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Social Network Analysis of Occupational Structures: A Case Study of Brazil, China, Germany, Russia, and the United States

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Abstract

This article investigates the complex dynamics of social stratification in the context of contemporary global capitalism, with a particular focus on the interplay of class positions and occupational categories across five major countries: Brazil, China, Germany, Russia, and the United States. The study aims to offer a nuanced understanding of social hierarchies by integrating network analysis into the examination of socioeconomic and occupational structures, providing an innovative methodological approach to traditional class-based analysis.

Keywords

Social Stratification, Network Analysis, Occupational Structure, Global Capitalism, Class-Based Analysis

1. Introduction

The study of social stratification lies at the very heart of sociology and is intrinsically linked to its central questions and concerns. By examining social stratification, it is possible to explore fundamental issues such as inequality, social mobility; it allows to analyse how different social classes are formed and maintained, and how these classes affect people's behavior, relationships, and opportunities. and overall to have a clear understanding of how our societies are structured.

Understanding social stratification also sheds light on the broader social structures and processes that underpin society and that currently matters to all of us. It prompts questions about the fairness and justice of societies, of the distribution of resources and the constrains that individuals face as a part of society. In this way, the study of social stratification is not just a theoretical exercise but a critical tool for addressing real-world issues and promoting social justice. It is through this lens that sociologists can contribute to a deeper understanding of social dynamics and work towards creating more equitable and inclusive societies.

Therefore, the increasing complexity of societies in our times, demands from us innovative ways to deal with the study of social structures. Having said this, the goal of this research is to develop a Social Network approach to the study of social stratification based on occupational categories, using datasets from the World Values Survey for Brazil, China, Germany, Russia, and the United States. These countries are major global and regional powers, significantly influencing the structuring of contemporary socioeconomic dynamics worldwide. The key objective of this research is to capture and analyse the interconnectedness and relationships within these occupational categories as revealed by datasets in a way that can be both alternative and complementary to more traditional approaches to the study of social stratification.

Additionally, this research aims to explore alternative methodological approaches to those commonly used in sociological research. In this context, network analysis serves as the methodological core of this work, representing a novel approach to understanding and mapping the intricate relationships and interactions within and between different social classes. By employing network analysis, this study seeks to provide deeper insights into the structural dynamics and connectivity that underpin contemporary socioeconomic systems.

2. Methodological and epistemological approaches in social stratification research

2.1. Supervised and non-supervised classification methods in social stratification research

The study of social stratification and hierarchization involves integrating diverse theoretical perspectives, which may originate from different epistemological traditions. For such integration to be effective, it must be linked to methodologies that are both empirically robust and logically coherent, and that align with the principles of sociological inquiry. Traditionally, social stratification has been understood as a problem of classification. However, an increasing number of scholars now advocate for the use of relational methodologies, which offer more nuanced ways of addressing the complexities of class relations (Rosenelli, 2013; Rawolle & Lingard, 2022). These approaches also provide an opportunity to merge the strengths and concerns of various frameworks, including intersectionality and analytical sociology.

In its classification form, the class structure can be deduced from underlying patterns that, while not immediately observable, can be elucidated through statistical modelling and classification algorithms. The classification of individuals based on their official work status has emerged as a predominant methodological strategy in contemporary sociological research as a way to approach the problem of social stratification (Rojas Ospina, 2023). These classifications, often derived from governmental or institutional employment categories, are employed as proxy variables in models designed to infer a wide range of social properties. This approach leverages the assumption that one's occupation or official work status can serve as a reliable indicator of various socio-economic factors, including income level, social class, education, and even lifestyle preferences.

To some extent, theoretical inconsistencies might originate from the epistemological complexities tied to the study of social classes. The absence of a singular, universally acknowledged definition of social class, coupled with the lack of a consistent approach for its operationalization, are issues that naturally emerge from the fundamental character of social science research itself (Hening & Liao, 2010), Therefore, the prevalent reliance on proxy variables or indicators, such as occupational categories, to represent social class persists and is likely to remain a useful methodological resource for sociologists in the future.

