ANÁLISE DA BASE EMPÍRICA PARA PESQUISA NA ÁREA LINGUÍSTICA

ANÁLISIS DE LA BASE EMPÍRICA DE LA INVESTIGACIÓN EN EL CAMPO DE LA LINGÜÍSTICA

ANALYSIS OF THE EMPIRICAL BASIS FOR RESEARCH IN THE FIELD OF LINGUISTICS

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RESUMO: A linguística constitui o estudo científico da linguagem humana, indicando que é uma análise completa, objetiva, sistemática e específica da linguagem. Este estudo dedica-se principalmente à análise da base empírica da pesquisa na área da linguística. Para tanto, utiliza-se um método descritivo, levando-se em conta inúmeros estudos relevantes. A análise demonstra que as avaliações dos falantes nativos da aceitabilidade dos modelos linguísticos sempre constituíram uma parte significativa dos dados linguísticos. Dito isso, os linguistas normalmente extraíram esses dados ao acaso e receberam os resultados de forma acrítica ou recusaram julgamentos de aceitabilidade total e igualmente acriticamente.

PALAVRAS-CHAVE: Base empírica, Linguagem humana, Linguística, Falantes nativos.

RESUMEN: La lingüística constituye el estudio científico del lenguaje humano, lo que indica que es un análisis exhaustivo, objetivo, sistemático y específico del lenguaje. Este estudio está dedicado principalmente al análisis de la base empírica para la investigación en el campo de la lingüística. Para ello se utiliza un método descriptivo y se tienen en cuenta numerosos estudios relevantes. El análisis demuestra que las valoraciones de los hablantes nativos sobre la aceptabilidad de los modelos lingüísticos siempre han constituido una parte significativa de los datos lingüísticos. Habiendo dicho eso, los lingüistas normalmente han obtenido dichos datos al azar y recibido los resultados sin crítica o han rechazado los juicios de aceptabilidad por completo e igualmente sin crítica.

PALABRAS CLAVE: Base empírica, Lengua humana, Lingüística, Hablantes nativos.

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ABSTRACT: Linguistics constitutes the scientific study of human language, indicating that it is a thorough, objective, systematic, and specific analysis of language.This study is mainly devoted to the analysis of the empirical base for research in the field of linguistics. To that end, a descriptive method is utilized, and numerous relevant studies are taken into account. The analysis demonstrates that Native speakers' assessments of the acceptability of linguistic models always have constituted a significant part of linguistics data. Having said that, linguists typically have haphazardly elicited such data and received the results uncritically or have refused acceptability judgments entirely and equally uncritically.

KEYWORDS: Empirical base, Human language, Linguistics, Native speakers.

Introduction

In the context of globalization, population mobility has reached unprecedented proportions. It is very difficult to distinguish and study traffic flows in numerous migration flows. However, the ability to do this is the key to developing a competent and effective policy for the prevention and disclosure of crimes related to human trafficking. It is this task that the scientific community faces today, and its implementation inevitably requires the creation of theoretical models based on reliable empirical data and effective methodology (Lancaster et al., 2020).

At the same time, modern researchers in the search for relevant reliable data are faced with a host of problems, which directly affects the quality of scientific research devoted to the disclosure of traffic patterns (Margić&Vodopija-Krstanović, 2018).

Most often, theories describing the nature and patterns of human trafficking are criticized for their descriptive nature, limited focus and coverage (for example, disclosing certain thematic and geographical aspects), unclear and opaque methodology, poor research design (for example, questionable assumptions, unreliable data sets), unrepresentative samples, unfounded conclusions, political or other bias of researchers, low-quality statistics (for example, forecasts with huge ranges or a low degree of reliability) (Nursulton, 2020).

The difficult situation with data sources inevitably causes problems in scientific research. Sh. Jan analyzed more than one hundred scientific articles on the topic of trafficking and found that only a small part of them contain original empirical data. Most of the published studies duplicate theses of governments, international

organizations and NGOs, even if they do not provide sources and methods for obtaining data. Duplication of questionable and unverified information in the international academic community is a serious problem and hinders progress in the study of the problem (Olulade et al., 2020).

Consider one negative example. In the reports of NGOs and scientific publications, it is often mentioned that from 30 to 60 thousand women and girls are taken out of Russia every year, who subsequently fall into sexual exploitation.

