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Predictive Modelling of Personal Remittances Received in India Using Machine Learning

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ABSTRACT

In 2022, India secured the highest remittances according to the World Migration Report, 2024 on account of migration. The present study examines the impact of net emigration and personal remittances received from abroad considering such factors as higher education enrolment and percentage of population using internet in India over more than two decades, spanning from 2000 to 2022. The distinctive contribution of the paper lies in its methodological use of regression, artificial neural network (ANN) and support vector machine (SVM) methods, using World Bank Development indicators for India. Primary results show a poor correlation of decreasing net emigrations with rising higher education enrolment and internet usage trends. However, personal remittances were found to be strongly correlated to these indicators. The results indicate a growing shift towards lesser emigrations numbers comprising of highly educated/skilled manpower as compared to a low skilled/less educated mass emigration in previous years. ANN maximised predictive accuracy of personal remittance models in comparison to the conventional regression method as well as SVM methods. The study will help formulate policies in the future, by applying effective modelling techniques to capture the complex dynamics trends in global migration.

1. INTRODUCTION

Migration is a global phenomenon influenced by a variety of factors. The study [1] defined an international migrant as "any person who changes his or her country of usual residence". Such migration could be a short-term change such as three to twelve months or long term beyond twelve months. While international migration impacts both the home and foreign economies, internal migration has an impact only on domestic economy or the country of origin. Such impact can be economic or non-economic. Forecasting human migration and its relationship to population growth, size and other indicators is crucial for a number of industry, planning, and strategy-related policies.

1.1 Overview of migration

In India, there are primarily two forms of migration. The first group of migrants are individuals with technical skills and who are members of the executive work force. They usually relocate to industrialised countries such as the United States, the United Kingdom and others. India is a significant supplier of unskilled and semi-skilled labourers, as well as professionals in the medical, scientific, technology, engineering, and mathematics (STEM) skill sectors. The second group of migrants comprise unskilled and semi-skilled workers make up a significant percentage of the migrant population and are primarily employed in blue-collar jobs in Middle Eastern nations, particularly in the oil and construction sectors [2]. People's movements and destination choices are influenced by a number of socio-economic and political factors. Individual behaviours lead to migration, but these behaviours also take on an overall social form. According to the recent statistics, about 216 million people would be forced to move/relocate by 2050 [3] due to various push and pull factors. Researchers have observed that economic development has a major impact on the migratory process [4, 5]. However, literacy is a very important factor affecting migration. In modern times, literacy includes both primary/secondary/tertiary education as well as digital literacy levels.

1.2 Factors and impact of migration

Numerous socioeconomic and technological elements influence migration and are important in determining people's decisions to relocate. The effects of digital literacy and education on migration patterns are examined in this part.

1.2.1 Effect of digital literacy on migration

Digital literacy is important in the context of migration since it helps migrants at different points of their trip. Digital literacy has a big impact on migration since it allows refugees to obtain information and stay connected, as well as facilitate marriage, work, and student migrations via online platforms [6]. Internet usage is important indicator of digital literacy because internet is used for various educational purposes, banking/ financial transactions, accessing government schemes and services, transportation, accessing information about agricultural markets, buyers, and migration avenues as well. Hence, in this study, internet usage in India (as a % of total population) was selected as one of the causes impacting migration for correlation and modelling.

1.2.2 Effect of education on migration

Education is another very important factor affecting migration. In the Indian scenario, tertiary education levels will dictate the migration trends very majorly. In other words, progressively lesser number of migrants having progressively higher qualifications are being/will be welcomed and deemed desirable migrants by the destination countries. Hence, in this study, tertiary school enrolment in India (as a % of total population) was selected as another cause impacting migration. The following subsection discusses the various impacts of migration on the local economy and other factors, with an emphasis on remittances.

1.2.3 Impacts of migration

Migration has a profound impact on unemployment, enhance the quality of life in migrant families, and help financially growth by alleviating labour shortages [7]. On the other hand, international migration and remittances allow other family members and community members to continue living in rural areas. International migration causes left-behind, tertiary-educated people from rural areas to favor metropolitan jobs [8-10]. One of the most important impacts is remittance. The following section throws light on various aspects of remittances, with a particular focus on Indian scenario.

1.3 Factors and impact of remittances

Remittance has been defined as "household income from foreign economies, arising mainly from the temporary or permanent movement of people to those economies" [11]. Personal remittances refer to the money transferred by individuals who are working and residing in foreign countries to their families or relatives in India.

1.3.1 Drivers of remittances

Political security in host nations influence remittance transfers [12]. The study [13] indicated that remittances in GCC host countries are more influenced by macroeconomic factors, particularly wage rate differences. On the other hand, factors such as social capital, transportation facilities and the extent of illicit trade influence the proportion of remittances using unofficial routes [14].

The following section provides insight into the role of higher education on remittances received by India.

1.3.2 Effect of education on remittance

A majority of the high-skilled jobs in high-income nations like the United States, the United Kingdom, and East Asia have benefited from a gradual structural shift in Indian migrants' primary destinations from largely low-skilled, informal employment in the Gulf Cooperation Council (GCC) countries. Hence, in this study, tertiary school enrolment in India (as a % of total population) was selected as a cause impacting remittances received in India for correlation and modelling.

1.3.3 Effect of digital literacy on remittance

Digital literacy forms an important part of the overall literacy of a modern individual. Digital literacy helps migrants process remittances back home with ease. It is notable that the 2030 Agenda for Sustainable Development sets a specific target for SDG Goal 10, by 2030 reduce to less than 3 per cent of the digital transaction costs of migrant remittances and eliminate remittance corridors with costs higher than 5 per cent. Hence, in this study, internet usage in India (as a % of total population) was selected as one of the causes impacting remittances for correlation and modelling.

1.3.4 Impacts of remittances

Remittances are recognised as a lifeline for many struggling families and communities. Family food needs, access to healthcare, a good education, and access to clean water and sanitation are all directly met through remittances [15, 16]. The increase in personal remittances has been a significant contributor to the Indian economy, as it not only helps support the families of the individuals who are working abroad but also helps boost the country's foreign exchange reserves. Additionally, these remittances have played a critical role in alleviating poverty and improving the standard of living for many Indian families.