Notably, there is a common approach among scholars to address both analytically and empirically the study of social stratification: to understand it as a problem of clustering or unsupervised classification (Hening & Liao, 2010). The exploration of systematic methods for the classification of social groups has been a cornerstone in the evolution of sociology since its inception. The theoretical foundations of social stratification emphasize the importance of classification in understanding societal structures, and the use of clustering methods can be traced back to early sociological paradigms (Dunham & Allen, 2011). Additionally, the categorization of social groups has historically shaped the study of inequality, with methods of classification being central to this analysis since the emergence of sociology (Williams, 2008). Early sociologists, laid the groundwork for these analytical techniques, setting the stage for modern methods of social classification (Brown, 2013).

This interest is exemplified in the development of social class schemes, stratification systems, and the delineation of socio-demographic structures, highlighting a theoretical commitment that dates back to the foundational periods of the discipline (Rojas Ospina, 2023). In recent empirical studies, the utilization of cluster analysis, alongside other dimensional reduction, and classification techniques, has seen a notable increase. This surge is predominantly due to advancements in computational technology, which have made it possible to explore sociological constructs with greater depth and subtlety (Białowolski, 2015).

Cluster analysis stands as a pivotal methodological framework in the study of social stratification. It systematically organizes elements or variables within a dataset into subsets or clusters, based on the similarity of characteristics. This technique has gained widespread adoption among researchers seeking to dissect and understand the nuanced layers of social stratification empirically (Fachelli & Roldán, 2012). The endeavour to achieve optimal classification within these clusters unfolds as a complex, multifaceted task. It navigates through a spectrum of algorithms, each with its unique operational logic and suitability to different types of data. These algorithms depend on various metrics and assumptions to yield consistent and reliable outcomes, underscoring that the definition of a cluster is inherently dynamic and may vary based on the chosen algorithm and the theoretical underpinnings of the research at hand.

At the core of this classification challenge lies the bifurcation between probabilistic and non-probabilistic approaches to address clustering or classification problems (Hening & Liao, 2010). Probabilistic methods, such as Latent Class Analysis (LCA), rely on statistical models to estimate the probability that a given data point belongs to a specific cluster. These methods assume that data points are generated by a mix of underlying probability distributions, making them particularly adept at handling ambiguity and overlapping clusters where membership is not strictly defined. Non-probabilistic approaches, on the other hand, such as Hierarchical Cluster Analysis (HCA), operate on a principle of minimizing variance within clusters without assuming any underlying statistical distribution. These techniques define cluster membership based on the closest centroid or other deterministic criteria, making them straightforward but potentially less flexible in dealing with data that naturally form non-spherical clusters or when the clusters have varying sizes and densities.

Though these methods are favoured for addressing social stratification due to their theoretical soundness and the enhanced accessibility of advanced computational tools, there often lacks a preliminary discussion on the rationale for choosing a specific clustering technique. However, to justify one's selection of a particular method does not mean claiming it as the sole and correct approach to such problems, as theoretical perspectives will always influence the empirical choices made by researchers.

The diversity of approaches inevitably leads to the acknowledgment that, from both a sociological and computational standpoint, there are no ideal methods for clustering. Yet, it is crucial to justify the choice of a method, considering the analytical requirements and objectives of the research. Generally, two primary assumptions are made when selecting a classification or clustering method in social class analysis: the aprioristic notions of class structure reflected in the researcher's preconceived composition of a finite set of clusters; or a tendency to overlook theoretical distinctions, viewing clustering solely through a statistical lens, where different clusters emerge merely as outcomes of varying distributions or density modes (Hening & Liao, 2010).

2.2. Multinomial estimation methods in social stratification research

Furthermore estimation methods are also widely used in the study of social stratification, although the theoretical purposes are sometimes not so explicit in the sense that contrary to the objective of developing class schemes that represent the social structure, researches dedicate their efforts to test the existence of statistically significant relations between variables that may be associated with the socioeconomic origin of individuals with desirable social outcomes (for example, income levels in relation to academic achievements), relying on well-established estimation methods such as econometric modelling and multinomial regression analysis (Kilne & Tamer, 2020), but without going further into analytical developments of general class models.

In this sense, multinomial logistic regression (MLR) and more advance methods of supervised classification and estimation that are based on MLR, are useful techniques to approach stratification problems. MLR is an advanced statistical technique that extends binary logistic regression to accommodate dependent variables with more than two categories. This approach is particularly well-suited for modelling categorical outcomes where the categories are nominal, although it is possible to run these types of models for ordinal data. For example, it can be used to predict the likelihood of individuals falling into various occupational categories (e.g., professional, managerial, technical, and manual jobs) based on a series of variables considered to be theoretically and causally relevant (gender, education level, etc) (Lestari & Playford, 2023) or to predict its belonging to a particular social class if training data for the model is available.

