

APPLICATION OF STATISTICAL INDICATORS TO MEASUREMENT EDUCATIONAL AND SCIENTIFIC PRODUCTIVITY AT THE UNIVERSITY

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The relevance of the article is due to the rapid development of global information systems and digital technologies, which affect the competitiveness of universities. In the context of the imbalance between rapid technological progress and changing university funding rules, there is a need for new methods of measuring and evaluating the educational and scientific productivity of universities. Such measurement is a difficult task, because educational and scientific activities are complex systems where there are many elements and factors that influence them, where processes are often described through the conceptual metaphor of “chaos”. But methods are emerging that allow these processes to be conceptualized, mathematically described, measured, and evaluated. The purpose of this study is to identify factors that influence the productivity and effectiveness of scientific and pedagogical activities of universities in order to develop a methodology that will allow for a deeper understanding of quantitative and qualitative indicators in university rankings. This methodology applies the Gini and Hoover coefficients/indices using the Lorenz curve to assess the productivity of the university's scientific and pedagogical activities. The results of the study confirmed the effectiveness of this method and showed that the use of the Gini Index to analyze the teaching workload of teachers can be a useful tool for the administration of educational institutions to increase transparency and fairness in the distribution of resources and responsibilities. Overall, the results of the study confirmed the feasibility of managing scientific activities and showed new opportunities for improving the tools for measuring and evaluating this activity in universities.

KEYWORDS

knowledge management, research assessment, university rankings, developing human capital, Lorenz curve, Gini index, Hoover Index, scientific productivity, education, university performance assessment

1 INTRODUCTION

Knowledge management processes (acquisition, creation, storage, sharing, and application) [Raudeliuniene 2025, Budur 2024, Bagherimajd 2024] are key drivers of innovation, productivity, and economic growth [Dyadyura 2021]. In today's world of global information systems and digital technologies, universities establish a sustainable competitive advantage that plays a decisive role in achieving sustainable development goals [Budur 2024, Klepanchuk 2022]. However, there are fundamental challenges [Maral 2025, Ziesemer 2022] related to addressing the imbalance between rapid technological progress, the dissemination and growing demand for high-quality knowledge [Caglayan 2025], and changes in university funding mechanisms, regulation of educational processes, and their internationalization [Luthra 2025, Kurbatov 2024]. A university's effectiveness is influenced by numerous factors. Beyond national-level factors, internal factors include the professional level of faculty, infrastructure, funding, and management quality [Cohen 2025].

To address this, the Ministry of Education and Science of Ukraine has recently developed a new Methodology for the state attestation of higher education institutions and research organizations in Ukraine. This methodology provides mechanisms for additional targeted support for the most capable and promising research teams. The introduction of mandatory accreditation processes for universities and the increasing influence of global rankings have heightened interest in the quantitative and qualitative aspects of scientific and teaching activities within these institutions [Guo 2023]. Ukraine has over 370 research institutions. Clearly, this number is excessive given the country's scale, demographic and economic changes occurring during the war. The current structure of research institutions is outdated, misaligned with the country's economic situation, and often inconsistent with global models for evaluating scientific achievements. One of the methodology's objectives is to provide founders and institutions with a tool to understand their position within the scientific landscape and explore possible scenarios for restructuring and reorienting their work. From a university strategy perspective, excellence in scientific activity and productivity in the teaching process should be primary criteria when deciding on the effectiveness of faculty's scientific and pedagogical work [Maral 2025].

Unfortunately, there is currently a lack of empirical research directly focusing on the relationship between the productivity of scientific and pedagogical staff and quantitative indicators in university rankings. Although more countries are implementing national higher education policies, there is a shortage of horizontal comparisons of national higher education initiatives across different countries.

The aim of this study is to identify factors influencing the productivity and effectiveness of universities' scientific and pedagogical activities, developing a methodology to deepen the understanding of quantitative and qualitative indicators in university rankings.

2 REVIEW OF LITERATURE

Numerous methodologies and approaches have been developed to measure the effectiveness of scientific and educational institutions [Guo 2023]. There are many global university rankings, with the most notable being Times Higher Education, Quacquarelli Symonds (QS), US News, and the Academic Ranking of World Universities (ARWU). As global university rankings have continuously improved in recent years, some studies have used these rankings as indicators to assess the impact of national

higher education initiatives. Global university rankings consist of comprehensive indicators that reasonably balance teaching, research, commercialization, and internationalization. Performance indicators for evaluating national higher education initiatives often align with those used in international university rankings, directly reflecting the initiatives' impact on university rankings [Pepe 2024]. To some extent, all major rankings rely on universities' scientific outputs. In recent years, due to the globalization of science and education and the availability of databases, new methodologies [Alqararah 2023] and information systems have been proposed to encourage, stimulate, and support the development and implementation of scientific research, leveraging resources that influence university ranking positions. However, measurement is a complex task due to the heterogeneity of involved institutions, the diversity of goals and expected benefits, and the differing perspectives of stakeholders, as high-value impact for one group may not be the same for another [Dmitrishin 2014]. This is a natural situation for scientific activity as a complex system with many elements and influencing factors [Prokopovych 2019], where processes are often described through the concept-metaphor "chaos" [Dmitrishin 2019]. Nevertheless, methods are emerging that allow these processes to be comprehended, mathematically described [Blesch 2022], measured, and evaluated.

