3	2	1.865
Difficulty Score= Hyperactivity Inattention symptoms +Emotional Symptoms +Peer Problem+ Conduct problem					
Difficulty Score	Survey1	13.880	13	12	5.409
	Survey2	11.195	11	12	5.162
	Survey3	15.138	15	13	5.765
Impact Score	Survey1	1.530	1	0	2.724
	Survey2	1.511	1	0	1.962
	Survey3	2.110	2	2	2.887

In survey 3, the mean and median values of the 'Difficulty' score and 'Impact' score were found to be the highest. The SDQ classifies the psychiatric state of a respondent in three bands, both for the ‘Difficulty’ score and the ‘Impact’ score. The three bands, namely, the ‘Normal’ band; the ‘Borderline’ band and the ‘Abnormal’ band signify the mental state of an individual as to whether they are normal, borderline problematic and severely problematic, respectively (Goodman, 1999). However, over time, an individual can switch from one band to another. Then the process can be modeled as a Markov chain, the three bands being the three states of the chain.

We denote by 0 the ‘Normal’ band, by 1 the ‘Borderline’ band, and by 2 the ‘Abnormal’ band of the ‘Difficulty’ score and the ‘Impact’ score. Table 3 presents the transition probabilities and stationary probability distribution (equilibrium) of the ‘Difficulty’ score for transition from surveys 1 to 2, 2 to 3, and 1 to 3.

Table 3. Three state Markov chain transition probabilities and the stationary distribution of ‘Difficulty’ score from observed data

Survey 1 To Survey 2				Survey 2 To Survey 3				Survey 1 To Survey 3			
States	0	1	2	States	0	1	2	States	0	1	2
0	0.6667	0.2424	0.0909	0	0.5795	0.1591	0.2614	0	0.5455	0.1818	0.2727
1	0.7742	0.1290	0.0968	1	0.5000	0.1538	0.3462	1	0.6452	0.1290	0.2258
2	0.6250	0.1875	0.1875	2	0.2667	0.2667	0.4666	2	0.3750	0.1875	0.4375
Stationary Distribution											
	0.6853	0.2127	0.1020		0.4545	0.1957	0.3498		0.5089	0.1744	0.3167

Stationary probabilities are the probabilities of being the system in a state in long term.

In an earlier study by the authors (Sabharwal *et al.*, 2024b), the QR and QRNN models (with one hidden node) were used to predict the relationship between the ‘Impact’ scores and the four scales of the ‘Difficulty’ scores (Sabharwal *et al.*, 2024b). The validity of the both QR and QRNN model was tested using the likelihood ratio (LR) where the null model (with no predictor) was compared with the full model (with all the given predictors) for all the three surveys. The results are presented in Table 4.

Table 4. Likelihood Ratio test for all three surveys data

Survey	Model	Q	p-value
1	QR	0.44	<0.001
	QRNN	0.43	<0.001
2	QR	0.36	<0.001
	QRNN	0.40	<0.001
3	QR	0.34	<0.001
	QRNN	0.36	<0.001

Q is the optimal quantile that has been obtained from the data. With each p-value less than 0.001, the full model is significantly different from the null model for all three surveys.

The two models, namely the QR model and the QRNN model, were compared on the basis of Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE). For all three surveys, errors were lower under the QRNN model than the errors under the QR model. Hence, the QRNN Model was found to be more robust than the QR model. However, the QR model (which is a parametric setup) provides the complete information about the predictors (estimates as well as significance) at a given/data-based quantile, while the QRNN (which is a non-parametric setup) provides the estimates in a specified range (obtained based on the quantile used in QR), and then the optimum quantile was selected from this range. This selected optimum quantile under the QRNN model provided the estimated predictor coefficients and respondent counts that were closest to the observed numbers across all severity categories.

Hence, both models were used simultaneously.

