

Suicide data analysis using multi-criteria decision-making

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Abstract

Suicide is a serious concern influenced with many socioeconomic, demographic, and psychological variables. A person commits suicide due to reasons like mental illness, inability to face pressure from family or peer, financial burden etc. varying for different sex or age groups. We use five different Multi-Criteria Decision-Making methodologies to analyze suicide data and examine the relationships between a number of characteristics, including gender, age and profession of victims, reasons for committing suicide and the methods used for it. We use majority voting to aggregate the results which may be useful to concerned authorities to create suicide prevention strategies.

Subject Classification: 68T99.

Keywords: MCDM, TOPSIS, VIKOR, MABAC, MAIRCA, CODAS, Suicide, Ensemble.

1. Introduction

One of the major public health issues that claims a lot of lives is suicide. Suicide is intentional taking of one's own life. It is death brought on by self-inflicted harm done with the aim to die. Every suicide-related death is a big tragedy having repercussions on the entire family members. As per the World Health Organization's (WHO) statistics, around one million individuals lose their lives to suicide annually, with an average suicide occurring every forty seconds [1]. Thirty-five thousand of the total deaths linked to suicide happened in India. The National Crime Records Bureau (NCRB) reports that over 150,000 lives are lost to suicide in India each year, making it a serious public health concern. The shockingly high suicide rates of India highlights the seriousness of the situation.

There are times in one's life when he/she is no longer able to cope with life's stresses which leads to impulsive suicides during such times of crisis [2] [3]. There are many different and intricate elements that contribute to suicide, including individual, biological, relational and societal, concerns. Individual factors of suicide include past suicide attempts, mental health issues like depression, thoughts of hopelessness, impulsive and aggressive tendencies, substance abuse, alcoholism, financial difficulties, unemployment, economic recession, social isolation and criminal problems etc. Biological factors include pre-existing chronic diseases and other health issues. Relational factors include issues with family communication, domestic losses, gender-based violence in relationships and child abuse. Societal factors include obstacles to mental health care, stigma surrounding psychiatric illness, intra-communal conflicts, and cultural differences resulting from migration, easy access to suicide vehicles, cultural, religious, and legal considerations. Research has

indicated that demographic factors, including age, gender, and educational attainment, also have a notable influence on suicide rates. Suicide rarely has a single reason; instead, it frequently has several reasons together which results in a suicide [4]. The causes of suicide in India are diverse and include societal and individual factors like mental illness, family problems, love affairs, poverty, failure in examinations, conflicts from extramarital affairs, and sexual harassment [5], [6]. These factors contribute to the anomic conditions in society, leading to isolation and loneliness, which in turn can lead to suicide [6], [7].

Research suggests that better property rights for women in India are associated with a decrease in the difference between female and male suicide rates, but an increase in both male and female suicides [8]. Education level, marital status, and occupation play a significant role in suicide rates in India. For instance, people with higher education levels and those currently married have higher suicide death rates [9]. Indian women face various stressors like domestic violence, conflict within households, dowry demands, changes in expectations about marriage relationships, widowhood and social exclusion that contribute to the high rates of suicide among them [8] [10]. Even though the number of suicide cases is rising, they can be partially avoided by being aware of risk factors associated with suicidal behaviour in the early phases of the suicidal process. The key to lowering the number of suicide deaths is prevention. Focused preventive strategies are required which should aim to enhance the care of suicidal people, along with psychiatric and pharmaceutical treatments as well as coordinated social and public health initiatives. Limiting access to pesticides along with addressing family problems, and involving various stakeholders in suicide prevention are identified as effective strategies to reduce suicides [11], [12]. Inappropriate media reporting, and legal conflicts are identified as major barriers to effective suicide prevention in India [11].

The aim of conducting an analysis on the causes of suicide is to develop preventive strategies that consider various factors like gender, age, and cause [13]. Developing preventive efforts can be aided by comprehending the causes of stress experienced by working professionals and determining the connection between suicidal ideation and stress [14]. This may help in developing a national suicide prevention strategy. There is an urgent need for targeted prevention and intervention programs to address the complex societal issues contributing to women's suicides in India.