Pennycook refers to the publication of the student of the Faculty of State and Municipal Employees of the Ural Academy of Public Administration Sysolyatina E.A., who writes "Basically, women and children are taken out of Russia for prostitution. Experts estimate their number at 30-60 thousand people a year. " The author does not provide information about who the expert is and what the assessment is based on; therefore, the reliability of the indicator raises serious doubts (Pennycook&Makoni, 2019).

There is very little serious academic research on human trafficking using analytical tools, and there is very little empirical material on which to base it.

One of the useful studies, in our opinion, is described in the work of Seo Yang Cho. The author sets himself the task of using regression models to analyze various factors that can influence traffic. Using statistics from 153 countries, she identifies the most significant push and pull factors. Based on the results of the analysis, she concludes that income and crime rates are important variables, and gender inequality serves as a constraint on the outflow of migration and trafficking. At the same time, the author also concludes that the factors affecting economic migration are similar to the factors affecting human trafficking (Politimou et al., 2019).

Another example of studying traffic patterns using an analytical statistical model is the work of British researchers Cockbain and Bowers. The authors set the task of identifying significant trends for the main types of crimes associated with human trafficking: sexual exploitation, labor exploitation, etc. On the basis of archival materials of law enforcement agencies, they formed a sample of 2630 victims and included in it various characteristics: from gender and origin of victims to location and the time of the crime (Ross, 2019; Shaykhislamov&Makhmudov, 2020).

Using polynomial logistic regression, Cockbain and Bowers attempted to identify predictors of a particular type of human trafficking. Their work focuses mainly on the domestic aspects of the UK. The third study based on the use of an analytical model to study traffic patterns, which we will consider as an example, is the work of Mejia (2016).

The author sets himself a number of ambitious tasks: to classify donor countries by degree, using time series regression to determine the factors explaining the dynamics of trafficking flows over time. In addition, the model hypothesizes that GDP per capita, unemployment, literacy and corruption, combined with factors of conflict and shock, are the cause of the formation and growth of the outgoing traffic flow (Spolsky, 2019).

On the one hand, the model is interesting and varied. On the other hand, the author uses statistics from the US Department of State, which can add political overtones to the indicators, which somewhat reduces the credibility of the data.

In the course of the study, the author uses two models to assess the impact of various factors on outbound trafficking and draws conclusions. However, it makes no sense to list these conclusions, since the quality of both models is very low: the coefficients of determination are 0.24 and 0.28. This means that the discovered patterns explain less than a third of the variance, and the predictive model is not effective enough: it is permissible to state the presence of interrelations by such parameters, but a more reliable result is required for modeling (Wang et al., 2020).

Studying the current state of affairs in the field of research into the patterns of trafficking, it can be assumed that the gaps in our current understanding of the phenomenon of human trafficking are largely due to the shortcomings of the empirical base and the complexity of working with it to obtain reliable substantiated results. In turn, these problems slow down the progress of science towards understanding trafficking and proposing effective mechanisms to prevent and detect it. In this study, we will consider in detail the main difficulties and features of the sources of traffic data and suggest ways to eliminate the problems.

Methods

The main sources from which you can get information about crimes related to human trafficking today:

- international organizations;

- government organizations;

- non-profit organizations;

- academic research.

Each of these sources has drawbacks and limitations that are important to consider when working with data.

The reports of international organizations are the most reliable and complete source of traffic data to date. The main entities that keep records are the United Nations (UN), the International Organization for Migration (IOM), and the International Labor Organization (ILO).

Information from these organizations is regularly published and updated in the form of reports and databases on trafficking-related crime. Examples of such documents are the annual Global Report on Trafficking in Persons published by the UN Office on Drugs and Crime, the Report of the Special Rapporteur on trafficking in persons, especially women and children), published by the Office of the United Nations High Commissioner for Human Rights. The capabilities of international organizations make it possible to take into account and record the statistics of most countries, which is an important advantage of this source. However, the data provided by the national governments are often incomplete or not transparent, as records are not kept correctly in the region.

Another popular source of global data on human trafficking is international NGOs. A popular and frequently cited source is the Global slavery Index, published annually by the Walk Free Foundation. There are also a number of smaller regional NGOs that publish estimates for specific countries or territories.

Often, reports and databases of NGOs are perceived critically by the scientific community and the data they publish are treated with great caution by researchers. Criticism of NGOs as sources of data on trafficking is based on the fact that human rights defenders themselves often do not have the resources and mechanisms to collect

reliable data; therefore, they are guided by unconfirmed data from expert assessments based on assumptions and generalizations that do not have any reliable scientific basis.