Table 5. Estimated value of predictor coefficients for QR (along with p-value) and QRNN models at quantiles selected by the models

Model	QR			QRNN		
	FIRST (Q=0.44)	SECOND (Q=0.36)	THIRD (Q=0.34)	FIRST (Q=0.43)	SECOND (Q=0.40)	THIRD (Q=0.36)
Coefficients	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Intercept	-0.5741 (<0.001)	-0.8750 (<0.001)	-1.1412 (<0.001)	-0.4039	-1.1378	-0.7544
Hyperactivity Scale	0.1667 (<0.001)	0.1250 (<0.001)	0.1494 (<0.001)	0.1333	0.1475	0.1053
Emotional	0.2222 (<0.001)	0.2500 (<0.001)	0.2474 (<0.001)	0.2666	0.3049	0.2281
Peer Problem	0.0556 (<0.10)	0.1250 (<0.001)	0.0957 (<0.05)	0.0151	0.1246	0.0877
Conduct Problem	-0.0926 (<0.01)	0.0000 (1.00)	0.0373 (0.5423)	-0.1025	0.0491	-0.0175

The results obtained through the QR and QRNN models were used to compute the transition probabilities across the three states of the estimated ‘Impact’ scores. Tables 6, 7, and 8 present the transition probabilities and stationary distributions of the observed ‘Impact’ scores, and the estimated ‘Impact’ scores by using QR and QRNN models for surveys 1 to 2, surveys 2 to 3, and surveys 1 to 3, respectively.

Table 6. Transition probabilities and stationary distribution for observed ‘Impact’ score and the estimated ‘Impact’ scores by using QR and QRNN model (transition from survey 1 to survey 2)

Observed Impact Score				Estimated Impact Score by Using QR Model				Estimated Impact Score by Using QRNN Model			
States	0	1	2	States	0	1	2	States	0	1	2
0	0.6078	0.1765	0.2157	0	0.5366	0.2439	0.2195	0	0.5882	0.1569	0.2549
1	0.5263	0.1053	0.3684	1	0.3846	0.3077	0.3077	1	0.6000	0.1000	0.3000
2	0.4237	0.1695	0.4068	2	0.3548	0.2581	0.3871	2	0.3966	0.2068	0.3966
Stationary Distribution											
	0.5398	0.1628	0.2974		0.4433	0.2649	0.2918		0.5316	0.1629	0.3055

Table 7. Transition probabilities and stationary distribution for observed 'Impact' score with estimated 'Impact' score by using QR and QRNN model (transition from survey 2 to survey 3)

Observed Impact Score				Estimated Impact Score by Using QR Model				Estimated Impact Score by Using QRNN Model			
States	0	1	2	States	0	1	2	States	0	1	2
0	0.5455	0.1212	0.3333	0	0.5370	0.1111	0.3519	0	0.5230	0.1385	0.3385
1	0.7143	0.0476	0.2381	1	0.5882	0.1471	0.2647	1	0.6818	0.0455	0.2727
2	0.2143	0.1905	0.5952	2	0.1707	0.2195	0.6098	2	0.2381	0.1905	0.5714
Stationary Distribution											
	0.4257	0.1409	0.4334		0.3790	0.1664	0.4546		0.4243	0.1471	0.4286

Table 8. Transition probabilities and stationary distribution for observed 'Impact' score with estimated 'Impact' score by using QR and QRNN model (transition from survey 1 to survey 3)

Observed Impact Score				Estimated Impact Score by Using QR Model				Estimated Impact Score by Using QRNN Model			
States	0	1	2	States	0	1	2	States	0	1	2
0	0.4706	0.1569	0.3725	0	0.4634	0.1951	0.3415	0	0.4706	0.1765	0.3529
1	0.7366	0.0002	0.2632	1	0.5000	0.0769	0.4231	1	0.6500	0.0500	0.3000
2	0.3729	0.1525	0.4746	2	0.3871	0.1613	0.4516	2	0.3793	0.1379	0.4828
Stationary Distribution											
	0.4674	0.1341	0.3985		0.4390	0.1624	0.3986		0.4600	0.1431	0.3969

4 Discussion and Conclusion

Markov chain models have been used extensively in longitudinal data studies due to the fact that these do not require any condition on the functional form of the data and are very well able to pick the path of transition over time. In case of data where the process is progressing over time, such as medical/psychological/bio-medical data, these models are of excellent help in not only charting out the progression of the data but also the probabilities of the process being in one of the possible states among the states of the set space. When applied to the cohort studies, these models can identify the proportions of the cohort in different states of the system. These models can offer structured estimates of model variables in the long term (Sonnenberg & Beck, 1993; Siebert *et al.*, 2012), thus being a useful tool in epidemiology and public health research.