On a broader sense, by employing MLR or multivariate methods similar to it, such as more advanced techniques based on machine learning or neural networks, researchers can account for multiple factors simultaneously, controlling for variables such as age, gender, geographic location, and so on, which may be related to a particular outcome that is of their particular interest. This allows for a more nuanced understanding of how socioeconomic background impacts various aspects of social life. Moreover, MLR provides insights into the relative importance of specific predictors and helps identify which factors are more critically associated with particular social outcomes.

While these statistical techniques are powerful and their used is extended to a variety of research problems that include social stratification ones, they are typically used more for testing hypotheses or establishing correlations rather than developing overarching theoretical frameworks of social class. This distinction highlights a pragmatic approach in some of the social stratification research, where the emphasis is on empirical findings and their implications rather than on theoretical advancements. This should not be considered to be a flaw or an inconsistency in this type of research, since its pragmatic nature is precisely why it has been so intensively adopted.

2.3. Paths to integration: relational thinking and network analysis in social stratification research

In addition to this type of methods, network analysis, has emerged as a promising approach in the study of social stratification and overall, it has become one of the major developments in quantitative research since it is suitable for the modelling of interdependent relationships in a variety of contexts in a different way than the traditional probabilistic and inferential statistical approaches. Furthermore, in the past decade, network analysis has been widely adopted as a methodological strategy in the study of communication patterns, power and kinship dynamics and epidemiology among others (McLevey, 2022) and its potential as an empirical strategy to approach social stratification problems has been growing as well (Ferrand, et al., 2018).

Network analysis is a methodological framework used to study the structure, dynamics, and properties of complex systems represented as networks. A network consists of a collection of nodes (representing entities such as individuals, organizations, or social positions) and edges (representing relationships or interactions between these entities). It examines the patterns of connections within these networks, aiming to uncover underlying structures and patterns of interaction, identify key nodes or groups, and understanding the flow of information, influence, positions, or resources studied.

Network analysis is also referred to as graph theory. However, more precisely, graph theory refers to the mathematical theory that deals with graphs as mathematical objects with particular properties and theorems. On the other hand, network analysis refers more to the empirical applications of graph theory principles to concrete research problems, which is the term used in this work.

By applying mathematical and computational techniques, network analysis enables researchers to quantify and analyse various network properties. This approach finds applications across diverse domains, including sociology, biology, computer science, and economics, where understanding the relational structure of complex systems is essential for gaining insights into their functioning and behaviour.

There are several distinct advantages and innovative insights in the study of social stratification when the problem is approach as a social network one. One key aspect is its ability to highlight the interconnectedness of individuals or groups within a society, showing how relationships and interactions contribute to social hierarchies. This interconnectedness can reveal emergent properties of social structures, such as the presence of tightly knit communities, influential individuals, or bridging nodes that connect otherwise separate groups. Furthermore, the visual nature of network analysis aids in understanding complex relationships and patterns that might be difficult to discern through numerical or tabular data alone.

In this sense, Network analysis can be viewed both as an alternative and as a complement to more extended approaches in the study of social stratification such as cluster analysis or inferential approaches like econometric models or multinomial regression models. Through network analysis, researchers can uncover emergent properties and structural features that may not be apparent at first sight, similar to what is done through approaches like Principal Component Analysis (PCA) or Latent Class Analysis (LCA) but with a bigger emphasis in the relations shared by the variables studied and the properties of a social stratification structure as a whole (Lambert & Griffiths, 2018).

In order to situate the present study within the broader landscape of contemporary scholarship, this section presents a curated overview of recent research addressing occupational structures and social stratification from both theoretical and methodological standpoints. The studies summarized below reflect the increasing complexity of class analysis in a globalized, data-rich environment. They illustrate how researchers are moving beyond traditional taxonomies by employing approaches such as latent class modelling, network analysis, and cross-national comparisons.

This emerging body of work emphasizes not only the structural dimensions of class and occupation but also the subjective and relational dynamics that shape individual and collective social positions. Methodological innovation is a common thread across these contributions, with growing attention to the integration of machine learning techniques, the use of relational data, and the challenges of achieving measurement equivalence across diverse national contexts. Together, these studies provide a robust foundation for understanding the evolution of stratification research and underscore the relevance of the present study's approach within this expanding intellectual landscape.