In their paper, Aggarwal [15] discuss the pressing need for approaches to deal with India's suicide problem. In order to provide policymakers and

medical experts with insights into the trends and drivers of suicide in India, this study uses five most popular different MCDM techniques (TOPSIS, VIKOR, MABAC, MAIRCA, CODAS) to analyze suicide data and majority voting ensemble method to collate the results. As far as we know, no one has used MCDM methods to analyze suicide data.

2. Theoretical Concepts

2.1 Multi-criteria Decision Making (MCDM)

A collection of techniques or procedures known as “multi-criteria decision-making” (MCDM) are used to assess, contrast, and prioritize various possibilities or alternatives according to simultaneous consideration of several factors/criteria. The main elements of the MCDM technique are the alternatives/choices, factors/criteria, the weights and impact of these criteria. In essence, this strategy uses the scores that have been calculated for each accessible alternative to choose the best one.

Decision-making consistency is ensured by the transparent and repeatable nature of MCDM. It is devoid of human bias resulting from manual decision-making because it is mathematical in nature. These techniques provide an organized and methodical approach which helps to simplify and manage challenging issues in decision making. MCDM is employed in different domains like engineering, business, and healthcare and also for making public policy [16].

There exists multiple MCDM techniques in literature. One of the popular MCDM technique in decision-making is Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [17] which contrasts options according to their deviation from best and the worst solution. The optimal solution is selected as the one which is closest to the ideal positive solution and farthest from negative ideal solution.

Multi-Criteria Optimization and Compromise Solution, or VIKOR (Vlsekriterijumska Optimizacija I Kompromisno Resenje) by Opricovic and Tzeng [18] is a compromised version of TOPSIS which uses linear normalization technique. The opponent has the least degree of personal remorse and the majority the most group utility in the solution obtained using the VIKOR method of adjusted ranking. Compromise solution that is closest to ideal solution is identified by method.

Developed by Pamučar and Ćirović in 2015 [19], the Multi-Attributive Border Approximation area Comparison (MABAC), finds the distance between each option and the border approximation area. The border approximation area stands for a middle ground between the ideal and

anti-ideal solutions. This space is used to quantify the distances between each option and the ideal and anti-ideal solutions. Finally option closest to the ideal solution is selected as the best option.

The MAIRCA method [20] assesses discrepancies between theoretical and empirical assessments. It looks for the superior alternative by calculating the difference between the two for each decision. The choice with the lowest utility score is the best one. The technique can be used with datasets that have both qualitative and quantitative requirements.

Combinative Distance-based Assessment (CODAS) method created by Ghorabae et al. in 2016 [21] uses both Euclidean and Taxicab distances to assess the performance of each choice. The total efficacy of an alternative is measured by these separations from the negative-ideal point. If two alternatives' Euclidean distances are very close to each other, the taxicab distance is used to compare them.

2.2 Ensemble MCDM

Different rankings are produced by using different MCDM methods even on giving the same input [22]. Ensemble approaches combine these results into a common consensus to increase the process's accuracy, robustness, and dependability [23]. Comparable to machine learning ensemble methods, which combine predictions from multiple models to reach a conclusion, ensemble MCDM combines the results of various MCDM approaches to produce a more thorough and dependable conclusion. Through the integration of numerous methodologies, ensemble MCDM methods offer a sophisticated approach to decision-making, resulting in more accurate, dependable, and balanced decisions in a variety of complicated scenarios.

Majority voting ensemble approach is a straightforward but efficient way to combine the output from several classifiers or decision-making algorithms. In this method a number of decision-making models that are appropriate for the given situation are chosen. Based on the specified criteria, each chosen model separately assesses the options and generates a decision or ranking. The choices made by each model are then compiled. This involves determining the number of votes each option gets from each of the individual models. The option that receives the most votes is chosen to be the final choice. When it comes to rankings, the option with highest overall rank is selected. This method has been shown to perform without requiring the domain expertise [24].

3. Method

National Crime Records Bureau (NCRB), India keeps track of data regarding the number of suicide fatalities in the country. This information is kept for a variety of characteristics, including age, gender, social class, economic condition, level of education, professional status, occupation, etc. Data is categorized into reasons like bankruptcy, failure in exams, rape, impotency etc. Classification based on number of suicides by different professionals is also available. We also have the data about the number of suicides committed by various methods like by consuming poison or by hanging etc. Essentially, the data is classified according to the gender and different age groups committing suicide along with the method, reason and professional status. Data was downloaded from NCRB site [25], pre-processed and formatted for our use. To study the reason for committing suicide by different age groups we constructed a *Reason Age* table as shown in Table 1. It has different age groups for both male and female along its rows and various reasons for committing suicide on the columns. Each entry t_{ij} contains the number of suicides committed by i^{th} gender age group and j^{th} reason.