The data for this study were collected through three surveys using the SDQ 17+ extended version during three different phases of the progression of COVID-19. Along with the unique nature of the virus and consequent disease progression, various socio-economic, demographic, and regional factors, and the preventive measures such as lockdown, closure of schools, colleges, and offices, and isolation/quarantine of the affected people had a great impact on the mental health of everyone. The young adults were particularly affected. (Sabharwal *et al.*, 2023; Goyal *et al.*, 2023; Sabharwal *et al.*, 2024a). As such, it is imperative to study not only the states of mental health of young adults at different points but also the progression/regression of mental health issues over the passage of time. The data for this study comprises 162 respondents common to all three surveys. Table 2 provides a general picture of the psychological health of young adults at the time of the three surveys. Although a data of 162 does not seem to be a representative data for a large country such as India but it is to be noted that it has been extracted from 1020, 743 and 934 responses of the college students of the three surveys and the demographic and socio-economic details of these 162 participants are similar to the larger data sets of the three surveys (Table 1). Survey 1 (May-June 2020) was conducted at a time when the full impact of the disease was not yet there, but the unprecedented lockdown was there. Although mean and median scores were within the 'normal' range of SDQ (0-15 for 'Difficulty' scores and 0-1 for 'Impact' scores), these were close to the upper values of normal scores. The statistics fell at the time of survey 2 (October 2020- February 2021) when a lifting of strong prevention measures was being anticipated. Survey 3 (January-February 2022) was conducted after the 'delta' wave of the pandemic, which had the highest impact on society. The mean and median scores of the respondents had crossed the 'Normal' ranges of both the 'Difficulty' and the 'Impact' scores. This transition of mental health issues of the respondents has been captured by the transition probabilities in Table 3. Table 3 gives an excellent picture of transitions over time with respect to behavioral problems (as measured by the 'Difficulty' score of SDQ). From survey 1 to survey 2, out of those in the 'Normal' state, 67% were still in the 'Normal' state, about 24% shifted to the 'Borderline' state, and only 9% shifted to the 'Abnormal' state. On the other hand, 62.5% of 'Abnormal' cases and 77% of the 'Borderline' cases at the time of the first survey were able to move back to the 'Normal' state at the time of the second survey. However, 26% of 'Normal' cases at the time of survey 2 were in the 'Abnormal' band at the time of survey 3. 47% in the 'Abnormal' band at the time of the second survey were still in the 'Abnormal' band.

Although the general shift in the prevailing circumstances over time was there from survey 1 to survey 3, still the stationary probabilities provide an excellent picture of long-term proportions of the respondents being in a particular band. About 51% of the respondents were in the 'Normal' band, 17% in the 'Borderline' band, and a staggering 32% in the 'Abnormal' band. These proportions are very different from the long-term proportions of 80%, 10% and 10% under normal times, as suggested by the SDQ and other manuals. The authors have reached at same conclusion using modeling on the complete data from the three surveys (Sabharwal *et al.*, 2023; Goyal *et al.*, 2023; Sabharwal *et al.*, 2024a).

Fitting a model to any data enables the researcher to draw a greater amount of information in comparison to the inferences drawn on the basis of data only. In an earlier paper, the authors used the QR and QRNN models to estimate the 'Impact' score on the basis of the four scales of the 'Difficulty' score. Whereas the QR model was able to obtain the estimates of four predictors using data-based quantile (ratio of 'Normal' category with

‘Affected’ categories), the QRNN model was able to pick the best quantile from the given range of quantiles and obtained the estimates of the individual predictors. However it did not provide the significance of the estimates, which were then obtained using the QR model at the quantiles estimated by the QRNN model. Finally, the results of the two models were used to estimate the proportions of ‘Impact’ scores in the three severity bands as a function of the four scales of ‘Difficulty’ scores. These models can be useful to estimate social dysfunction problems when the researcher has used the basic version of SDQ only.