This lack of NGO reports is clearly seen in the example of the Russian index in the Global Slavery Index. It is calculated by extrapolating data from surveys conducted in Ukraine, Belarus, Bulgaria, Moldova and Romania. At the same time, no polls are conducted in Russia itself. Criticizing the Global Slavery Index, R. Weitzer notes that the index is formed on the basis of non-standardized sources: media reports, surveys of the population of other countries, estimates of anonymous NGOs, obscure experts and biased government organizations. How these sources were selected is not disclosed, moreover, it is doubtful that they have

In addition to collecting and compiling national data on trafficking, in some countries there are specialized units that prepare government reports on the state of affairs in the world. A prime example of such a report is the annual Trafficking in Persons Report (TIP Report), which is published by the US Department of State. The scope of the study is comparable to the leading reports of international organizations, each country is assessed, a separate profile is drawn up for it. However, the data from this source cannot be considered outside the political context, in this regard, their objectivity is questionable.
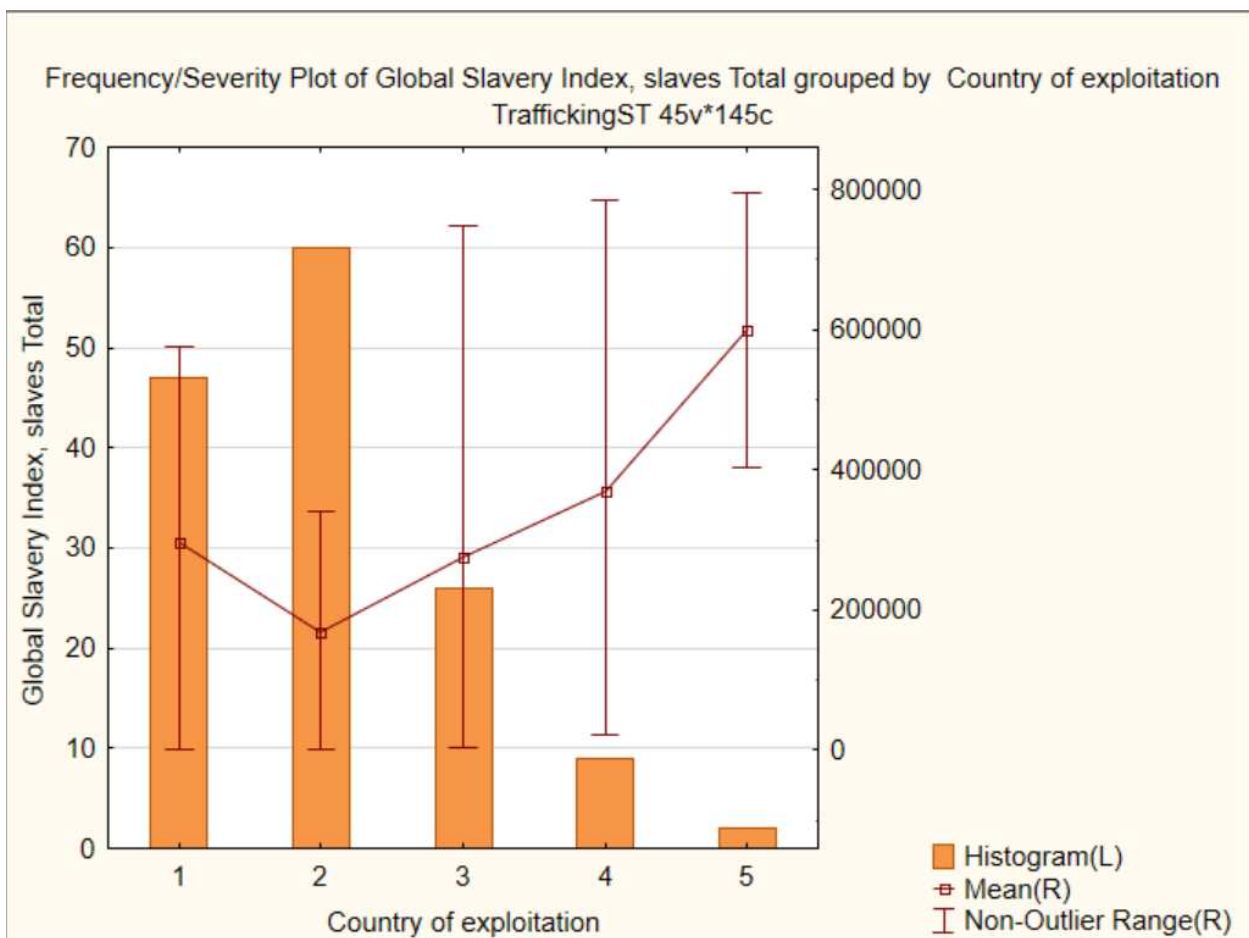
Results and discussion

The very first difficulty faced by any researcher who wants to study the patterns of traffic on reliable empirical material is the choice of an indicator that will be accepted as an estimate of the level of traffic. As we noted earlier, in open sources there are several variants of databases containing quantitative estimates of this phenomenon.