Similarly, to analyse the method of suicide in different age groups we constructed a *Method Age* table as shown in Table 2. It has different age

Table 3
Profession Age Table

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
F_0-14	526	569	49	30	7	98	9	167	7340	382
F_15-29	10495	127415	1472	2299	80	2114	1703	9156	24887	10459
F_30-44	9347	96636	1204	1958	123	2190	1699	5977	1059	6160
F_45-59	5096	43579	664	1110	347	1099	743	2678	84	2573
F_60+	1836	17044	228	133	1130	288	77	644	22	971
M_0-14	515	0	107	33	2	155	6	177	7279	499
M_15-29	42205	0	9602	7166	205	18177	4208	30012	31332	35783
M_30-44	64287	0	14180	10187	352	29989	8443	40103	2054	34765
M_45-59	45070	0	9330	6848	1858	19306	6224	23041	243	17313
M_60+	18546	0	2368	1022	7230	4696	213	3517	23	5469

P1: Farming , P2: House Wife, P3: Professional, P4: PSU, P5: Retired, P6: Self-Employed, P7: Govt Service, P8: Private, P9: Student, P10: Unemployed

Table 4 States Suicide Table

Patient Information		Vital Signs		Physical Exam		Laboratory Tests		Imaging Studies		Treatment Plan		Follow-up		Notes	
Name	Age	Height	Weight	BP	HR	Temp	SpO2	Glucose	HbA1c	X-ray	Ultrasound	Medication	Dosage	Next Visit	Comments
John Doe	45	175	75	120/80	72	37.2	98	100	5.6	Chest X-ray	Abdominal US	Metformin	500mg BID	2 weeks	Stable, no symptoms.
Jane Smith	52	160	60	110/70	68	36.8	97	95	6.2	None	None	Insulin	10 units TID	1 month	Good control, slight weight gain.
Michael Johnson	38	180	80	130/90	85	37.5	96	110	7.8	ECG	None	Aspirin	81mg QD	3 months	Controlled hypertension, monitor glucose.
Emily Davis	29	165	65	115/75	70	37.0	99	90	5.1	None	None	None	None	6 months	Excellent health, all vitals normal.
David Wilson	60	170	70	125/85	75	37.3	97	105	6.5	ECG	None	Statins	20mg QD	1 year	Stable, good response to treatment.
Sarah Brown	41	168	68	118/78	72	37.1	98	98	5.8	None	None	None	None	3 months	Stable, no changes needed.
Robert Lee	55	178	78	122/82	73	37.2	97	102	6.0	ECG	None	Metformin	500mg BID	2 months	Controlled, slight improvement in glucose.
Jennifer White	33	162	58	112/72	69	36.9	98	92	5.3	None	None	None	None	4 months	Stable, all parameters within range.
Christopher Green	48	172	72	120/80	71	37.1	97	100	5.7	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Amanda Black	50	166	62	116/76	70	37.0	98	96	6.1	None	None	Insulin	10 units TID	2 months	Good control, stable weight.
Daniel King	35	170	65	120/80	72	37.1	99	90	5.2	None	None	None	None	5 months	Excellent health, all vitals normal.
Michelle Hall	42	164	60	114/74	68	36.9	98	94	5.5	None	None	None	None	3 months	Stable, no symptoms.
Kevin Young	58	176	76	124/84	76	37.3	96	108	6.8	ECG	None	Statins	20mg QD	1 year	Controlled, good response to treatment.
Nicole Adams	30	163	59	113/73	69	36.9	98	92	5.3	None	None	None	None	4 months	Stable, all parameters within range.