The present study seeks to understand the relationship between tertiary school enrolments and internet usage in India with the migration and remittances received from abroad. Since, the internet usage really took off in India after the year 2000, and the tertiary education database is continually available (without any data gaps) only from the year 2000 onwards, this study considered the period 2000 to 2021 for correlation analysis and predictive modelling of migration and remittances in terms of tertiary schooling and internet usage. This study explicitly focused on the application of machine learning techniques to enhance the prediction accuracy of the developed migration and remittance regression method.

This paper is divided into five sections. The introduction and overall context of the study are given in the section one. In depth literature reviews on topics like remittances, migration, higher education, internet usage, and digital literacy are provided in section two included, the research gap perceived during the literature review. Section three outlines the methodology used to answer the main research question How can machine learning be applied to enhance the predictive modelling accuracy of net migration and personal remittances in the Indian context. The results and their discussion are presented in section four, and the conclusions limitations and suggestions are provided in the concluding section five.

2. LITERATURE REVIEW

Remittances are critical for bridging the ‘gaps’ in the financial accounts of countries. This is why the Reserve Bank of India (RBI) offers additional benefits to the non-resident Indian (NRI) deposits from time to time. Despite the fact that India is a big economy, remittances have always had a substantial impact on its economic indicators [17].

The promotion of education has also been greatly aided by migration, as immigrants' financial support to their families enhances the educational opportunities and quality of life for their families enhances the educational opportunities and quality of life for their wards [18, 19]. Researchers [20] have investigated how remittances affect the growth of higher education in the topmost remittance receiving countries. According to research findings, a significant number of migrants stated that the internet helped and encouraged them to relocate, as well as slightly impacted their choice of location [21, 22]. Machine learning models have been employed to forecast origin/destination flows of human migration [23], and neural network modelling has been applied to assess the impact of international migration on a nation's economic and demographic expansion [24]. Partial dependency plots (PDP) were used for evaluating machine learning models and demonstrating their feasibility in modelling international migration. A dataset of yearly international bilateral migration from 175 origin countries to 33 OECD destinations between 1960 and 2010 was used to train and assess the machine learning model [25]. Support vector machine (SVM) and particle swarm optimization (PSO) based machine learning methods have been employed to forecast the duration of stay of international migrants. It has also been argued that there is no "best" migration prediction model that accurately fits all kinds of migration trends data [26, 27]. Machine learning models for predicting reverse migrations have been reviewed, and an ensemble model has been created to determine the volume of migration between source and host countries based on data of migratory drivers collected through surveys [28, 29].

The above literature review shows that migration is affected by digital literacy and usage of internet among the population, apart from educational qualifications of migrants. Similarly, remittances also impact these domestic economic indicators. Lastly, machine learning provides promising avenues to model and predict migration, remittances and related economic indicators. Therefore, a study was undertaken to assess using artificial neural network to improve predictive modelling accuracy of personal remittances in India.

The subsequent segment gives details of the research gap and methodology adopted in the present study to predict migration and remittances.

2.1 Research gap

Despite their widespread usage in predicting remittance inflows, ARIMA and other conventional econometric models often fail to capture the complex, nonlinear dynamics inherent in this kind of data [30]. Recent studies have shown that machine learning models like ANN, Random Forests (RF), and SVM improve prediction accuracy in economic forecasting tasks [31]. However, there aren't many comprehensive comparison studies evaluating the efficacy of these machine learning techniques for remittance prediction.

3. METHODOLOGY

The brief literature review presented in the previous section shows that predictive modelling of personal remittances based on higher educational enrolment and internet usage in India is an open research problem. This has been the motivation of the study which attempts to throws light on how ANN can be used to improve the predictive modelling accuracy of personal remittances received in India, over two decades from 2002-2021.

The period of the study ranged between 2000–2021, and was selected as it helped analyse contemporary trends across two decades. This period besides providing contemporary trends, also covers two major global episodes that have a significant influence on individual remittances. The first being the global financial crises 2008 and later the Covid pandemic in 2019 -20 (Since data was only available till 2021, the crucial period post pandemic could not be studied the period 2022 and 2023.). While the pandemic led to restrictions in travel, economic downturns, and technological advancements that changed the way remittances are delivered, patterns of migration and remittance movements have changed significantly on a global scale. It is however, observed that online platforms have made remittances easier and less expensive. Hence the present research study focused on developing predictive models for personal remittances and net emigration trends in India based on higher educational enrolment and internet usage in the domestic population.

The researchers collated detailed and relevant data from World Bank Development Indicators 2022 [3]. This data was organised with regards to migration, personal remittances received (Billion US$), individuals using internet (% population) and tertiary school enrolment (gross %) for the period 2000 to 2021. Thereafter, correlation analysis was carried out between the selected causes viz. internet usage and higher education enrolment with the selected effects viz. net emigration and personal remittances. Subsequently, regression technique was derived with net emigration and personal remittances individually considered as the predicted variables; with the internet usage and higher education enrolment as predictors for each of these outcomes. Finally, ANN and SVM were employed to develop the same models with higher prediction accuracy.

3.1 ANN methodology

In the present study, a two layered single input single output feedforward neural network was utilised.

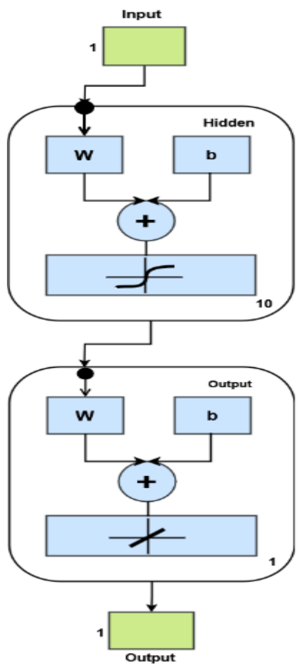

Figure 1. Two layered feedforward ANN with single input, single output and 10 hidden layer nodes

This network was designed to include 10 neurons in the hidden layer and 1 neuron in the output layer. ANN researchers have found that inclusion of 10 neurons in the hidden layer results in a near optimal solution that minimizes the prediction error [32]. A network with a single hidden layer is usually sufficient for function approximation tasks, and choosing 10 neurons avoids overfitting in limited-sample situations by striking a balance between generalization and complexity [33].

Additionally, previous comparison studies have demonstrated that ANN performs better than SVM in remittance forecasting tasks in terms of prediction accuracy and computational efficiency, especially when the data does not exhibit high- frequency time-dependence [34].