For comparative analysis, we used variables reflecting the absolute number of victims of exploitation from the Global Slavery Index database ("SlavesPer1000" var.). We also have statistics on the number of registered cases of exploitation, which are kept by international institutions ("Country of exploitation" var.). As expected, these indicators should correlate with each other, since they are different measures of the same phenomenon. However, there is no relationship between these variables: the correlation coefficient of the "Country of exploitation" and"slavesPer1000" variables is –0.09.

Since "Country of exploitation" is an ordinal variable, we also checked Spearman's nonparametric correlation, however, no dependence was found: the coefficient was -0.08.

The absence of any statistically significant correlation between the two datasets reflecting the level of exploitation indicates that, most likely, one of the variables does not correctly reflect the essence of the phenomenon under study, and we need to choose the one that is more representative.

As we mentioned,"Country of exploitation" variable comes from a more reliable source and relies on specific empirical evidence of recorded crimes. The variable slavesPer1000 is an indicator derived by NGO analysts based on a variety of assumptions, hypotheses, anonymous assessments, as well as surveys conducted often outside the territory for which the assessment is being made. The situation is similar with the indicator reflecting total number of people in slavery (SlavesTotalvar.), coming from the same NGO's dataset.

Frequency/Severity Plot of Global Slavery Index, slaves Total grouped by Country of exploitation
TraffickingST 45v*145c

For a closer look at the relationship between the two variables reflecting the level of exploitation in the country, we plotted the distribution of the estimated number of victims of the Global Slavery Index, grouping 145 observations according to the rank

estimate of the number of detected cases of IOM exploitation (Country of exploitation). As can be seen from the distribution histogram, most countries have a low or medium level of exploitation; only 11 countries have high indicators (rank 4 and 5). In this segment, the IOM and the Global Slavery Index average have some similarities. However, the scatter of values, taking into account the exclusion of emissions in the segment with rank 4, is very high.Global Slavery Index ranks countries with a confirmed high level of exploitation as countries where the number of cases of exploitation is medium or low.

In the segment of medium and low number of confirmed cases of exploitation by IOM (rank 1-3), the Global Slavery Index behaves haphazardly. Countries with the lowest number of detected crimes in the ranking have the same indicators as countries with tens of times more victims. At the same time, for other states where the number of recorded cases of exploitation is not minimal, the indicator is underestimated and they have the best estimate of the entire Global Slavery Index rating.

Of course, assessing the overall level of the problem of trafficking by the number of victims identified is a rough extrapolation. The number of identified victims may vary not only depending on the total number of victims, but also on the ability to identify them, the specifics of the data collection methodology, etc. But to date, we have no reason to completely deny the relationship between the number of detected cases and the total number of victims. Much more doubtful is the Global Slavery Index rating, where this dependence is most often violated, and, in addition, the calculation methodology of which is based on partially closed data that cannot be verified and analyzed, as well as on representative surveys conducted not always on the territory that is subject to assessment.

In connection with the above, we have reason to consider the IOM indicator as a more correct and objective assessment of the number of victims of exploitation in the country, and we use it for statistical analysis.

Having chosen the optimal indicator for measuring the level of trafficking in different countries, it is also necessary to select statistics reflecting various socio-economic aspects. Data on such indicators are available in various sources, but they also have a number of flaws - noise, gaps, lack of comparable data for individual countries. But the main difficulty that they carry is the specifics of the data itself.

In order to study the specifics of the data using an example, we selected 44 variables for 144 countries. These variables reflect different socio-economic indicators for 2018, as late statistics are not yet fully available.

An important parameter that we should pay attention to is the normality of the distribution of variables. Depending on how much the distribution differs from the normal, it is required to adjust the research methodology.

The normal, or Gaussian, distribution is parametric. The parameters that determine the normal distribution are the arithmetic mean of a variable (mathematical expectation) and its standard (root-mean-square) deviation. A significant part of statistical methods, such as regression analysis, principal component analysis, and others, are focused on working with variables whose distribution does not differ much from normal, that is, they belong to parametric methods. In reality, very often there are significant deviations from the normal distribution in the data and such methods can give poor results.