Academic publication networks (e.g., well-known databases like Scopus and Web of Science, or research project databases such as the European Cordis, which tracks projects from international programs like Horizon and Erasmus) serve as the primary tool for assessing a country's innovative potential through comprehensive indices of university publication activity. These data enable temporal segmentation and in-depth network analysis. While alternative assessments of university scientific activity exist, the use of index-related tools ensures the relevance and depth of performance analysis.

Country	GII – Rank	GII - Score	Gini index (UN, 2021) %
Switzerland	1	68.3	32.25
United Kingdom	2	62.42	33.12
Sweden	3	62.4	30.0
Netherlands	4	61.58	28.31
USA	5	60.1	41.78
Finland	6	59.97	26.89
Singapore	7	59.36	38.6
Ireland	8	59.13	30.77
Luxembourg	9	59.0	35.11
Denmark	10	57.7	28.5
Ukraine	64	36.45	28.1

Table 1. Comparison of countries worldwide by Gini index and Global Innovation Index [22]

Global innovation indicators play a significant role in understanding and assessing a country's innovative and scientific potential on a global scale [Demeter 2022]. Over the past decade, the Global Innovation Index (GII) has supported national innovation strategies and provided valuable insights into applied sustainable innovations at the national level. It also helps identify conditions for the dissemination of innovations and their importance to a country's development. The GII stands

out from other composite innovation indicators by emphasizing components related to intangible assets such as trademarks, global brand value, and industrial designs. This feature allows researchers, business leaders, and policymakers to leverage the GII for creative intangible innovations tied to assets (Table 1) [Osare 2023]. According to 2021 UN data, Ukraine has the lowest coefficient (28.1), while the United States has the highest (41.78). These data suggest that the Gini index does not fully correlate with the Global Innovation Index (GII). Innovative and scientific activity significantly contributes to a country's GDP growth. Consequently, income distribution, its relationship with economic activity, and social welfare have become key focuses of numerous theoretical and empirical studies in recent years [Haye 2021]. These studies evaluate the trade-off between efficiency and equity. One tool in these studies is the Gini index evaluation methodology. Periodic reports with summary statistics on income or wealth distribution have become common [Demeter 2022]. Major international databases such as ILOSTAT (International Labour Organization), the Human Development Report (UNDP-HDR), the World Inequality Database (UNU-WIID), the Poverty and Inequality Platform (PIP) of the World Bank, and the World Income Database (WID) provide grouped data. Using grouped income or wealth data, the Gini index can be estimated by comparing the statistical characteristics of income distribution with theoretical distributions such as log-normal, Beta-II, generalized Pareto, or mixed distributions [Osare 2023, Mitrovic 2023]. This can involve defining a parametric form for the Lorenz curve.

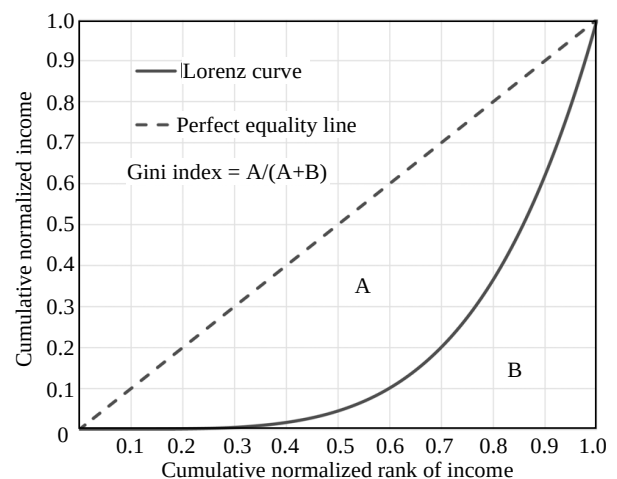


Figure 1. Calculation of the Gini index as the ratio of the area between the ideal line of equality (dotted) and the Lorenz curve (A) to the total area under the ideal line of equality (A + B)

The advantage of the Gini index is that it assesses the inequality of an entire income distribution with a single statistic, which is relatively easy to interpret, ranging from 0 to 1. For example, in the global economy, this enables comparisons across countries with different population sizes [Fleurbay 2025]. Additionally, Gini index data are widely available, regularly updated, and reported by countries and international organizations [Gavilan-Ruiz 2024]. Despite its strengths as a measure of income inequality, a lower Gini index does not always indicate a more even income distribution compared to a country with a higher Gini index, as Lorenz curves for two countries may intersect, reflecting different distributions of innovation levels (Table 1). The Gini index can be derived using the Lorenz curve plot, constructed in a Cartesian coordinate system where the x-axis represents the cumulative normalized rank of income from lowest to highest (x), and the y-axis represents the cumulative normalized income from lowest to highest (y) (Fig. 1). If the axes

are swapped, the ranking feature is on the x-axis, and the sample size is on the y-axis.