Figure 1 shows a schematic of this network built in Matlab software.

The 'w' and 'b' terms shown in Figure 1 indicate the weights and biases of the hidden and output layer nodes. These weights and biases are adjusted through multiple iterations wherein the machine learning network 'learns' to build a relationship model between the input (in the present case, the economic indicators) and the output (in the present work, the remittance).

3.2 SVM methodology

SVM, a supervised learning technique, generates an optimal hyperplane to split classes with the maximum margin [35]. Using kernel functions, it manages both linear and non-linear classification efficiently [36]. In addition to improving generalization, SVM reduces classification error. Because of its resilience, it is frequently used in many different fields. In this study, Coarse Gaussian, Medium Gaussian, Fine Gaussian, Cubic, Quadratic and Linear SVM types were applied for validation of ANN results.

Kernel Scale for Cubic, Quadratic and Linear are automatic, and for Coarse Gaussian, Medium Gaussian, Fine Gaussian its 4, 1, 0.25 respectively.

The following section presents the results and discussions of this study.

4. RESULTS AND DISCUSSION

This section presents the overall trends of the selected economic indicators and net emigration, followed by correlation analysis, regression, ANN and SVM technique results.

4.1 General trends

As mentioned in the previous section, the sorted data obtained from World Bank [2] was firstly analysed for yearly trends from 2000 to 2021. Figures 2-5 depict the yearly trends of net emigration, personal remittances, internet usage and higher education enrolment in India during the selected period, respectively.

Figure 2 indicates that net emigration increased during the period 2005-08, when it crossed 80,000 emigrants. Thereafter, emigrant counts rapidly dropped till 2012. Net emigrations again picked up till 2015, and again in 2018-19, saw a severe drop in 2020, primarily due to the Covid-19 pandemic. Overall, net emigration was lower in the second decade of the 21st century. There are a number of reasons for the drop in Indian emigration since 2008, including the economic uncertainties brought on by the 2008 global financial crisis, India's emigration rate has decreased as a result of stricter immigration laws in certain nations, such as the US and the UK. India's economy has expanded dramatically, creating more job and business prospects. Because of this, Indians are no longer as likely to go for employment overseas, particularly in lower-skilled fields [37]. The COVID-19 pandemic has been linked to a reduction in migration as a result of closed borders and increased restrictions on travel. Additionally, as many Western countries' populations have aged, there has been less demand for foreign labour, while India's youthful population has demonstrated less desire to go (Pew Trust).

Figure 3 depicts a steadily growing trend in personal remittances received by Indians during 2000 – 2022. This trend was not affected even during the Covid-19 pandemic affected years. Hence, this trend indicates the growing presence and affluence of the Indian diaspora abroad. This diaspora is contributing to the national economy back home in more and more influential ways than ever before through remittances, which crossed 111 billion US dollars in the year 2022. Figure 4 shows a steadily increasing percentage of Indian population using the internet, which was at 0.5% in 2000 and reached 46% in 2021. Internet usage picked up pace after 2010, and started increasing almost exponentially 2019 onward. Internet usage goes hand in hand with digital literacy and proliferation of hand-held mobile communications technologies, which have started making big inroads in the rural parts of India. Internet usage is now also closely linked with the educational sector, and the increasing percentage of internet users positively impact educational enrolment. Higher education enrolment helps the country to supply highly qualified and skilled emigrants, which translates into higher remittances back home. Figure 5 shows the gross enrolment ratio of tertiary education in India i.e., ratio of total enrolment at the tertiary level to the total population of the age group (18-23) that officially corresponds to the tertiary level of education in India. This enrolment ratio has also increased over the past two decades, from less than 10% in 2000 to more than 30% in 2021. The years 2007 to 2015 witnessed a relatively higher rate of increase in tertiary education enrolment. This ratio is expected to increase even more in the near future, which will translate into higher educated migrants and subsequent remittances as well.

4.2 Correlation and regression results

This section presents the results of correlation and regression between the causes (tertiary school enrolment and % population using internet) and the effects (net emigration and personal remittances received) selected in this work.

Figure 6 shows that net emigration and tertiary school enrolment are poorly correlated to each other over the past two decades. Net emigration experiences an overall decreasing trend since the year 2010, whereas tertiary school enrolment in India has been gradually rising during the same period. Table 1 shows this correlation to be at 0.206.

Figure 7 shows that net emigration and internet usage are negatively correlated to each other over the past two decades.

Net emigrations are on an overall decreasing trend since the year 2010, whereas tertiary school enrolment in India is on a continuous rise during the last twenty years. Table 1 shows this correlation to be at -0.216.

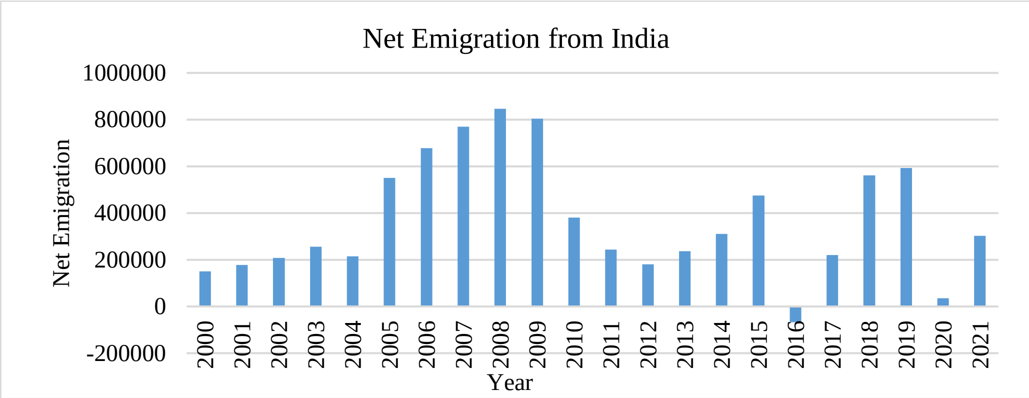

Figure 2. Indian net emigration trends during the past two decades [2]