Brandon Taylor	40	171	66	121/81	71	37.1	97	100	5.7	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Stephanie Miller	37	167	67	117/77	71	37.0	98	96	5.9	None	None	None	None	3 months	Stable, no symptoms.
Gregory Scott	43	177	73	126/86	77	37.3	96	110	7.5	ECG	None	Statins	20mg QD	1 year	Controlled, good response to treatment.
Christina Baker	32	161	57	111/71	67	36.8	98	92	5.3	None	None	None	None	4 months	Stable, all parameters within range.
Nathan Evans	24	169	64	119/79	69	36.9	98	94	5.5	None	None	None	None	3 months	Stable, no symptoms.
Hannah Roberts	39	169	69	119/79	73	37.0	97	100	5.7	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Tyler Phillips	23	168	63	118/78	68	36.8	98	92	5.3	None	None	None	None	3 months	Stable, no symptoms.
Samantha Turner	35	165	61	115/75	70	37.0	98	96	5.9	None	None	None	None	3 months	Stable, no symptoms.
Jonathan Price	43	179	76	127/87	79	37.4	95	115	8.0	ECG	None	Statins	20mg QD	1 year	Controlled, good response to treatment.
Katherine Cook	32	163	59	113/73	69	36.9	98	94	5.5	None	None	None	None	3 months	Stable, no symptoms.
Austin Bell	28	171	66	121/81	71	37.1	97	100	5.7	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Megan Ward	36	166	62	116/76	70	37.0	98	96	5.9	None	None	None	None	3 months	Stable, no symptoms.
Dylan Allen	25	170	65	120/80	72	37.1	99	90	5.2	None	None	None	None	5 months	Excellent health, all vitals normal.
Alexis Young	33	164	60	114/74	68	36.9	98	94	5.5	None	None	None	None	3 months	Stable, no symptoms.
Caleb King	40	176	72	124/84	74	37.2	96	108	6.8	ECG	None	Statins	20mg QD	1 year	Controlled, good response to treatment.
Isabella Garcia	27	162	55	110/70	65	36.8	99	88	4.9	None	None	None	None	4 months	Excellent health, all vitals normal.
Diego Hernandez	31	173	68	122/82	73	37.1	97	100	5.7	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Sophia Martinez	24	160	50	108/68	60	36.7	99	85	4.7	None	None	None	None	3 months	Excellent health, all vitals normal.
Lucas Rodriguez	35	175	70	120/80	72	37.1	98	95	5.6	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Mia Lopez	29	165	60	115/75	70	37.0	98	92	5.4	None	None	None	None	4 months	Stable, no symptoms.
Benjamin Wilson	42	178	75	125/85	75	37.2	96	105	6.5	ECG	None	Statins	20mg QD	1 year	Controlled, good response to treatment.
Charlotte Brown	38	168	65	118/78	72	37.1	97	98	5.8	None	None	None	None	3 months	Stable, no symptoms.
James Taylor	50	172	72	120/80	71	37.1	97	100	5.7	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Aria White	26	163	52	110/70	62	36.7	99	88	4.8	None	None	None	None	3 months	Excellent health, all vitals normal.
Leo Green	33	170	65	120/80	72	37.1	98	95	5.6	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Olivia Black	30	161	55	110/70	65	36.8	99	88	4.9	None	None	None	None	4 months	Excellent health, all vitals normal.