Tables 6, 7, and 8 provide the transition probabilities for the observed ‘Impact’ scores, the estimated scores using the QR model, and the estimated scores using the QRNN model for transitions from survey 1 to 2, from survey 2 to 3, and from survey 1 to 3, respectively. Also, stationary probability distributions have been obtained. The QRNN model has outdone the QR model in the prediction of ‘Impact’ scores. These tables validate the findings of Table 3. Not only were the behavioral problems pertinent, but a large chunk of young adults were facing social dysfunction issues as well. Again, the long-term proportions were disturbing as the cohort under study was a cohort of seemingly healthy young adults without any visible or identified mental health issues.

The standard proportions of a healthy population in the three categories of states, viz. ‘Normal’, ‘Borderline’ and ‘Abnormal’ have been estimated to be 80%, 10% and 10% respectively (Goldberg & Williams, 1988; Lovibond & Lovibond, 1995; Goodman, 1999). The results of this study established the transitions in mental health of young adults in crisis times and that standard transitions fail during such periods. A similar shift has been found by the authors of this study in their previous works (Sabharwal *et al.*, 2023; Goyal *et al.*, 2023; Sabharwal *et al.*, 2024a). The issue needs to be tackled at a holistic level at such times. Further, some recent studies have shown that these proportions are shifting over time, even in healthy times, so the standard manuals may need to be revisited to examine if the standard proportions need any modifications (American College Health Association, 2008; Kumar GS *et al.*, 2012).

Acknowledgments

The authors would like to thank reviewers and editors for their comments and suggestions.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization: GOYAL, B., SABHARWAL, A, **Data curation:** GOYAL, B., SABHARWAL, A.; **Formal analysis:** GOYAL, B., SABHARWAL, A.; **Investigation:** GOYAL, B., SABHARWAL, A., JOSHI, M.L.; **Methodology:** GOYAL, B., SABHARWAL, A., JOSHI, M.L.; **Software:** GOYAL, B., SABHARWAL, A., JOSHI, M.L.; **Supervision:** GOYAL, B., SABHARWAL, A.; **Validation:** GOYAL, B., SABHARWAL, A., JOSHI, M.L.; **Visualization:** GOYAL, B., SABHARWAL, A.; **Writing - original draft:** GOYAL, B., SABHARWAL, A., JOSHI, M.L.; **Writing - review and editing:** GOYAL, B., SABHARWAL, A., JOSHI, M.L.