The Gini index ranges from 0 to 1. The closer it is to zero (where area A is small), the more even the income distribution. The closer it is to one (where area A is large), the more uneven the distribution. Numerous studies have proposed various parametric functional forms for directly estimating the Lorenz curve. These include one-parameter Lorenz curves [Shen 2024], two-parameter Lorenz curves, and three-parameter Lorenz curves [Siddiq 2023]. Estimating the parameter(s) of the Lorenz curve using the maximum likelihood (ML) method was suggested, assuming each income share follows a joint Dirichlet distribution, while some authors proposed using error minimization techniques. A simple method for estimating the Lorenz curve using three indicators: the Gini index, lower- and upper-income shares, tied to a functional form based on the weighted average of an exponential function and a special form defined by the Pareto distribution was also presented in the literature.

3 MATERIALS AND METHODS

The study's concept involves applying the Gini and Hoover indices using the Lorenz curve to evaluate the productivity and efficiency of a university's scientific and pedagogical activities. The study also employs the Hoover index, also known as the Robin Hood index, which measures inequality on a scale from 0 (perfect equality) to 1 (maximum inequality). It represents the share of the total activity that would need to be redistributed from units above the equal-share level to units below it to achieve an equal distribution. The Hoover index (H) is calculated using the formula:

$$H = 12 \cdot \sum i = \ln|p_i - s_i| \quad (1)$$

where: p_i – the share of the i -th group (e.g., i -th faculty member) in the total number of faculty members. If faculty are individual units, then $p_i = 1/n$, where n is the total number of faculty; s_i – the share of the i -th group in cumulative scientific activity (e.g., total scientific activity scores).

The research was conducted using empirical data (for 2024) from Odesa Polytechnic National University (Ukraine), which consistently holds average positions in university rankings.

4. RESULTS

This study analyzes statistical data provided by the educational and scientific institutes of Odesa Polytechnic National University, covering publication activity, research topics and grants, graduate student defenses, patents and certificates, student scientific work, and organizational activities.

Fig. 2 presents the distribution characteristics of scientific contributions to the overall scientific activity of academic staff at Odesa Polytechnic National University. The scientific activity of 522 academic staff members was analyzed.

Each employee is assigned a teaching load, which includes research activities at the university. The hours of the teaching load can be converted into points or represented on another scale. The analysis focuses on a specific teacher and a numerical indicator that characterizes their teaching and research load.

Figure 2 shows a variation series, where the horizontal axis represents the number of teachers at Odesa Polytechnic National University, and the vertical axis represents the numerical indicator characterizing the completed teaching and research load. This relationship is characterized by a certain "average", which reflects the contribution of each teacher, and also has so-called "tails", corresponding to higher or lower

contributions of academic staff. We obtain a distribution that can be transformed by subtracting those who make a greater contribution, and then the first number decreases, starting from zero and ending with the largest number after subtracting the smallest. With a uniform contribution, theoretically, a straight line segment (the red line in Figure 2) would be obtained. Ideally, the "tail" would be slightly smaller, or the beginning would be slightly larger, and then this segment would indicate a uniform contribution from all teachers. If there were such a uniform contribution, given that the maximum contribution was, for example, 2700 hours or another number of hours, the number of teachers who did not meet the 500-hour plan would be less than 20%. That is, approximately 15...17% of teachers would not fulfill the required number of hours. Such a distribution is considered uniform with a sufficiently high "tail" (a large number of "leaders") [Krenicky 2022]. If there are fewer "leaders", the distribution appears simpler.

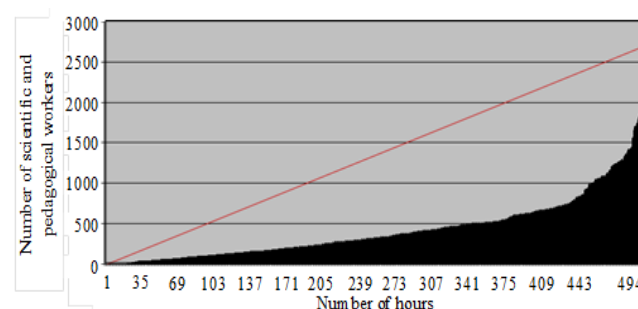


Figure 2. Degree of stratification of the scientific community at Odesa Polytechnic National University. Gini index: 0.68. Hoover coefficient: 0.6

The black curve in Figure 2 represents the ranked distribution of individual scientific and teaching workload among faculty members, while the red line represents a reference case of uniform contribution. The Gini index was calculated separately from the cumulative normalized distribution of workload using the standard Lorenz-curve approach and reached 0.68. The Gini index was 0.68.

The corresponding Hoover index, calculated according to Eq. (1), was 0.6. In this case, it is a relative length, defined as the ratio of the leg of the largest "tail" magnitude. If we were to redistribute the hours evenly among all teachers, the distribution would be smaller because the area of the triangle would need to correspond to the distribution boundary (black line). In this case, the 500-hour norm would not be met and would shift to the right by 1/2. This indicates a significant stratification within the scientific community at Odesa Polytechnic National University in terms of scientific contribution.