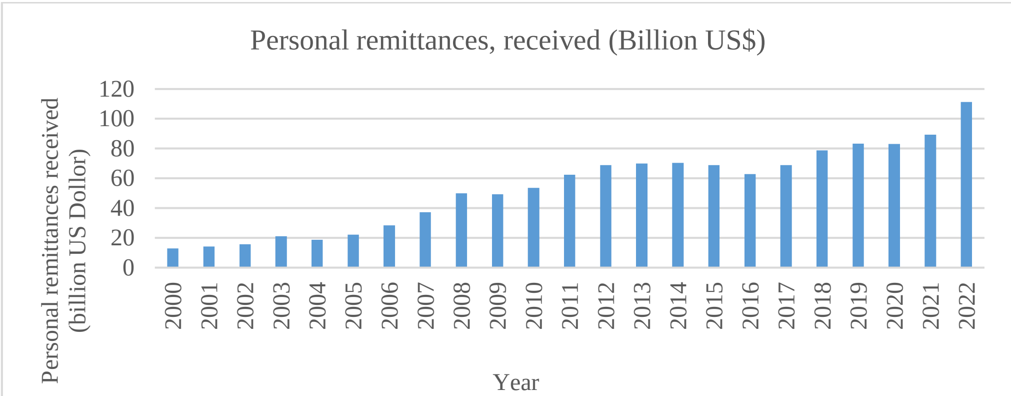

Figure 3. Personal remittances received by Indian during the past two decades [2]

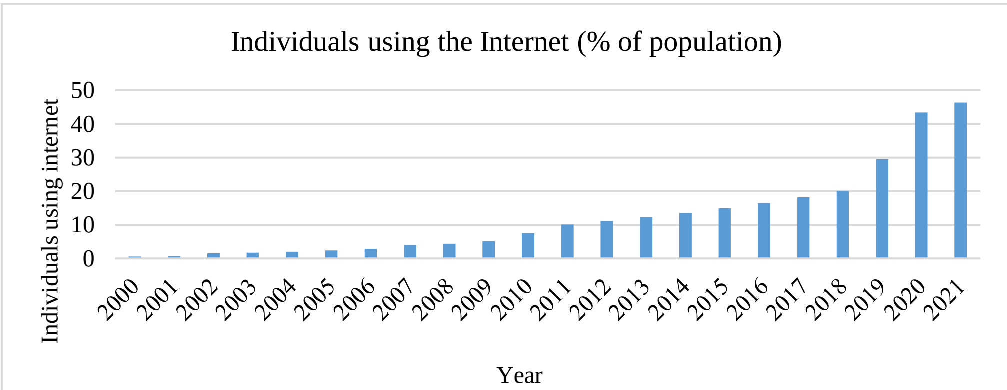

Figure 4. Percentage of population using internet in India during the past two decades [2]

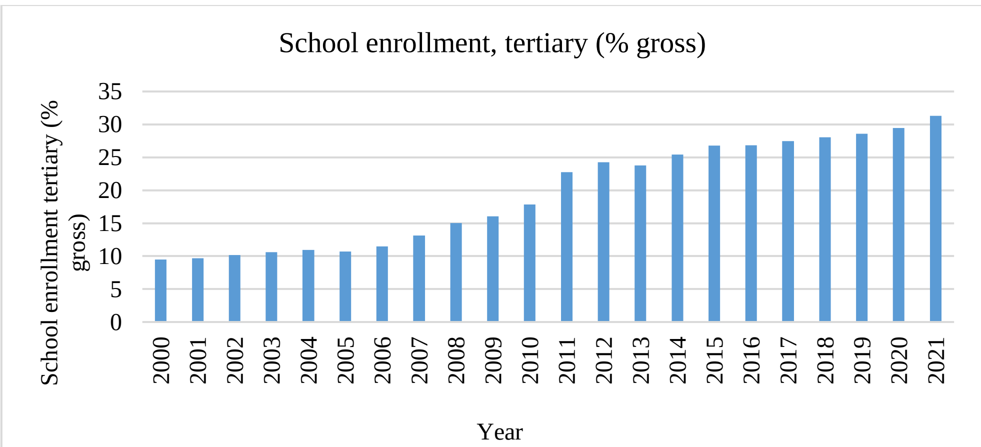

Figure 5. Gross tertiary school enrolment ratios in India during the past two decades [2]

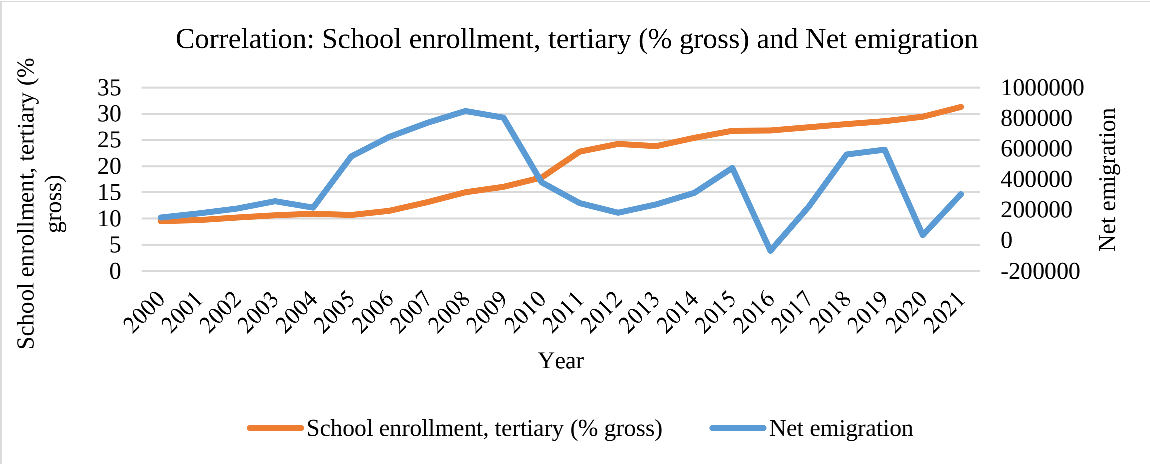

Figure 6. Correlation plot of net emigration with tertiary school enrolment (2000-2021) [2]