References

1. American College Health Association-National College Health Assessment Spring 2007 Reference Group Data Report (Abridged). *Journal of American College Health* **56**(5), 469–480, 2008. <https://doi.org/10.3200/jach.56.5.469-480>
2. Cannon, A. J. Quantile regression neural networks: implementation in R and application to precipitation downscaling. *Computers & Geosciences*, **37**, 1277-1284 (2011). <https://doi.org/10.1016/j.cageo.2010.07.005>
3. Cipresso, P., Borghesi, F., & Chirico, A. Affects affect affects: A Markov Chain. *Frontiers in Psychology*, **14** (2023). <https://doi.org/10.3389/fpsyg.2023.1162655>
4. Claudio, D., Moyce, S., Albano, T., Ibe, E., Miller, N., & O’Leary, M. A Markov Chain model for mental health interventions. *International Journal of Environmental Research and Public Health*, **20**(4), 3525 (2023). <https://doi.org/10.3390/ijerph20043525>
5. Collins, L. M., & Lanza, S. T. Latent class and Latent transition analysis. In *Wiley series in probability and statistics*. (2009). <https://doi.org/10.1002/9780470567333>
6. Duffy, S. W., Day, N. E., Tabár, L., Chen, H. H., Smith, T. C. Markov models of breast tumor progression: some age-specific results. *J Natl Cancer Inst Monogr.* **93** (7) (1997). <https://doi.org/10.1093/jncimono/1997.22.93>
7. Farooqi, A. A Comparative Study of Kendall-TheilSen, Siegel Vs Quantile Regression with Outliers. *Wayne State University Dissertations.* 2352. (2019). https://digitalcommons.wayne.edu/oa_dissertations/2352
8. Goel, K., Grover, G., Sharma, A. & Bae, S. Multistate Markov model for predicting the natural disease progression of type 2 diabetes based on hemoglobin A1c. *Journal of Nephro pharmacology*, **8**(1), 4 (2018). <https://doi.org/10.15171/npj.2019.04>
9. Goldberg, D. P., & Williams, P. D *A user’s guide to the General Health Questionnaire*. In NFER-Nelson eBooks. (1988). <https://ci.nii.ac.jp/ncid/BA23507592>
10. Goodman, R. The Extended Version of the Strengths and Difficulty Questionnaire as a Guide to Child Psychiatric Caseness and Consequent Burden. *The Journal of Child Psychology and Psychiatry and Consequent Burden*, **40**(5), 791-799 (1999). <https://doi.org/10.1111/1469-7610.00494>
11. Goyal, B., Sabharwal, A., Chauhan, V., & Joshi, L. M. Psychological health of Indian youth during COVID-19: a study through three chronological surveys. *International Journal of Public Health*, **12**(2), 752-763 (2023). <http://doi.org/10.11591/ijphs.v12i2.22420>
12. Grover, G., Sabharwal, A., Kumar, S., & Thakur, A. K. A Multi-State Markov model for the progression of chronic kidney disease. *Turkiye Klinikleri Journal of Biostatistics*, **11**(1), 1–14 (2019). <https://doi.org/10.5336/biostatic.2018-62156>
13. Grover, G., Seth, D., Vajala, R., & Swain, P. K. A multistate Markov model for the progression of liver cirrhosis in the presence of various prognostic factors. *Chilean Journal of Statistics*, 15–27 (2014). <https://www.researchgate.net/publication/272576126>
14. Huang Q, Zhang H, Chen J, & He MJJB. Quantile regression models and their applications: a review. *Journal of Biometrics & Biostatistics*, **8**(3), 1-6 (2017). <https://doi.org/10.4172/2155-6180.1000354>
15. Jackson, C. Multi-State Models for Panel Data: The msm Package for R. *Journal of Statistical Software*, **38**(8), 1–28 (2011). <https://doi.org/10.18637/jss.v038.i08>
16. Kemeny, J. G., & Snell, J. L. *Finite Markov chains*. (1976). <http://ci.nii.ac.jp/ncid/BA03539406>