Let us consider the reverse construction of the diagram. If in Figure 2 the horizontal axis represented the number of teachers and the vertical axis represented the hours allocated to scientific work, then a reverse relationship can be constructed (Figure 3a). In this case, the vertical axis will represent the number of teachers, and the horizontal axis will represent the number of hours worked by specific teachers. Intervals can be taken from 0 to 250 hours, corresponding to 200 teachers, and from 250 to 500 hours, corresponding to approximately 125 teachers.

The diagram shows that, in fact, 350 teachers did not reach 500 hours. From Figure 3, it is evident that this figure corresponds to 340 teachers not reaching 500 hours. If we take the number of teachers as 350 out of 500, it turns out that actually 70% do not meet the norms set for them. Let's consider the situation with teachers who have met the 500-hour norm. Approximately 100 teachers are around the average (in the interval of 500...750 hours) (Fig. 3a). Further, the number of teachers sharply decreases (to approximately 25...30) in the interval of 750...1000

hours, and then sharply increases to 50 in the interval above 1000 hours. This forms the so-called “tail”.

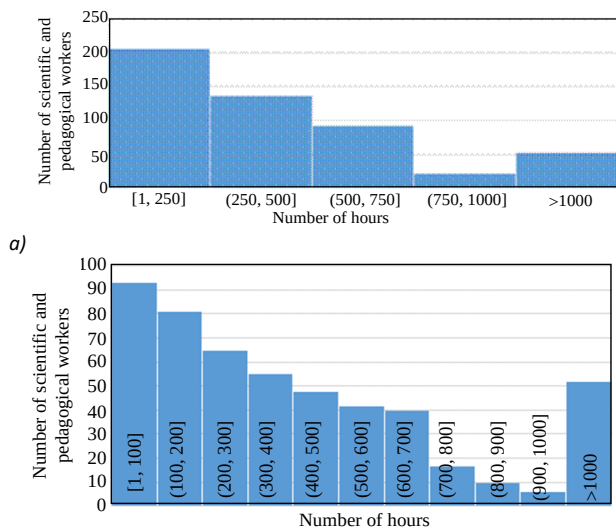


Figure 3. Distribution of scientific workload among teachers at Odesa Polytechnic National University. Total hours – 220,819.7, number of teachers – 433, average – 529: a) interval division – 250; b) interval division – 100

If we were to construct economic graphs to analyze the stratification of society by income, the situation would be the same: most people have low incomes, then the curve follows a similar pattern, and there is a dip, meaning there is a certain income level that no one has. A “gap” appears, which indicates a very small number of people being considered. Beyond that, the “tail” represents the “wealthy individuals”. That is, those who are wealthy either in terms of financial income or in terms of hours of scientific work. In Fig. 2b, a similar diagram is presented, but with intervals of “100” instead of “250”. The trend here is also similar. Up to approximately 700 hours, the distribution follows a gradually decreasing trend, followed by a dip between 700 and 1000 hours and a subsequent high-value “tail”. An important indicator of the scientific activity of teachers is the number of their publications in journals indexed by the Scopus database. In Fig. 4, a variation series is constructed, which reflects the share of publications for each author in journals indexed by the Scopus database.

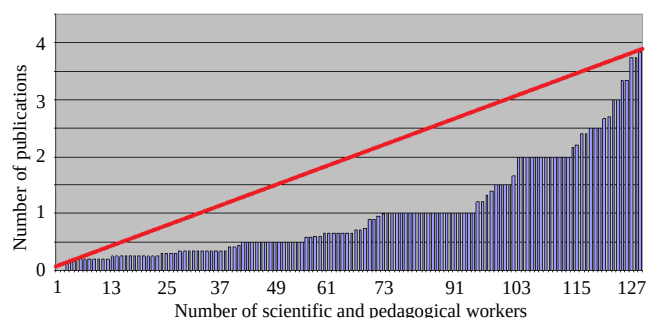


Figure 4. Degree of stratification of the scientific community at Odesa Polytechnic National University regarding publication activity in journals indexed by the Scopus database. Gini index – 0.47

The Lorenz curve in Fig. 4 corresponds to the distribution in Figures 2 and 3. However, this relationship does not account for teachers who have no publications in journals indexed by the Scopus database. If this category of teachers were included, the Gini index would be closer to 1. It should be noted that faculty members with no publications indexed in Scopus were not included in this analysis. Therefore, the Gini index of 0.47

characterizes the distribution among publishing faculty members only and cannot be directly interpreted as the publication-activity inequality of the entire university staff. Returning to the relationship in Fig. 4, we see that the curve is convex downward. It will always have this appearance. It should be noted again that employees who have no articles in journals indexed by the Scopus database were not included. In Fig. 5, a histogram of publication activity in journals indexed by the Scopus database is presented, but in this case, the “tail” is examined in more detail. It turns out that if the “tail” is not expanded, the histogram will show a “gap” and a “tail”.