Table 1: Related Works

Authors	**Year**	**Title**	**Study Objective**	**Methodology**	**Key Findings**	**Implications**
Connelly, R., Gayle, V., & Lambert, P. S.	2016	*A Review of occupation-based social classifications for social survey research*	To review occupational classification schemes used in social surveys and assess their research utility	Theoretical and methodological literature review	Evaluates strengths and weaknesses of systems like ESeC, ISCO, and NS-SEC; calls for refinement	Theoretical and methodological: supports critical use of occupation-based classifications in stratification studies

Ferrand, A., Mounier, L., & Degenne, A.	2018	*The diversity of personal networks in France: Social stratification and relational structures*	To explore how personal networks vary across social strata in France	Empirical network analysis using survey data	Shows relational patterns tied to occupational status and class; networks reflect stratified structures	Empirical and theoretical: reinforces the role of networks in reproducing social stratification
Gross, C., & Goldan, L.	2023	*Modelling intersectionality within quantitative research*	To integrate intersectional perspectives into quantitative models	Conceptual and methodological discussion	Highlights tensions and synergies between statistical modelling and intersectionality frameworks	Theoretical: encourages intersectional awareness in stratification modelling
Hennig, C., & Liao, T. F.	2010	*Comparing latent class and dissimilarity based clustering for mixed type variables with application to social stratification*	To evaluate and compare latent class analysis (LCA) and dissimilarity-based clustering for mixed data types	Comparative methodological analysis	Demonstrates trade-offs in flexibility, interpretability, and robustness between clustering methods	Methodological: supports careful selection of clustering models in stratification research
Hennig, C., & Liao, T. F.	2013	*How to find an appropriate clustering for mixed-type variables with application to socio-economic stratification*	To develop guidance for selecting clustering methods for mixed data	Applied statistical modelling and diagnostics	Offers practical evaluation criteria and links method choice to research goals	Methodological and practical: helps guide empirical stratification research
Huang, X.	2021	*Subjective Class Identification in Australia: Do Social Networks Matter?*	To examine whether personal networks influence subjective class identification	Empirical survey analysis	Network composition shapes subjective class perception, beyond income or education	Theoretical and empirical: justifies including network structures in class identity studies

Kline, B., & Tamer, E.	2020	*Econometric analysis of models with social interactions*	To offer a formal econometric framework for social interaction models	Econometric theory and modelling	Presents tools to estimate peer effects and endogenous social networks	Methodological: guides integration of social interactions in inequality analysis
Lukac, M., Doerflinger, N., & Pulignano, V.	2019	*Developing a cross-national comparative framework for studying labour market segmentation*	To construct cross-nationally comparable models of labor segmentation	Latent Class Analysis (LCA) across national surveys	Shows LCA's capacity to reveal hidden patterns across countries	Methodological and empirical: strengthens LCA's use for international comparisons
Muthukrishna, M., et al.	2020	*Beyond WEIRD psychology: Measuring and mapping scales of cultural and psychological distance*	To propose cultural distance metrics for cross-cultural comparability	Large-scale quantitative analysis	Maps cultural/psychological variation and its implications for generalization	Theoretical and methodological: supports context-sensitive cross-national research
Saez, E., & Zucman, G.	2020	*The Rise of Income and Wealth Inequality in America*	To analyze long-term wealth and income distribution trends in the U.S.	Distributional macroeconomic accounts	Documents rising inequality and stagnation for the majority	Empirical: contextualizes stratification research in U.S. economic trends
Savage, M., et al.	2013	*A New Model of Social Class? Findings from the BBC's Great British Class Survey*	To redefine class structure using capital forms beyond income	Large-scale survey + Latent Class Analysis	Identifies seven new social classes in the UK	Theoretical and empirical: challenges and updates traditional class models
Weeden, K. A., & Grusky, D. B.	2004	*Are there any big classes at all?*	To question broad class groupings in favor of occupational micro-classes	Theoretical and empirical labor market analysis	Argues detailed occupations are more predictive of stratification outcomes	Theoretical and methodological: supports occupational-level models, like your network-based approach

Source: elaborated by author

3. Materials and Methods

3.1. Sources and sample

The World Values Survey (WVS) is a global research initiative dedicated to the scholarly examination of social, political, economic, religious, and cultural values across the world. The project aims to evaluate the influence of values' stability or evolution over time on the social, political, and economic development of countries and societies. The primary research tool employed by the project is a representative comparative social survey, conducted globally every five years. The WVS boasts an extensive geographical and thematic scope, and the free availability of survey data, along with project findings accessible to the general public, has elevated it to become one of the most authoritative and widely utilized cross-national surveys in the field of social sciences. Currently, the WVS stands as the largest non-commercial cross-national empirical time-series investigation of human beliefs and values ever undertaken (Haerpfer et al., 2022).