17. Koenker R. Quantile Regression. In: *Econometric Society Monographs*, **38**. Cambridge University Press, Cambridge, New York 368pp. (2005) <https://doi.org/10.1017/CBO9780511754098>
18. Koenker R. & Machdo JAF. Goodness of fit and related inferences processes for Quantile Regression: *Journal of the American Statistical Association*. **94** 1296-1310 (1999). <http://doi.org/10.1080/01621459.1999.10473882>
19. Koenker RW & Bassett G. Quantile Regression, Cambridge: Cambridge University Press. (2005). https://assets.cambridge.org/97805218/45731/frontmatter/9780521845731_frontmatter.pdf
20. Kumar, G., Jain, A., & Hegde, S. Prevalence of depression and its associated factors using Beck Depression Inventory among students of a medical college in Karnataka. *Indian Journal of Psychiatry*, **54**(3), 223 (2012). <https://doi.org/10.4103/0019-5545.102412>
21. Kumar, U. D. *Business Analytics*, 2ed: The Science of Data-Driven Decision Making. Wiley (2022). <https://www.wileyindia.com/business-analytics-2ed-the-science-of-data-driven-decision-making.html>
22. Kwok, A. Research on the application of Markov chain. *Theoretical and Natural Science*, **11**(1), 147–150 (2023). <https://doi.org/10.54254/2753-8818/11/20230395>
23. Lovibond, S. H., & Lovibond, P. F. *Manual for the Depression Anxiety Stress Scales (2nd ed.)*. Sydney: Psychology Foundation of Australia. (1995). <https://search.worldcat.org/title/Manual-for-the-depression-anxiety-stress-scales/oclc/222009504>
24. McCarthy, K. J., Liu, S. H., Kennedy, J., Chan, H. T., Mayer, V. L., Vieira, L., Glazer, K. B., Van Wye, G., & Janevic, T. Prospective transitions in hemoglobin A1c following gestational diabetes using Multistate Markov Models. *American Journal of Epidemiology*. (2024). <https://doi.org/10.1093/aje/kwae219>
25. Medhi, J. *Stochastic processes* (2nd ed.). New Age International (P) Ltd. (2017). https://books.google.co.in/books/about/Stochastic_Processes.html?id=DnCWgeoaKQC&redir_esc=y
26. Merlo, L., Petrella, L., & Tzavidis, N. Quantile Mixed Hidden Markov Models for Multivariate Longitudinal Data: An Application to Children’s Strengths and Difficulties Questionnaire scores. *Journal of the Royal Statistical Society Series C (Applied Statistics)*, **71**(2), 417–448 (2022). <https://doi.org/10.1111/rssc.12539>
27. Norris, J. Markov Chains. Cambridge University Press, Cambridge. (1998). <https://doi.org/10.1017/CBO9780511810633>
28. Putter, H., Van Der Hage, J., De Bock, G. H., Elgalt, R., & Van De Velde, C. J. H. Estimation and prediction in a Multi-State model for breast cancer. *Biometrical Journal*, **48**(3), 366–380 (2006). <https://doi.org/10.1002/bimj.200510218>
29. Rabiner, L. A tutorial on hidden Markov models and selected applications in speech recognition. *Proceedings of the IEEE*, **77**(2), 257–286 (1989). <https://doi.org/10.1109/5.18626>
30. Rendle, S., Freudenthaler, C., & Schmidt-Thieme, L. Factorizing personalized Markov chains for next-basket recommendation. *Proceedings of the 19th International Conference on World Wide Web*, 811–820 (2010). <https://doi.org/10.1145/1772690.1772773>
31. Sabharwal, A., Goyal, B., & Joshi, L. M. Psychological Health of Young Adults as Measured through Internalising and Externalising Scores of Strength and Difficulty Questionnaire. *Migration Letters*, **21**(S4), 1511-1520 (2024a). Retrieved from <https://migrationletters.com/index.php/ml/article/view/7565>
32. Sabharwal, A., Goyal, B., & Joshi, L. M. A Study to Assess the Psychological Health of Young Adults through Quantile Regression and Quantile Regression Neural Network Models. *Afr.J.Bio.Sc.* **6**(9) (2024b). <https://doi.org/10.33472/AFJBS.6.9.2024.4693-4708>

33. Sabharwal, A., Goyal, B., Chauhan, V. S., Joshi, L. M., & Goyal, V. Evaluating the effect of COVID-19 pandemic on the psychological health of young adults in India. *International Journal of Public Health Science (IJPHS)*, **12**(1), 311 (2023). <https://doi.org/10.11591/ijphs.v12i1.21527>
34. Siebert, U., Alagoz, O., Bayoumi, A. M., Jahn, B., Owens, D. K., Cohen, D. J., & Kuntz, K. M. State-Transition Modeling: A report of the ISPOR-SMDM Modeling Good Research Practices Task Force-3. *Value in Health*, **15**(6), 812–820 (2012). <https://doi.org/10.1016/j.jval.2012.06.014>
35. Sonnenberg, F. A., & Beck, J. R. Markov models in medical decision making. *Medical Decision Making*, **13**(4), 322–338 (1993). <https://doi.org/10.1177/0272989x9301300409>
36. Srikanth, P. Using Markov Chains to predict the natural progression of diabetic retinopathy. *DOAJ (DOAJ: Directory of Open Access Journals)*, **8**(1), 132–137 (2015). <https://doi.org/10.3980/j.issn.2222-3959.2015.01.25>
37. Taylor, J. W. (2000). A quantile regression neural network approach to estimating the conditional density of multiperiod returns. *Journal of Forecasting*, **19**(4), 299–311 (2000). [https://doi.org/10.1002/1099-131x\(200007\)19:4](https://doi.org/10.1002/1099-131x(200007)19:4)
38. Zhang, G. Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, **50**, 159–175 (2003). [https://doi.org/10.1016/s0925-2312\(01\)00702-0](https://doi.org/10.1016/s0925-2312(01)00702-0)