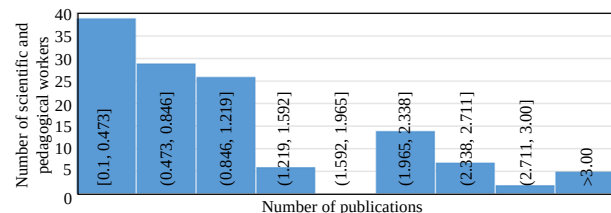


Figure 5. Degree of stratification of the scientific community at Odesa Polytechnic National University regarding publication activity in journals indexed by the Scopus database. Gini index – 0.47

However, when the “tail” is broken down by indicators, it takes on a form that corresponds to the same distribution law. Thus, we propose a hypothesis that a standard normal distribution does not exist, and a normal distribution always has “tails”. We formulate the question: does the “tail” of a normal distribution have its own “tail”? If so, this hypothesis can be applied to any distribution, meaning every distribution has a certain “tail”, and the “tail” follows the same distribution. In other words, we can speak of a law of fractal distribution with “tails”. The distribution between the teaching staff and workload in hours was studied for each academic and research institute of Odesa Polytechnic National University. For individual academic and research institutes, the number of teaching staff is smaller, so there is less statistical data, or it may be entirely absent.

Fig. 6 presents an analysis of the distribution of scientific workload among the academic staff of the Institute of Computer Systems at Odesa Polytechnic National University. The scientific activity of 101 academic staff members was analyzed.

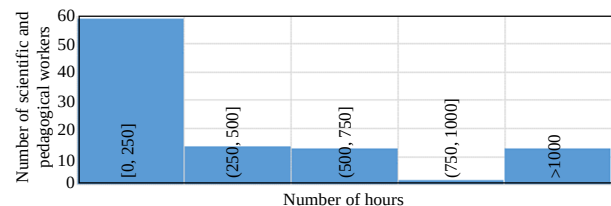


Figure 6. Distribution of scientific workload among teachers of the Institute of Computer Systems at Odesa Polytechnic National University. Total hours – 42,121, number of teachers – 101, average – 417

The Gini index for publications in Scopus was 0.68, which is a relatively high indicator. Overall, across the university, this index is higher. Whether there is a correlation between them has not yet been considered. Fig. 7 presents an analysis of the distribution of scientific workload among the academic staff of the Institute of Digital Technologies, Design, and Transport at Odesa Polytechnic National University. The scientific activity of more than 74 academic staff members was analyzed.

The “tail” for this institute is “not large”. This is why the Gini index is low. If the “tail” were “higher”, both the average and the Gini index would increase. In other words, the average and the Gini index essentially reflect the presence of a “tail”.

Fig. 8 presents an analysis of the distribution of scientific workload among the academic staff of the Institute of Economics and Management at Odesa Polytechnic National University. The scientific activity of 77 academic staff members was analyzed.

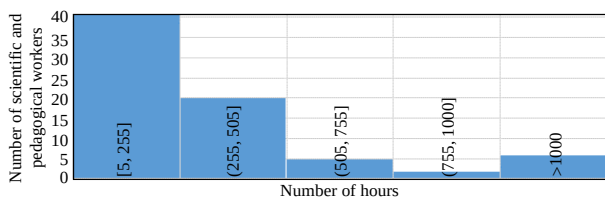


Figure 7. Distribution of scientific workload among teachers of the Institute of Digital Technologies, Design, and Transport at Odesa Polytechnic National University. Total hours – 23,947.5, number of teachers – 74, average – 323

It can be stated that in this institute, the scientific activity of teachers is being managed. It follows that by managing scientific activity, it is possible to shift the initial bars and obtain a normal distribution law with a “tail”, meaning that a normal distribution law with a “tail” is ideal for society (and the university). However, there will always be “outliers”. If we exclude these “outliers”, we simply shift the normal distribution, but new “outliers” will emerge. Thus, excluding “outliers” is methodologically inappropriate.

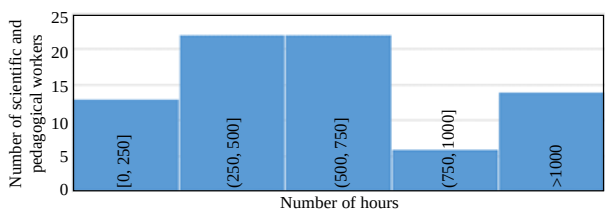


Figure 8. Distribution of scientific workload among teachers of the Institute of Economics and Management at Odesa Polytechnic National University. Total hours – 46,181, number of teachers – 77, average – 599. Gini index – 0.46

Fig. 9 presents an analysis of the distribution of scientific workload among the academic staff of the Institute of Public Service and Management at Odesa Polytechnic National University. The scientific activity of 51 academic staff members was analyzed.