Noah Brown	28	169	64	119/79	69	36.9	98	94	5.5	None	None	None	None	3 months	Stable, no symptoms.
Ava White	36	166	62	116/76	70	37.0	98	96	5.9	None	None	None	None	3 months	Stable, no symptoms.
Ethan Green	25	170	65	120/80	72	37.1	99	90	5.2	None	None	None	None	5 months	Excellent health, all vitals normal.
Madison Black	32	163	59	113/73	69	36.9	98	94	5.5	None	None	None	None	3 months	Stable, no symptoms.
Lucas Brown	40	171	66	121/81	71	37.1	97	100	5.7	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Chloe White	29	162	58	112/72	69	36.9	98	92	5.3	None	None	None	None	4 months	Stable, no symptoms.
Benjamin Green	37	167	67	117/77	71	37.0	98	96	5.9	None	None	None	None	3 months	Stable, no symptoms.
Sophia Black	34	164	60	114/74	68	36.9	98	94	5.5	None	None	None	None	3 months	Stable, no symptoms.
Matthew White	41	174	71	123/83	73	37.2	96	106	6.6	ECG	None	Statins	20mg QD	1 year	Controlled, good response to treatment.
Isabella Green	27	162	55	110/70	65	36.8	99	88	4.9	None	None	None	None	4 months	Excellent health, all vitals normal.
Diego Brown	31	173	68	122/82	73	37.1	97	100	5.7	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Sophia White	24	160	50	108/68	60	36.7	99	85	4.7	None	None	None	None	3 months	Excellent health, all vitals normal.
Lucas Green	35	175	70	120/80	72	37.1	98	95	5.6	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Mia Black	29	165	60	115/75	70	37.0	98	92	5.4	None	None	None	None	4 months	Stable, no symptoms.
Benjamin White	42	178	75	125/85	75	37.2	96	105	6.5	ECG	None	Statins	20mg QD	1 year	Controlled, good response to treatment.
Charlotte Green	38	168	65	118/78	72	37.1	97	98	5.8	None	None	None	None	3 months	Stable, no symptoms.
James Black	50	172	72	120/80	71	37.1	97	100	5.7	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Aria White	26	163	52	110/70	62	36.7	99	88	4.8	None	None	None	None	3 months	Excellent health, all vitals normal.
Leo Green	33	170	65	120/80	72	37.1	98	95	5.6	ECG	None	Aspirin	81mg QD	1 year	Stable, good overall health.
Olivia Black	30	161	55	110/70	65	36.8	99	88	4.9	None	None	None	None	4 months	Excellent health, all vitals normal.
Noah Brown	28	169	64	119/79	69	36.9	98	94	5.5	None	None	None	None	3 months	Stable, no symptoms.
Ava White	36	166	62	116/76	70	37.0	98	96	5.9	None	None	None	None	3 months	Stable, no symptoms.
Ethan Green	25	170	65	120/80	72	37.1	99	90	5.2	None	None	None	None	5 months	Excellent health, all vitals normal.
Madison Black	32	163	59	113/73	69	36.9	98	94	5.5	None	None	None	None	3 months	Stable, no symptoms.
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Sophia Black	34	164	60	114/74	68	36.9	98	94	5.5	None	None	None	None	3 months	Stable, no symptoms.
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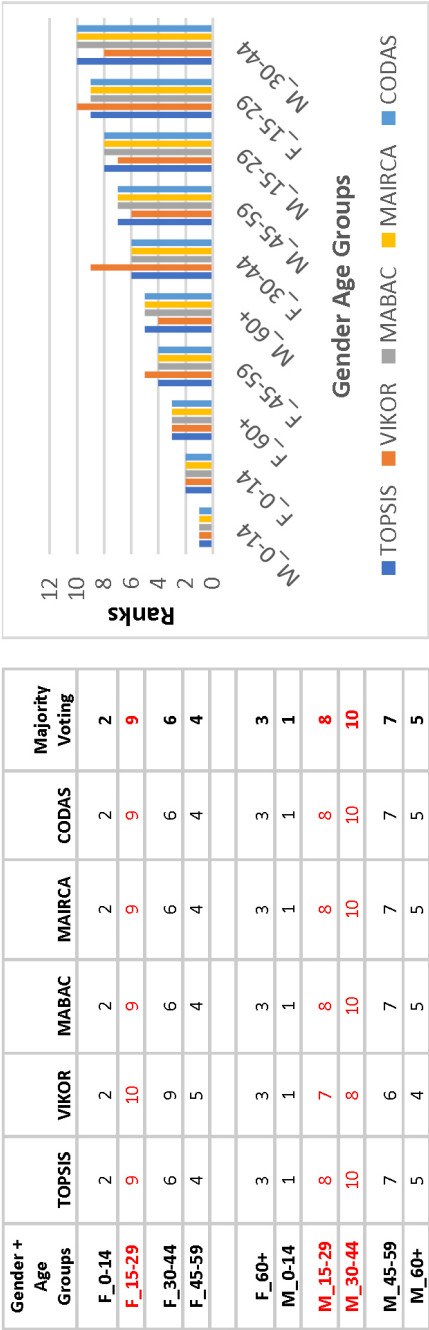