By examining the descriptive statistics of the variables, one can see that most of them have a distribution that is not normal, as evidenced by high values % of skewness and kurtosis.

Table 3.1 - Descriptive statistics of variables

Variable	Average	Median	Art deviation	Asymmetry	Excess
SlavesTotal	247 666,67	52 500,00	798 432,20	7,52	65,87
SlavesPer1000	5,40	4,19	5,13	3,26	15,67
Country of exploitation (inExpl)	2,02	2,00	0,94	0,82	0,37
sourceCountry	2,03	2,00	1,00	1,04	0,79
KTrafficking	10,08	8,00	8,45	2,10	5,23
Google	87 516,25	8 800,00	386 025,02	6,71	50,42
Population	49 778 013,89	11 545 500,00	162 877 572,54	7,35	57,23
Birth rate	21,27	19,32	10,60	0,60	-0,84

Variable	Average	Median	Art deviation	Asymmetry	Excess
Fertility rate	2,79	2,30	1,39	1,00	-0,03
Adolescent fertility	49,63	37,95	42,04	1,04	0,67
Death rate	8,07	7,56	2,90	0,43	-0,03
Life expectancy	71,45	73,65	8,05	-0,63	-0,41
Population growth	1,39	1,25	1,33	0,17	0,32
Population 65+	8,53	5,87	6,18	0,80	-0,69
Population 0-14	27,92	27,16	10,92	0,34	-1,22
Int Migrant stock %	8,02	3,42	13,64	3,64	15,58
Ref inflow	115 853,06	8 212,00	315 993,79	5,70	42,25
Ref Outflow	102 069,78	1 719,00	522 464,33	8,74	85,11
Asyl Seekers pending	18 800,67	881,00	67 273,54	6,49	46,87
Remittance inflows	4 171,78	1 321,18	9 280,66	4,88	28,36
Remittance outflows	3 111,73	293,83	8 358,48	4,98	30,39
Mobile subscriptions	108,10	113,11	35,29	-0,34	0,45
National income per capita	9 874,01	3 891,89	13 573,03	2,02	3,73
Unemployment %	7,98	6,29	6,02	1,42	1,88
Employment 15-24	37,78	38,00	14,98	0,47	-0,26
Inflation	2,18	1,89	9,25	0,25	5,31
Natural resources rent %	7,18	3,10	9,24	1,82	3,31
Nxpenditure	4,43	4,30	1,73	0,96	3,11

Variable	Average	Median	Art deviation	Asymmetry	Excess
education %					
Literacy %	90,99	98,73	15,08	-2,10	4,04
secEduc+ 25+	62,83	64,66	27,48	-0,25	-1,20
Tuberculosis	110,88	46,50	141,91	1,79	2,75
Undernourishment %	10,85	5,55	12,09	1,74	2,75
Rural population %	41,51	42,20	22,10	0,22	-0,84
Forest	260 730,89	39 775,00	892 145,34	6,54	49,08
World Heritage	7,94	4,00	10,62	2,68	7,63
Happiness Ind	5,30	5,30	1,13	0,08	-0,75
Freedom choices	0,48	0,47	0,44	9,54	106,46
Social support	1,19	1,25	0,31	-1,01	0,83
GINI index	38,18	36,35	7,94	0,65	0,08
Gender Inequality Index	0,36	0,38	0,19	-0,02	-1,05
womenParlam	22,73	20,17	11,28	0,41	-0,25
Corruption	41,47	37,00	18,64	0,87	0,13
Global Peace index	2,10	2,05	0,49	1,00	1,05
Battle-related deaths	331,44	0,00	2 174,58	9,11	88,99
Note - Calculated by the author.					

At this stage of the analysis, we come to the conclusion that in order to study trafficking, it is necessary to use a diversified analytical apparatus, including nonparametric methods that are resistant to anomalies Art distribution, outliers, etc. They do not rely on such quantities as arithmetic mean or average deviation and do not have any requirements for the type of distribution.

Rank variables are the most difficult to analyze. These include phenomena that cannot be directly measured, for example, inequality, the nature of political systems, many social and cultural characteristics. Nevertheless, it is important and necessary to include them in complex analytical models in order to assess the impact of all possible factors on the desired value. In order to transform, generalize and organize information on such variables, a number of generalizations and assumptions are always required.