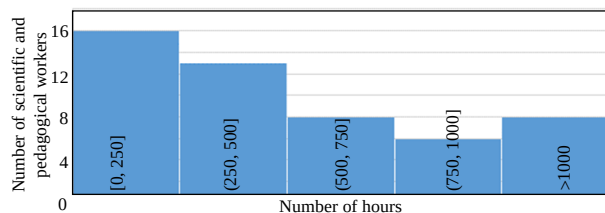


Figure 9. Distribution of academic workload among faculty members of the Institute of Public Service and Management, Odesa Polytechnic National University. Total hours – 26,996.5; number of faculty members – 51, average – 529. Gini index – 0.5

Fig. 10 presents an analysis of the distribution of academic workload among academic staff of the Institute of Humanities, Odesa Polytechnic National University. The scientific activity of 57 academic staff members was analyzed.

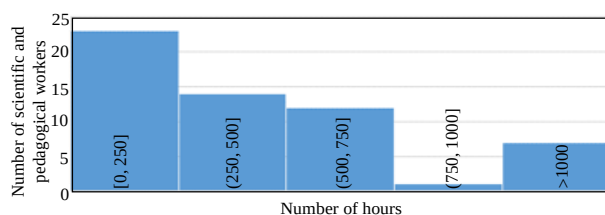


Figure 10. Distribution of academic workload among faculty members of the Institute of Humanities, Odesa Polytechnic National University. Total hours – 24,861.86; number of faculty members – 57, average – 436. Gini index – 0.5

Fig. 11 presents an analysis of the distribution of academic workload among academic staff of the Institute of Medical Engineering, Odesa Polytechnic National University. The scientific activity of 23 academic staff members was analyzed.

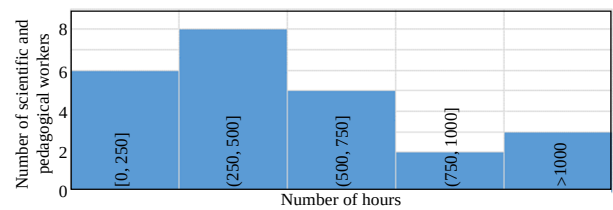


Figure 11. Distribution of academic workload among faculty members of the Institute of Medical Engineering, Odesa Polytechnic National University. Total hours – 12,789.25; number of faculty members – 23, average – 556. Gini index – 0.38

Fig. 12 presents an analysis of the distribution of academic workload among academic staff of the Institute of Electrical Engineering and Electromechanics, Odesa Polytechnic National University. The scientific activity of 23 academic staff members was analyzed.

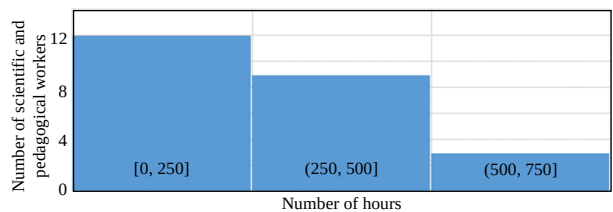


Figure 12. Distribution of academic workload among faculty members of the Institute of Electrical Engineering and Electromechanics, Odesa Polytechnic National University. Total hours – 6,382.5; number of faculty members – 23, average – 277.5. Gini index – 0.32

Example of a distribution without a “tail”. Statistics – the lowest in the university. The Gini index is low because there is no “tail”, no stratification. Fig. 13 presents an analysis of the distribution of academic workload among academic staff of the Institute of Energy, Odesa Polytechnic National University. The scientific activity of 24 academic staff members was analyzed.

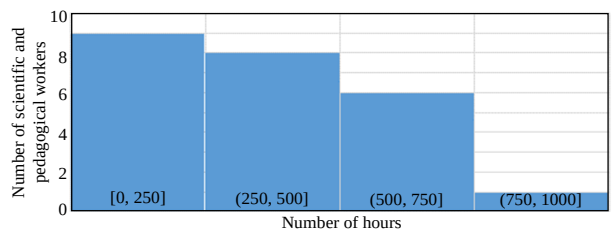


Figure 13. Distribution of academic workload among faculty members of the Institute of Energy, Odesa Polytechnic National University. Total hours – 9,033; number of faculty members – 24, average – 376. Gini index – 0.1

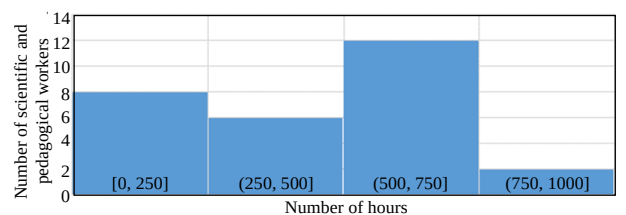


Figure 14. Distribution of academic workload among faculty members of the Institute of Artificial Intelligence and Robotics, Odesa Polytechnic National University. Total hours – 11,867; number of faculty members – 28, average – 423. Gini index – 0.1

Similar situation: absence of a “tail”. Almost uniform distribution. Fig. 14 presents an analysis of the distribution of

academic workload among academic staff of the Institute of Artificial Intelligence and Robotics, Odesa Polytechnic National University. The scientific activity of 28 academic staff members was analyzed.

High indicators due to graduate students. This is an anomaly: few faculty members, but they are engaged in a single type of activity focused on training graduate students. If they perform this activity, it results in high indicators, but it is impossible to ensure that graduate students are evenly distributed among all faculty members. Fig. 15 presents an analysis of the distribution of academic workload among academic staff of the Ukrainian-German Institute, Odesa Polytechnic National University. The scientific activity of 30 academic staff members was analyzed.