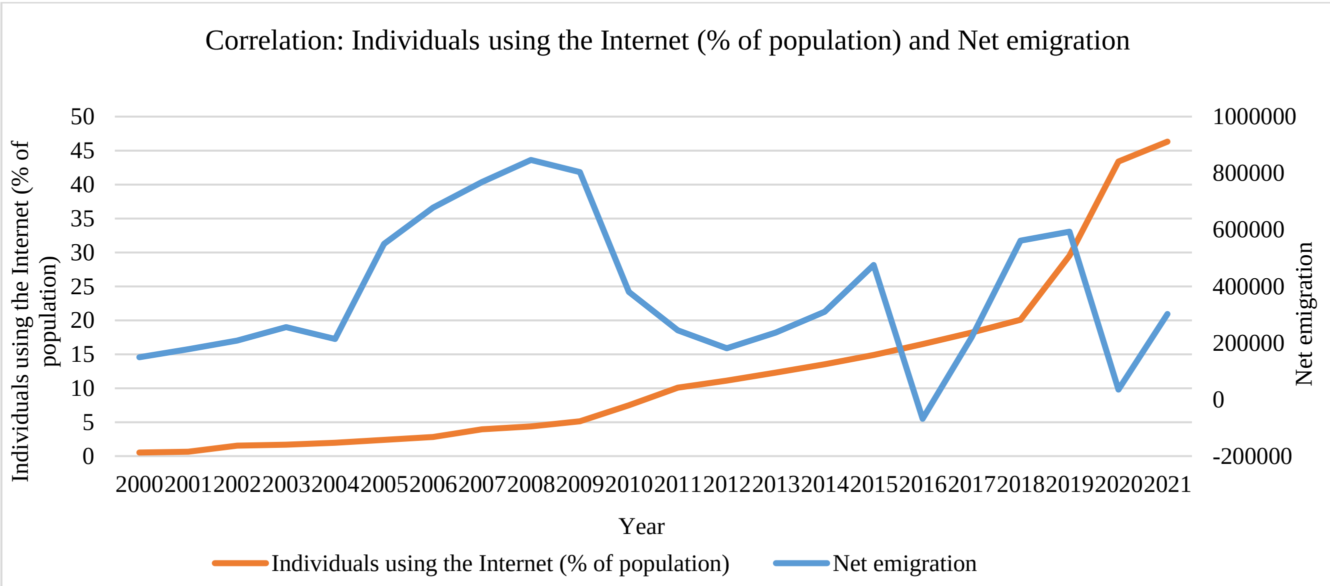

Figure 7. Correlation plot of net emigration with tertiary school enrolment (2000-2021) [2]

Table 1. Correlation and regression (R-squared) results

Input (Cause)	Output (Effect)	Correlation	Regression (R-squared)
School enrollment, tertiary (% gross)	Personal remittances, received (Billion US$)	0.972	0.945
School enrollment, tertiary (% gross)	Net Emigration	0.206	0.042
Individuals using the internet (% of population)	Net Emigration	-0.216	0.047
Individuals using the internet (% of population)	Personal remittances, received (Billion US$)	0.826	0.683

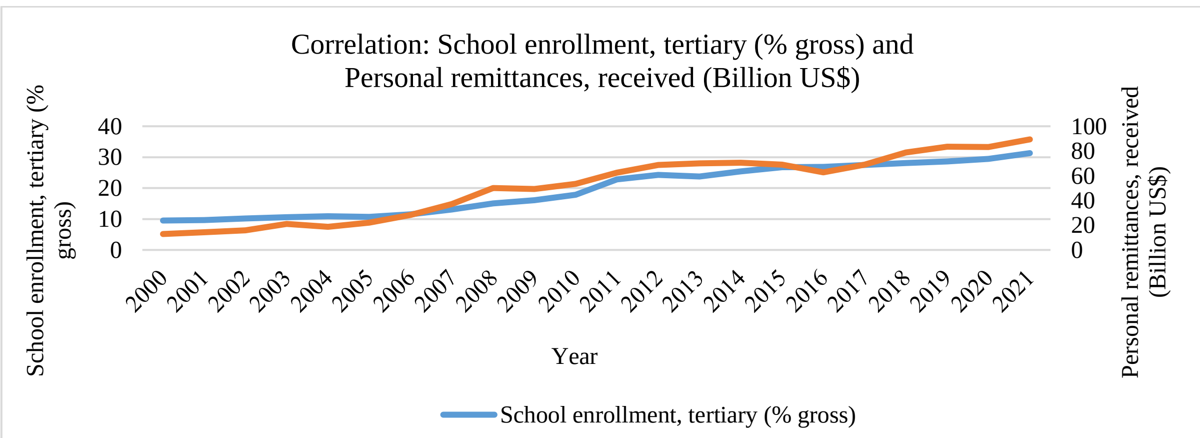

Figure 8. Correlation plot of personal remittances with tertiary school enrolment (2000-2021) [2]

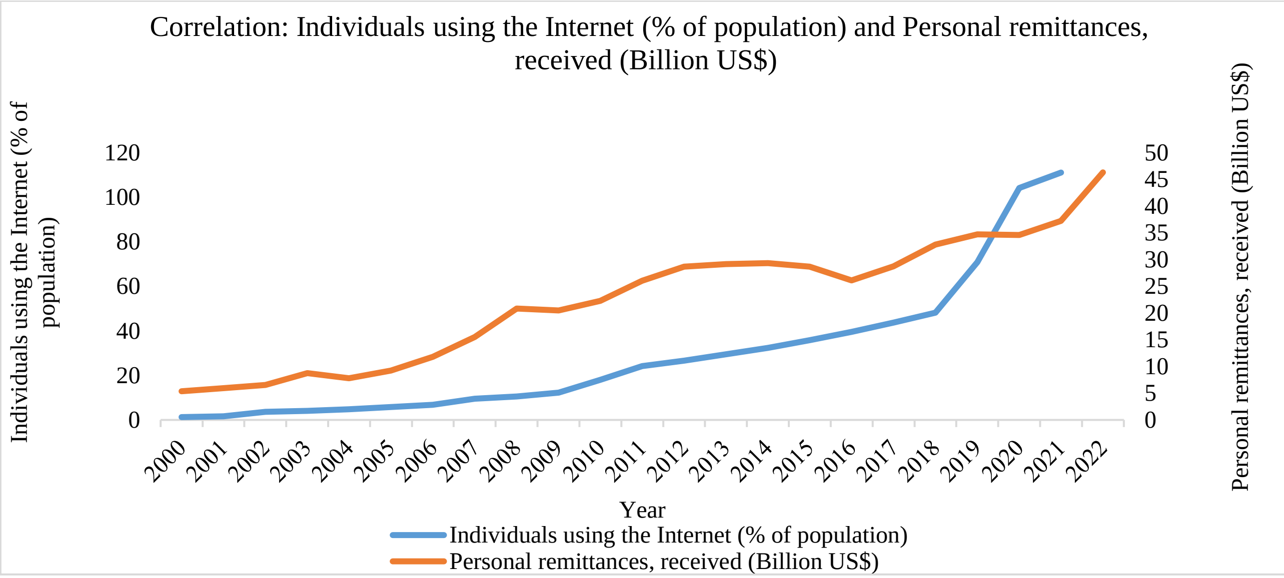

Figure 9. Correlation plot of personal remittances with internet usage (2000-2022) [2]