So, there are specific models for measuring inequality, happiness, security using a variety of "artificial" coefficients and indices. In the absence of generally accepted methodologies, variables can be estimated indirectly through related quantitatively measurable indicators. Examples of such indicators in our study are the gender inequality index, the corruption perception index, and the happiness index.

It is important to understand that any such assessment leads to the loss of some information and "blurring" of the original feature. This is exactly what happens with the key variable reflecting the level of exploitation in the country and the volume of outgoing traffic, which in our case is a rank scale from 1 to 5. For the analysis, we use parametric and nonparametric statistics.

	K. Pearson		To Spearman	
	inExpl	SourceCountry	inExpl	SourceCountry
Population	0,1	0,18	0,2	0,43
Birth rate	-0,33	0,03	-0,36	0,1
Fertility rate	-0,33	-0,01	-0,35	0,07
Adolescent fertility	-0,4	0,06	-0,4	0,23
Death rate	-0,04	0,13	-0,06	0,07
Life expectancy	0,28	-0,12	0,29	-0,23
Population growth	-0,14	-0,13	-0,18	-0,08
Population 65+	0,2	-0,06	0,21	-0,02
Population 0-14	-0,34	0,04	-0,37	0,11
Int Migrant stock	0,21	-0,31	0,19	-0,42

%				
Ref inflow	0,2	-0,05	0,07	-0,15
Ref Outflow	-0,02	0,04	-0,04	0,38
Asyl Seekers pending	0,25	0,08	0,18	-0,18
remittance inflows	0,12	0,24	0,32	0,35
remittance outflows	0,39	0,04	0,44	-0,07
Mobile subscriptions	0,3	-0,01	0,27	-0,09
national income per capita	0,2	-0,27	0,31	-0,32
Unemployment %	-0,07	-0,27	-0,07	-0,31
Employment 15-24	-0,14	0,16	-0,18	0,18
Inflation	-0,06	0,35	-0,06	0,36
natural resources rent %	-0,19	-0,17	-0,25	0,01
expenditure education %	-0,1	-0,14	-0,08	-0,15
Literacy %	0,31	0,07	0,38	-0,08
secEduc+ 25+	0,38	0,05	0,38	0,02
tuberculosis	-0,16	0,14	-0,24	0,32
undernourishment %	-0,27	0,02	-0,34	0,17
Rural population %	-0,19	0,22	-0,19	0,28
Forest	0,21	0,18	-0,09	0,3
World Heritage	0,21	0,04	0,27	0,06

Happiness Ind	0,27	-0,07	0,3	-0,11
Freedom choices	-0,05	0,03	0,06	0,03
Social support	0,21	0,06	0,19	-0,02
GINI index	-0,28	0,07	-0,34	0,15
Gender Inequality Index	-0,34	0,1	-0,38	0,14
womenParlam	-0,06	-0,01	0,01	-0,01
Corruption	0,12	-0,27	0,17	-0,29
Global Peace index	-0,01	0,16	-0,08	0,2
Battle-related deaths	-0,01	-0,01	-0,07	-0,03

Note - Calculated by the author.

Using the example of the table of correlations, one can make sure that the main parameters reflecting the level of traffic often demonstrate statistically significant reliable dependencies (p-level for which is less than 0.05, that is, the probability of error is no more than 5%. Such dependencies in the tables are marked in red), however, all these dependencies are weak. Nevertheless, for the rank variable, a weak, but reliably established relationship cannot be ignored, and all dependencies, the correlation coefficient exceeds 0.3, should be considered in further analysis.

Many connections were found with the demographic block. They are interpreted as follows: the lower the birth rate, the higher the life expectancy, the smaller the proportion of children in the structure of the population, the higher the exploitation rate.

From the "migration" block, the values of remittance outflows (outgoing money transfers of migrants) and Mobile subscriptions (the number of new mobile connections) are highlighted. The second indicator, however, is not confirmed by the Spearman coefficient, but the first one only gets stronger when checked. Therefore, we can confidently state a positive relationship between the level of exploitation and the amount of money transferred abroad. We will not count the number of transfers as a

factor of influence, since it is more a consequence than a cause. But for us it is important as a characteristic symptom of trafficking. In addition, in the future we will make sure that this relationship is confirmed by other analytical methods.