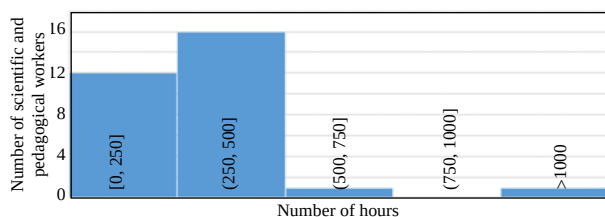


Figure 15. Distribution of academic workload among faculty members of the Ukrainian-German Institute, Odesa Polytechnic National University. Total hours – 10,584.4; number of faculty members – 30, average – 352. Gini index – 0.54

Most faculty members of this institute work in the humanities direction. The average and the Gini coefficient are correlated. Fig. 16 presents an analysis of the distribution of academic workload among academic staff of the Institute of Information Security, Radioelectronics, and Telecommunications, Odesa Polytechnic National University. The scientific activity of 13 academic staff members was analyzed.

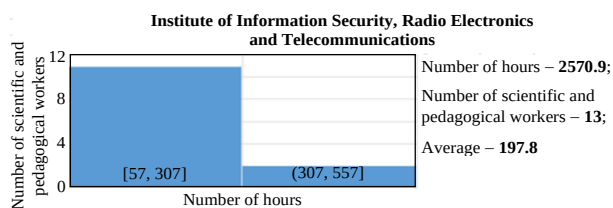


Figure 16. Distribution of academic workload among faculty members of the Institute of Information Security, Radioelectronics, and Telecommunications, Odesa Polytechnic National University. Total hours – 2,570.9; number of faculty members – 13, average – 197.8

Fig. 17 presents an analysis of the distribution of academic workload among academic staff of the Institute of Distance and Correspondence Education, Odesa Polytechnic National University. The scientific activity of 6 academic staff members was analyzed.

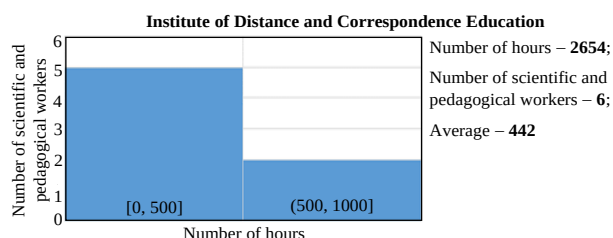


Figure 17. Distribution of academic workload among faculty members of the Institute of Distance and Correspondence Education, Odesa Polytechnic National University. Total hours – 2,654; number of faculty members – 6, average – 442

Fig. 18 presents an analysis of the distribution of academic workload among academic staff of the Ukrainian-Polish Institute, Odesa Polytechnic National University. The scientific activity of 12 academic staff members was analyzed.

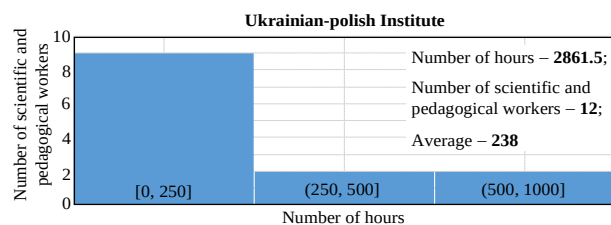


Figure 18. Distribution of academic workload among faculty members of the Ukrainian-Polish Institute, Odesa Polytechnic National University. Total hours – 2,861.5; number of faculty members – 12, average – 238

Fig. 19 shows a diagram with information about the main types of workload for faculty members.

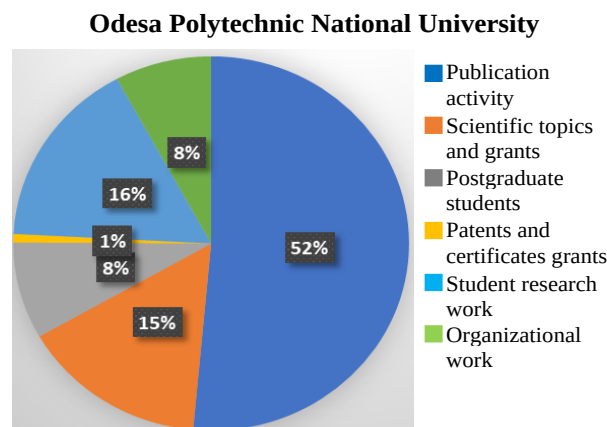


Figure 19. Distribution by types of workload at Odesa Polytechnic National University

DISCUSSION

In a more general sense, the Gini index is a quantitative measure of statistical equality in the context of non-negative datasets with positive mean values. The Gini coefficient has been used in many disciplines beyond its traditional applications. Its use has expanded, covering a wide range of scientific fields. General findings indicate that calculated Lorenz curves correspond to actual observations. This simple method can be useful in situations with limited access to data on the distribution of certain indicators. However, in cases with broad access to data, the functional form of the Lorenz curve estimation presented in the study is more effective. Moreover, the study showed that the calculated Gini index values, based on the specified functional form, closely align with their actual observations. Tracking the Gini index over time will allow for assessing the effectiveness of measures aimed at a fairer distribution of the educational and scientific workload of university staff.