Figure 1

Results obtained by different MCDM methods and Majority Voting from Reason Age Table

Figure 1(a), Figure 1(b) Ranks for different gender age groups

groups for both male and female along the rows and various methods used for committing suicide on the columns. Each entry t_{ij} contains the number of suicides committed by i^{th} gender age group using j^{th} method. Finally, we constructed a *Profession Age* table as shown in Table 3 to study the profession of different gender age groups committing suicides. It has different age groups for both male and female along the rows and along the columns it has their profession. Each entry t_{ij} contains the number of suicides committed by i^{th} gender age group of j^{th} profession.

To find the most vulnerable age group for committing suicide in relation to all the criteria such as reasons, methods, and profession taken together, we concatenated *Reason Age* table, *Method Age* table and *Profession Age* table. The *States Suicide* table was constructed to analyse suicides in Indian states based on all criteria such as reason for committing suicide, method used, the level of education, profession and the marital status of people who committed suicide as shown in Table 4. The table has Indian states on the rows and all these criteria on the columns.

We analysed the dataset constructed to extract valuable information about various variables of suicide. Python code using *pymcdm* [26] library was used for the task. PyMCDM, python package created especially for MCDM, is a useful tool for researchers, analysts, and decision-makers in a variety of domains since it offers a strong foundation for using multiple criterion decision-making techniques. It gives users a complete toolkit and approach to solve MCDM issues, allowing them to assess and prioritize options according to a variety of factors. To gain more confidence in our results we used five different MCDM methods, namely TOPSIS, VIKOR, MABAC, MAIRCA and CODAS. We used Majority voting ensemble

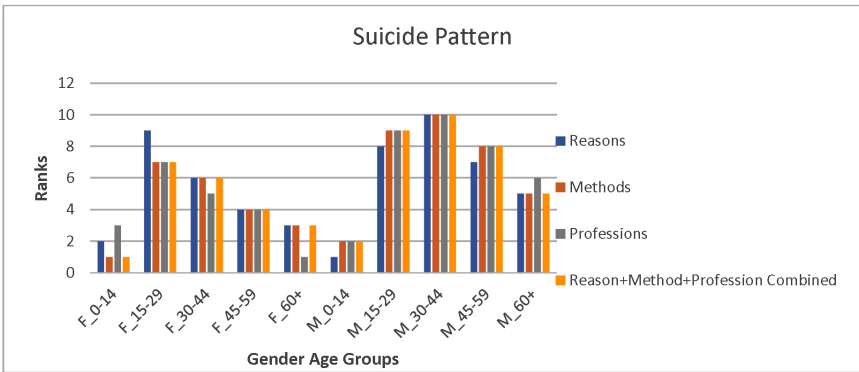


Figure 2
Ranks of age groups obtained from Tables 1, 2, 3 & 1 to 3 concatenated

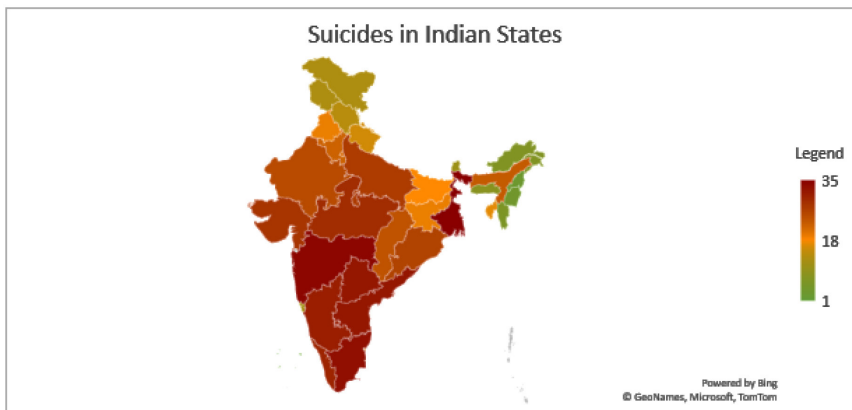


Figure 3

Incidents of suicide in Indian states

method to aggregate the obtained results from different MCDM algorithms.

4. Experiments and Results

We used five MCDM techniques (TOPSIS, VIKOR, MABAC, MAIRCA, CODAS) on *Reason Age* table to find out the most vulnerable (indicated by highest rank 10) age group amongst males and females based on the reason for committing suicide. The results obtained were combined using majority voting ensemble method and are shown in Figure 1. As is seen in Figure 1(a), suicide is more common among the Indian males aged 30 to 44 years and 15 to 29. In females, maximum suicides are committed by those between the ages 15 to 29 years. Graphical representation of ranks is shown in Figure 1(b).