It is interesting to note that the benchmark did not respond to the variables reflecting the number of migrants and refugees in the country. According to many theoretical models, exploitation in the country should be expected to increase with the increase of the latter two phenomena. However, this is not the case, and if we consider the distribution of countries depending on the level of exploitation, we will see that the largest number of migrants is concentrated in countries with an average level of human trafficking (Figure 3.1).
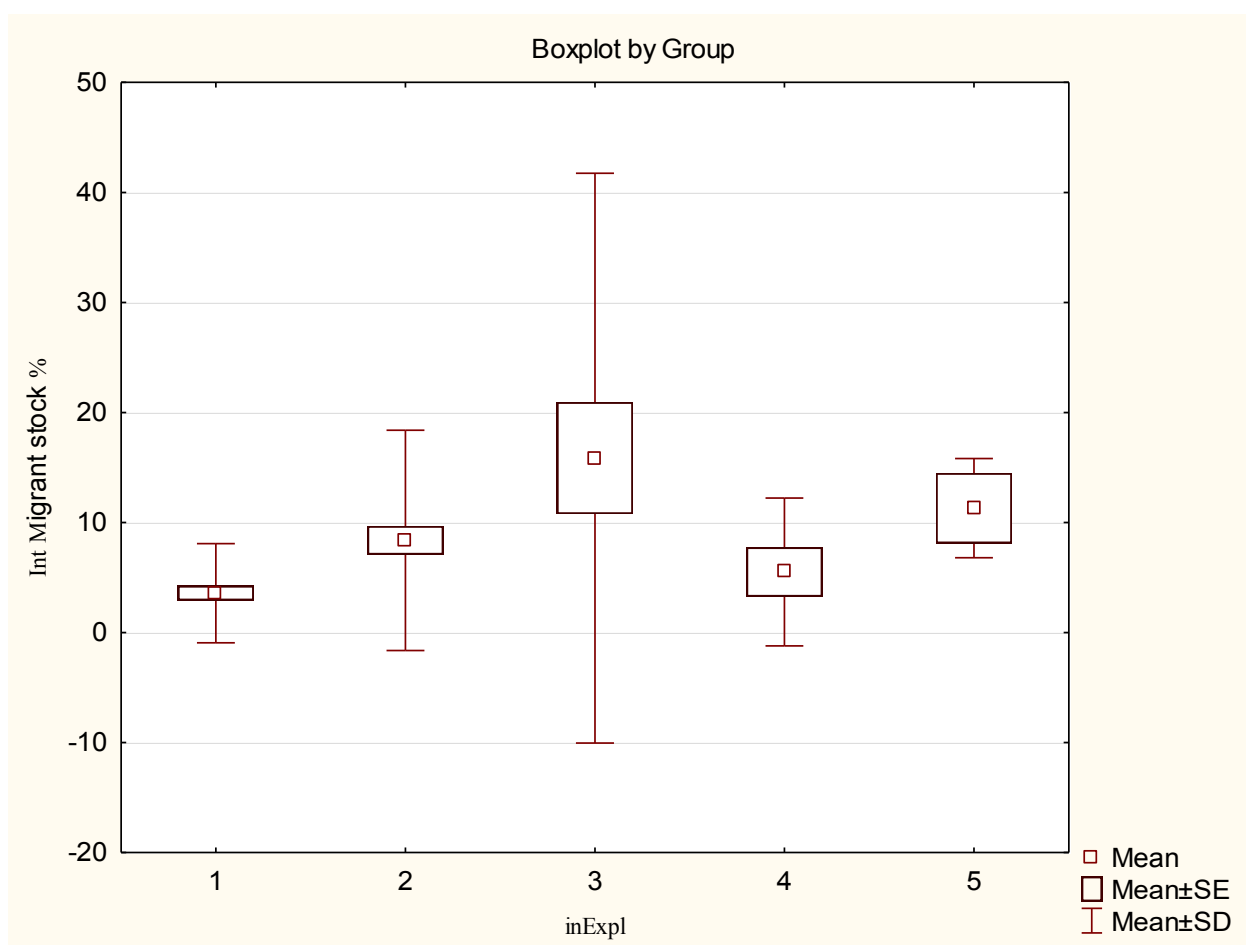
Note - Compiled by the author.

Figure 3.1 - Diagram describing the distribution of migrants by country depending on the value of the exploitation factor

InExpl reacted weakly to economic indicators: only one correlation was found with the indicator of net national income per capita.

The block containing various social factors turns out to be rich in dependence, and the nonparametric correlation confirmed them with a high degree of reliability. These dependencies can be characterized as follows: the higher the literacy rate, the higher the level of education, the index of happiness, the number of cultural heritage sites, and the lower the threat of hunger, the higher the exploitation rate.