Figure 8 shows that personal remittances and tertiary school enrolment are closely correlated to each other over the past two decades. Both trends are on a continuous rise during the last twenty years. Table 1 shows this correlation to be at 0.972. This correlation indicates that higher tertiary school enrolment translates into emigration of highly educated workforce, that results into higher remittances sent back to the country.

Figure 9 shows that personal remittances and internet usage are positively correlated to each other over the past two decades. Both trends are on a continuous rise during the last twenty years, but are not as closely correlated as remittances and tertiary school enrolment. Table 1 shows this correlation to be at 0.826. This correlation indicates that higher internet usage is a contributing factor to the emigration of digitally-skilled workforce, that contributes towards higher remittances sent back to the country.

Table 1 also depicts the R-squared values of regression between each pair of individual inputs and the respective outputs. These R-squared values resemble the respective correlation values, and clearly establish that 1) net emigration cannot be effectively predicted on the basis of tertiary school enrolment and internet usage, whereas 2) personal remittances received can be predicted moderately well on the basis of internet usage and 3) personal remittances can be accurately predicted on the basis of tertiary school enrolment. Hence, the personal remittances' pair of cause and effects were subsequently modelled using ANN and SVM to further improve the respective prediction accuracies.

4.3 Machine learning and SVM prediction results

The ANN and SVM results pertaining to the modelling and prediction of personal remittances based on tertiary school enrolment and internet usage (individually), are highlighted in this segment.

Table 2 shows that ANN maximised prediction accuracy of personal remittances based on tertiary school enrolment to 98.88 %, as against 94.5 % obtained via regression method. In case of personal remittances based on internet usage, ANN was able to improve prediction accuracy by a significant margin, up to 92.25% from 68.30 % obtained from regression. The SVM models also outperformed regression model results, but were unable to surpass the prediction accuracy achieved by the bilayered ANN models. In general, the non-linear kernel SVMs outperformed their linear counterparts. Most SVMs were significantly more successful in achieving higher prediction accuracy for predicting remittances based on tertiary school enrollments as compared to the internet usage. These findings demonstrate that ANN is superior at simulating the intricate socioeconomic factors affecting remittance inflows, as per the data utilised in the current study. Hence, the following subsections present detailed results of only the bilayered ANN models.

Table 2. ANN and SVM prediction results (R-squared)

Input (Cause)	Output (Effect)	ANN	SVM 1 Coarse Gaussian	SVM 2 Medium Gaussian	SVM 3 Fine Gaussian	SVM 4 Cubic	SVM 5 Quadratic	SVM 6 Linear
School enrolment, tertiary (% gross)	Personal remittances, received (Billion US$)	0.9888	0.83	0.93	0.95	0.97	0.98	0.87
Individuals using the internet (% of population)	Personal remittances, received (Billion US$)	0.9225	-0.01	0.92	0.09	0.79	0.61	-1.66

4.3.1 ANN results: Personal remittances and tertiary school enrolment

This section presents various hyper parameters of ANN that were tuned to maximise the prediction accuracy of the selected outcome in this study. Epochs represent the number of iterations of learning/training cycles that the ANN undergoes to establish a model between the given pair of input and output variables. Performance criterion refers to the error between the actual and the ANN predicted values. Gradient refers to the step-learning rate of the ANN algorithm, which keeps on reducing as it reaches closer to the optimal solution. Mu indicates whether the algorithm is moving towards gradient descent (higher mu) or towards Newton's method (lower mu) while searching for the global optimal solution [38]. Validation fail checks refer to the checks carried out by the algorithm whether its prediction is getting worse than before. The algorithm was set to terminate itself after six consecutive validation fails. This means that algorithm terminated itself after it found that its validation accuracy was becoming worse or in other words, validation accuracy was not improving consecutively over six epochs.

Table 3 presents the initial, target and final stopping values of the feedforward ANN hyper parameters for predictive modelling of personal remittances based on tertiary school enrolment. The epochs were terminated by the number of validation fail checks reaching the target value of six at the 9th epoch, as shown in Figure 10. The algorithm achieved a minimum training performance error of 2.01 at the ninth epoch (Table 3). However, the best validation performance of 2.6446 mean squared error was achieved at the third epoch (Figure 11).

Table 3. Two layered feedforward networks with sigmoid hidden layer neurons and linear output layer neurons

School Enrollment Remittance, Unit	Initial Value	Stopped Value	Target Value
Epoch	0	9	1000
Performance	1.12E+03	2.01	0
Gradient	1.49E+03	15	1.00E-07
Mu	0.001	0.01	1.00E+10
Validation Checks	0	6	6

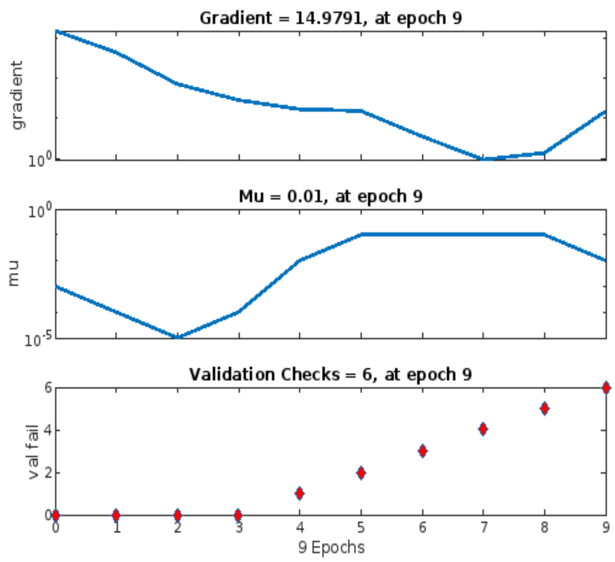

Figure 10. Training states (school enrolment remittance)