Similar method was applied to obtain results from all other tables. This involved using all five methods of MCDM followed by majority voting ensemble method to obtain the result. *Method Age* table was used to find the most vulnerable age group according to the method used for committing suicide. We used *Profession Age* table to find out the most vulnerable age group according to their profession. We concatenated *Reason Age* table, *Method Age* table and *Profession Age* tables to find the most vulnerable age group according to all the above factors taken together. Figure 2 shows the results obtained from *Reason Age* table, *Method Age* table and *Profession Age* tables and the combined tables (1 to 3).

Using MCDM on States suicide table gave us insight into the Indian state where maximum suicides have taken place taking all factors into account. The results are shown in Figure 3. Authorities may take

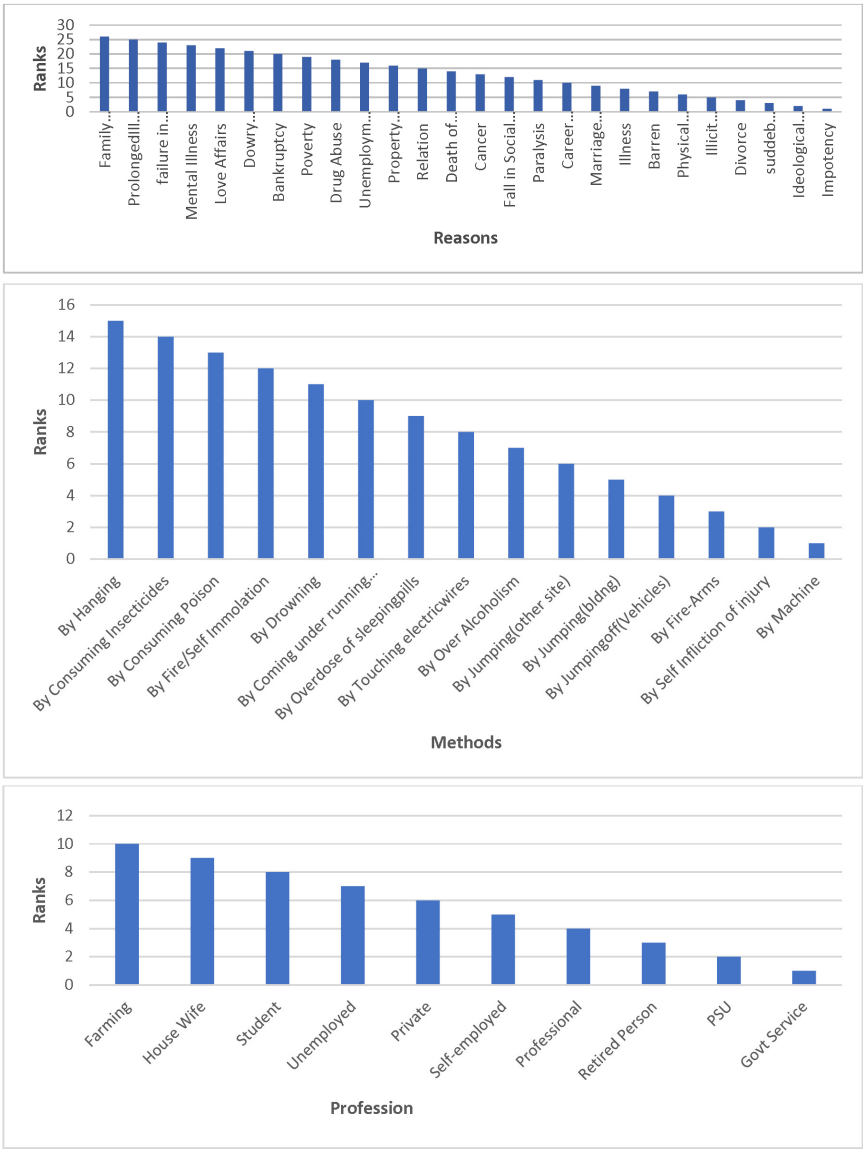


Figure 4
Analysis of traits of people committing suicide
Figure 4(a), Figure 4(b), Figure 4(c) Reasons, Methods and Professions

appropriate steps from this information with a special focus on states like West Bengal, Maharashtra, and Tamil Nadu etc. Northeastern states reported the minimum number of suicides.