Conclusion

Having considered the features of traffic data, which today can be the basis for analytics and study, we are convinced that the accounting and assessment of this phenomenon is far from perfect today. Nevertheless, the available data make it possible to identify important and statistically significant patterns for constructing analytical models.

Based on the results of the analysis, it can be argued that the most appropriate sources reflecting the situation with trafficking on an international scale can be considered the data of international organizations on the total number of identified victims. This indicator does not reflect the entirety of the phenomenon, however, it contains information on how the risk of trafficking in different countries is correlated.

The data of NGOs available today do not completely agree with the data of international organizations and the method of obtaining them is not entirely transparent: in its calculations, the rating is based on data arrays that are not available for review in open sources. Due to these peculiarities, the use of NGO statistics as an empirical base can lead to erroneous conclusions.

Of course, advancing research in this area requires improving the empirical base, and work in this direction is being carried out at the international and regional levels.

To obtain comparable representative statistics on trafficking, it is necessary to develop a unified methodology for accounting for trafficking at the international level. This methodology can be developed and implemented through the UN structures, which are currently active participants in the study and prevention of trafficking. In addition, UN institutions are competent in the selection of assessment methods and have the resource to integrate the new methodology at the state level and further collect and synthesize information in the form of statistical reporting.

As for the information resources of NGOs, in order to improve the mechanism of their assessment, it is necessary to make adjustments to the existing methodology. First of all, you can sacrifice complexity in favor of transparency: today the assessment is based on a very large number of factors, each of which, in turn, can be poorly or incompletely measured. Reducing the dimension of the data in this case reduces the overall error in estimating the traffic level. In addition, the poll results should be excluded from the statistical base of NGOs in the form in which they are taken into account at the moment. Assessing the risk of trafficking in one territory based on surveys conducted in another territory is a serious assumption, the justification of which needs proof, and proof is impossible without a reliable empirical base.

Despite the limitations of the available data, it is very important to continue collecting them and improve the accounting mechanisms. Already today, as we could see, on the basis of the available indicators, it is possible to detect important regularities that can shed light on the principles of traffic distribution. Deepening knowledge of the problem will allow for the creation of more reliable and complex models, which, in the end, will form the basis of a reliable assessment mechanism. Having a reliable assessment model, in turn, will allow tracking trafficking channels and calculating the level of risk for different regions, as well as highlighting indicators, influencing which through government regulation measures, it is possible to reduce the number of crimes related to human trafficking.

References

Lancaster, H. S., Lien, K. M., Chow, J. C., Frey, J. R., Scherer, N. J., & Kaiser, A. P. (2020). Early speech and language development in children with nonsyndromic cleft lip and/or palate: A meta-analysis. Journal of Speech, Language, and Hearing Research, 63(1), 14-31.

Margić, B. D., & Vodopija-Krstanović, I. (2018). Language development for English-medium instruction: Teachers' perceptions, reflections and learning. Journal of English for Academic Purposes, 35, 31-41.

Nursulton, S. (2020). The Significance and Significance of Modern Linguistic Trends in Uzbek Linguistics. International Journal of Progressive Sciences and Technologies, 16-18.

Olulade, O. A., Seydell-Greenwald, A., Chambers, C. E., Turkeltaub, P. E., Dromerick, A. W., Berl, M. M., ... & Newport, E. L. (2020). The neural basis of language development: Changes in lateralization over age. Proceedings of the National Academy of Sciences, 117(38), 23477-23483.

Pennycook, A., &Makoni, S. (2019). Innovations and challenges in applied linguistics from the global south. Routledge.

Politimou, N., Dalla Bella, S., Farrugia, N., & Franco, F. (2019). Born to speak and sing: Musical predictors of language development in pre-schoolers. Frontiers in Psychology, 10, 948.

Ross, A. S. (2019). U and non-U: an essay in sociological linguistics. In The Importance of Language (pp. 91-106). Cornell University Press.

Shaykhislamov, N. Z. U., &Makhmudov, K. S. U. (2020). Linguistics and Its Modern Types. Academic Research in Educational Sciences, (1).

Spolsky, B. (2019). Linguistics and the language barrier to education. In Linguistics and Adjacent Arts and Sciences (pp. 2027-2038). De Gruyter Mouton.

Wang, Y., Williams, R., Dilley, L., & Houston, D. M. (2020). A meta-analysis of the predictability of LENA™ automated measures for child language development. Developmental Review, 57, 100921.