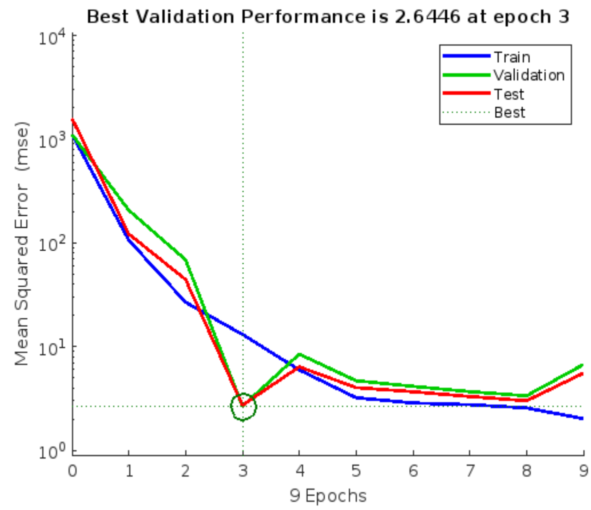

Figure 11. Best validation performance (school enrolment and remittance)

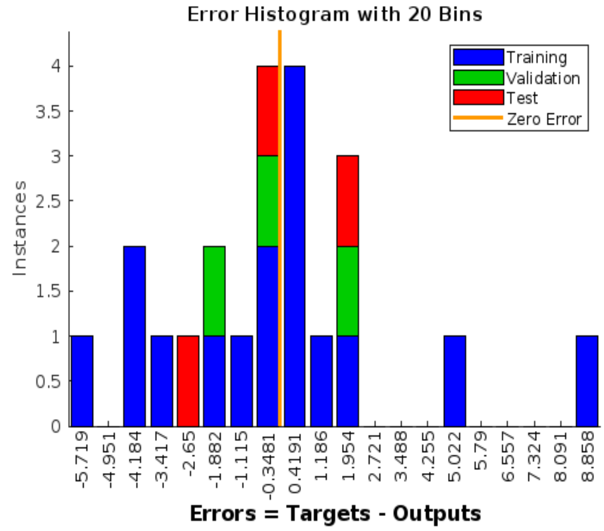

Figure 12. Error histogram (school enrolment and remittance)

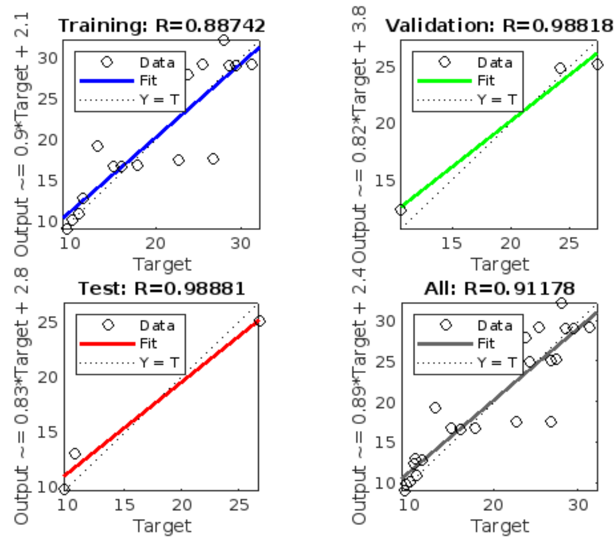

Figure 13. Regression plots (school enrolment and remittance)

Figure 12 shows the error histogram of the personal remittances' ANN model based on tertiary school enrolment. This figure shows very few error bins of small magnitudes for testing and validation as compared to training, indicating high testing/validation accuracy over training accuracy, as is evident from Figure 13. Figure 13 shows that the training, validation, testing and overall accuracies were 88.742%, 98.818%, 98.881% and 91.178% respectively, which are quite impressive in comparison the conventional regression prediction accuracy of the same.

4.3.2 ANN results: Personal remittances and internet usage

Table 4 presents the initial, target and final stopping values of the feedforward ANN hyper parameters for predictive modelling of personal remittances based on internet usage. The epochs were terminated by the number of validation fail checks reaching the target value of six at the 17th epoch, as shown in Figure 14. The algorithm achieved a minimum training performance error of 0.794 at the 17th epoch. However, the best validation performance of 0.78578 mean squared error was achieved at the 11th epoch (Figure 15).

Figure 16 shows the error histogram of the personal remittances' ANN model based on internet usage. This figure shows fewer error bins of smaller magnitudes for training and validation as compared to testing, indicating high training/validation accuracy over testing accuracy, as is evident from Figure 17. Figure 17 shows that the training, validation, testing and overall accuracies were 99.913%, 98.677%, 92.252% and 99.633% respectively, which are quite impressive in comparison the conventional regression prediction accuracy of the same.

Table 4. Internet usage remittance

Unit	Initial Value	Stopped Value	Targe Value
Epoch	0	17	1000
Performance	5.63E+03	0.794	0
Gradient	1.43E+04	0.785	1.00E-07
Mu	0.001	0.001	1.00E+10
Validation Checks	0	6	6

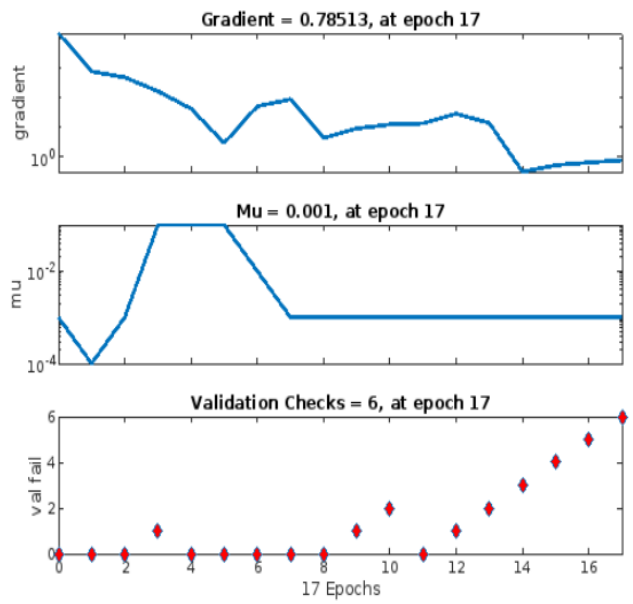

Figure 14. Training states (internet usage and remittance)