Figure 4 shows the result of our in-depth study of traits of the people committing suicide. We used *Reason Age* table to study the main reason behind suicides for all age groups for both males and females. MCDM methods followed by majority voting was done to get the results as shown in Figure 4(a). We found that problems in family was the main reason due to which people committed suicide. Also, failure in exam or their inability to cope with prolonged illness was also the reason for them to take their lives quite often. Similarly, *Method Age* table was used to find the most frequently used method to commit suicide. Most of the people had hanged themselves to commit suicide. Many people had committed suicide by consuming insecticides or poison as shown in Figure 4(b). Running MCDM on *Profession Age* table gave us insight into the profession of the people committing suicides as shown in Figure 4(c). According to the results, maximum number of suicides were committed by farmers or house wives.

To find the most vulnerable age group along with gender and the common reason to commit suicide, all the results obtained from *Reason Age* table are combined and are shown in Table 5. We observe that females in the age group 15 years to 29 and males in the age group of 15 years to 44 years commit suicide mainly due to family problems, unable to face failure in exam or unable to cope with prolonged illness. Also, females aged 30 years to 44 years and males aged 45 years to more than sixty years commit suicide due to a dowry demands, broken love affair or some mental health issue. We also conclude that females aged 45 years and above, both males and females till 14 years of age commit suicide because of poverty, drug abuse or bankruptcy.

Similarly, the most vulnerable age group for both males and females and the common method used to commit suicide was inferred by combining all the results obtained from *Method Age* table and are shown in Table 6. We conclude that males of age 15 to 59 commit suicide mostly by hanging or by consuming poison or insecticides. Further females in the age group 15 to 44 years and males aged sixty plus commit suicide by self-immolation, drowning or by jumping in front of vehicle. Also, females aged 45 years and above both males and females till 14 years of age commit suicide by consuming alcohol or excess sleeping pills, or due to electric wires. Similarly, the profession of the most vulnerable age group for both males and females was inferred by combining all the results obtained from

Profession Age table and are also shown in Table 6. We conclude that farmers, unemployed youth and male students who commit suicide belong to age group 15 to 59. Further females in the age group 15 to 44 years and males aged sixty plus who commit suicide either are doing private job or are self-employed professionals. Also, females aged 45 years and above, both males and females till 14 years of age who commit suicide are retired or are government/PSU employees.

Table 5
Reasons, Age and Gender groups

Age group	Gender	Reasons
15 to 29	Females	Family Problem, Failure in Exam, Prolonged illness
15 to 44	Males	
30 to 44	Females	Dowry demands, Mental Health, Love affair
45 to sixty plus	Males	

Table 6
Method, Profession, Age and Gender groups

Age group	Gender	Method	Profession
15 to 59	Males	Hanging, Consuming Insecticides and Poison	Farming, Unemployed students
15 to 44	Females	Self-Immolation, Drowning, Jumping in front of vehicle	Private-job, Self-employed, Professional
Sixty plus	Males		

5. Conclusion

From our analysis of suicide data, we conclude that in India younger people generally unemployed youth or students or even farmers commit suicide mainly due to unemployment, failure in exam, family problems, poverty etc by hanging or by consuming poison or insecticides. Also, steps should be taken by the authorities to help the farmers and the unemployed with a special focus on states like West Bengal, Maharashtra, and Tamil Nadu etc. There is an urgent need of a multifaceted strategy for India's suicide prevention. Steps should be taken to bridge gap between rich and poor tackling socioeconomic activity, providing employment, skill-based education and affordable mental health services etc. Regulating and limiting the sale of highly toxic pesticides can greatly lower the suicide

rate in rural areas where pesticide consumption is a popular means of suicide. It is worth noting that many students commit suicides as they are unable to face failure in exam so, teaching young people about coping strategies, stress management, and asking for help by incorporating mental health education into the curriculum beginning at school level should be a mandatory requirement. Not only students but parents need to be taught about parenting, how to handle failures of their children and how to recognize and respond to indicators of mental illness in kids and teenagers. Campaigns to increase public awareness, programs for economic support like job opportunities, cash incentives for disadvantaged groups, and support for education. Programs made keeping women in mind should be of high priority.

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