The results of this study may be useful for improving and developing scientometric indicators. Applying the Gini index to analyze academic workload can be a valuable tool for educational institution administrations to enhance transparency and fairness in the distribution of resources and responsibilities. The Gini index can be applied to analyze the distribution of scientific activity among university faculty, similar to how it is used for analyzing academic workload.

Several studies have shown that the Gini index is less sensitive to inequality in the “tails” of income distribution, while the share ratio does not account for inequality in the middle of the workload distribution among faculty members. In the context of faculty scientific activity, the Gini index can help assess how evenly various types of scientific work are distributed among faculty. This may include: publications in scientific journals (articles, monographs); participation in conferences

(presentations, abstracts); supervision of scientific projects and grants; dissertation defenses (supervision and reviewing); inventive activity (patents); peer reviewing of scientific works; participation in scientific councils and expert groups.

Application of the Gini Index to Scientific Activity:

Fairness Assessment: Determining whether all faculty members have opportunities to engage in scientific activity or if scientific activity is concentrated among a small group.

Identifying Imbalances: A high Gini Index may indicate that some faculty members are overburdened with scientific work while others have insufficient opportunities for development.

Monitoring Changes: Tracking the Gini Index over time allows for evaluating the effectiveness of university policies in supporting and incentivizing scientific activity.

Analyzing Influencing Factors: Studying how various factors (e.g., position, academic degree, experience) affect the distribution of scientific activity.

How to Calculate the Gini Index for Scientific Activity?

Calculating the Gini Index for scientific activity is more complex than for academic workload, as it requires accounting for different types of scientific work. Possible approaches:

Point System: Assign points for various types of scientific activity (e.g., publication in Scopus – 10 points, conference participation – 2 points, grant supervision – 5 points). Then calculate the total points for each faculty member.

Weighting by Importance: Assign different weight coefficients to various types of scientific activity, considering their impact and significance.

Separate Analysis by Activity Type: Calculate the Gini Index separately for each type of scientific activity (e.g., separately for publications, separately for grants).

After determining the quantitative assessment of scientific activity for each faculty member, the procedure for calculating the Gini Index is similar to that used for academic workload:

Data Collection: Gather information on each faculty member's scientific activity (e.g., number of publications, participation in grants, etc.).

Data Transformation: Convert different types of scientific activity into a quantitative form (e.g., using a point system).

Data Sorting: Sort faculty members in ascending order of their scientific activity.

Constructing the Lorenz Curve: Graphically represent the cumulative share of faculty members and the cumulative share of their scientific activity.

Calculating the Gini Index: Compute the area between the line of absolute equality and the Lorenz curve.

Challenges and Limitations:

Complexity of Accounting for All Types of Scientific Activity: Not all types of scientific work are easily quantifiable.

Varied Quality of Scientific Work: Quantity does not always reflect quality. The level of journals, conferences, and grants must be considered.

Different Scientific Fields: Comparing scientific activity across different disciplines can be challenging.

Subjectivity in Evaluation: Assigning points or weight coefficients may be subjective.

The Gini Index can be a useful tool for assessing and monitoring the distribution of scientific activity in higher education institutions, promoting a fairer and more effective allocation of resources and opportunities. In practice, both the Gini Index and the Hoover Index are often used for a comprehensive analysis of inequality. The Gini Index provides an overall picture, while the Hoover Index complements it by showing the extent of the imbalance in terms of hypothetical redistribution. This allows educational institution management not only to identify the issue of inequality in scientific activity but also to assess the

potential scale of efforts needed to address it. The Hoover Index is useful when you want to understand the specific magnitude of the inequality problem and answer the question: "What percentage of scientific achievements needs to be redistributed to ensure an equal contribution from each faculty member?" It is a more "operational" indicator.

CONCLUSIONS

The research results demonstrated that the application of the Gini and Hoover coefficients/indices using the Lorenz curve can be effective for evaluating the productivity and efficiency of the university's academic and scientific activities. Applying the Gini Index to analyze the academic workload of faculty members can be a valuable tool for educational institution administrations to enhance transparency and fairness in the distribution of resources and responsibilities. The Gini Index can also be used to analyze the distribution of scientific activity among university faculty, similar to its application in analyzing academic workload. This approach not only proved its effectiveness but also allowed for the formulation of a hypothesis that a standard normal distribution does not exist, and a normal distribution always has "tails". The theoretical significance of this hypothesis arises from the question: does the "tail" of a normal distribution itself have a "tail"? If so, this hypothesis can be applied to any distribution, meaning every distribution has a certain "tail", and the "tail" follows the same distribution. Thus, there is a basis to discuss a law of fractality in distributions with "tails." Overall, the research results confirmed the appropriateness of managing scientific activity and highlighted new opportunities for improving the tools for measuring and evaluating this activity in universities.

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