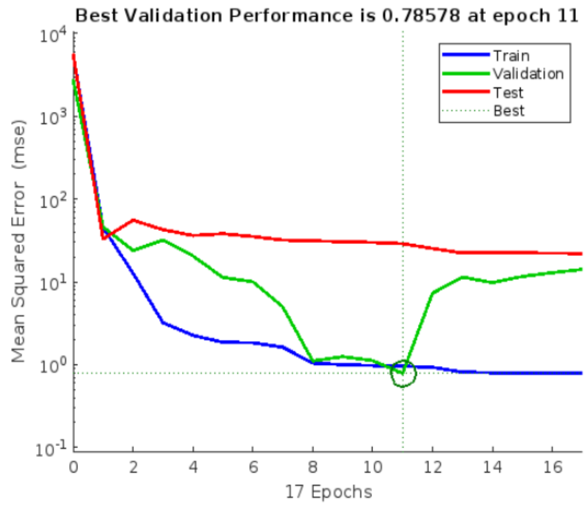

Figure 15. Best validation performance (internet usage and remittance)

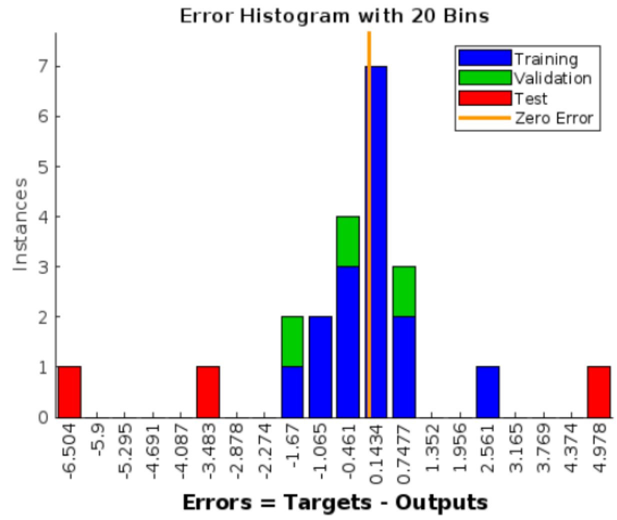

Figure 16. Error histogram (internet usage and remittance)

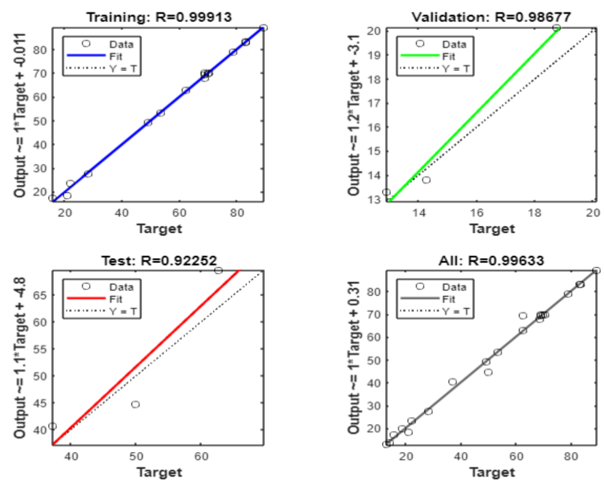

Figure 17. Regression plots (internet usage and remittance)

5. CONCLUSIONS, LIMITATION, AND FUTURE RECOMMENDATION

This section presents the conclusions, limitation of this study and future recommendations for researchers as well as government organizations.

5.1 Conclusions

This study focused on predictive modelling of net emigration and personal remittance (selected effects) received from abroad, based on tertiary school enrolment and percentage of population using internet in India (selected causes). This study used correlation, regression, ANN and SVM methods on a databased sourced from the World Bank for the above-mentioned indicators, for a period spanning the last two decades. Correlation and regression analysis were conducted for both outcomes (effects) based on both inputs (causes). However, ANN and SVM were carried out only for the outcome of personal remittances due to the high correlation and regression R-squared values obtained for both the selected causes. The ANN improved prediction accuracy of personal remittances to 98.88% and 92.25% against 94.5% and 68.3% attained by regression analysis, as well as the results obtained by the best performing SVM models i.e. 98% (quadratic SVM) and 92% (medium Gaussian SVM) for the tertiary school enrolment and % of Indian population using the internet, respectively. The net emigration effect was found to have weak and negative correlations with tertiary school enrolment and internet usage respectively.

Results also indicated that net emigration is declining over the past few years against progressively rising tertiary school enrolment and % of population using the internet in India. Hence, increasing prevalence of higher education and digital literacy is accompanied with lesser number of individuals migrating abroad. However, since the value of remittances being received from abroad is also rising substantially, it may be concluded that the quality of individual's migrants abroad has immensely improved, while lesser in number, but are highly skilled/educated as well. Hence, the emigration trends are shifting from higher volume low skilled to lower volume higher skilled/educated individuals. Secondly, this work shows that the effects of emigration (such as remittances) need to be accounted for while correlating with domestic socio-economic indicators, even though emigration itself may not have any significant correlations with the same.

5.2 Limitations

This study's limitations firstly include its focus on only two independent variables i.e., internet usage and tertiary education limits the wider applicability of the predictive models since there are other socioeconomic determinants that do impact remittances in general. Secondly, the robustness of the predictive analysis is also limited by the accuracy of the secondary data source utilised in this study. Thirdly, it is important to note that correlation cannot be construed as causality always. While the accurate predictions made by the machine learning models do indicate the significant impacts of internet usage and tertiary education factors on remittances, these results do not intend to imply that only these two factors are completely responsible for remittance trends. In other words, other factors must also be considered in further studies to obtain more reliable remittance models.

5.3 Future recommendation

Future studies should focus on more diverse and emerging factors (nationally as well as internationally) that are changing the ever-evolving landscape of remittances received from emigrants abroad. The ever changing geopolitical dynamics, rising nationalism in destination countries and resistance against emigration must also be considered in the upcoming research investigations in this field.

National organizations need to maintain and make available publicly accessible records of socio-economic indicators as well as emigration related parameters. Such records would support more detailed and accurate research that will help government organizations dovetail policies and allocate resources to certain sectors to push indicators favourable to the national economy, such as remittances received from abroad.

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