The World Values Survey (WVS) currently comprises seven waves spanning from 1981 to 2022, with an eighth wave planned for 2024-2026. This research is based on data collected during the seventh wave, covering the period between 2017 and 2022 and includes data for 80 different countries. The preferred sample type for the World Values Survey is a full probability sample of the population aged 18 years and older. In cases where a full probability sample is impractical due to inaccuracies or the absence of census data, WVSA allows for the application of a national representative random sample based on multi-stage territorial stratified selection.

For the purpose of this research five countries were selected: Brazil, China, Germany, United States and Russia. The countries selected for this analysis were chosen due to several key factors. First, each of these nations represents the largest economy within its respective region and it plays a pivotal role in the regional dynamics of their respective contexts, thereby by analysing their class and occupational structure it is possible to acquire a comprehensive view of the potential differences and similarities of societies commonly understood to differ between them both on a socioeconomic and cultural scale but that are highly relevant on a global scale. Up next, samples sizes are presented for each of the countries selected.

Table 2: Sample sizes per selected countries

Country	Sample size
Brazil	1.762
China	3,036
Germany	1,528
Russia	1,810
United States	2,596

Source: elaborated by author with data from (WVS, 2023).

For the graph analysis, the variables chosen—educational level, gender, self-identifying class, and income scale. These variables were selected to ensure consistency in comparing cases across the five countries studied, while minimizing issues such as collinearity and redundancy.

Additionally, this selection aimed to reduce missing data as much as possible, allowing for a more robust and reliable analysis of social stratification.
The educational level variable indicates the highest level of education attained by the respondent, based on the International Standard Classification of Education (ISCED-2011). The variable categorizes educational attainment into the following levels:

- ISCED 0: Early childhood education / no education
- ISCED 1: Primary education
- ISCED 2: Lower secondary education
- ISCED 3: Upper secondary education
- ISCED 4: Post-secondary non-tertiary education
- ISCED 5: Short-cycle tertiary education
- ISCED 6: Bachelor's or equivalent
- ISCED 7: Master's or equivalent
- ISCED 8: Doctoral or equivalent

In this study, only the educational level of the respondent was considered. Missing data were cleaned to ensure the accuracy of the analysis.

The income scale variable represents the respondent's self-reported household income group, where 1 indicates the lowest income group and 10 indicates the highest income group within their country. Respondents were asked to select a number that best reflects their household's total income, including wages, salaries, pensions, and other income sources. The scale provides a relative ranking of income, with lower numbers corresponding to lower income groups and higher numbers to higher income groups. Missing data were cleaned to ensure the accuracy of the analysis.
The self-identifying class variable reflects how respondents perceive their own social class, based on a subjective self-assessment. Respondents were asked to identify which social class they feel they belong to, choosing from the following options:

- Upper class
- Upper middle class
- Lower middle class
- Working class
- Lower class

This variable provides insight into how individuals position themselves within the social hierarchy, regardless of objective measures like income or education level. The responses capture the respondent's personal sense of class identity. Missing data were cleaned to ensure the accuracy of the analysis.

The gender variable in this analysis is dichotomous, meaning it is divided into two categories: male and female. This variable captures the respondent's self-identified gender. The occupational groups variable refers to the occupational classification of the respondent based on their current or most recent job. This variable was collected in the World Values Survey (WVS) and categorizes respondents into specific job groups, which form the basis of the analysis in this study. For the analysis, only the responses of the respondents were considered. The occupational groups are categorized as follows:

- Professional and technical (e.g., doctor, teacher, engineer, artist, accountant, nurse)
- Higher administrative (e.g., banker, executive in big business, high government official, union official)
- Clerical (e.g., secretary, clerk, office manager, civil servant, bookkeeper)
- Sales (e.g., sales manager, shop owner, shop assistant, insurance agent, buyer)
- Service (e.g., restaurant owner, police officer, waitress, barber, caretaker)
- Skilled worker (e.g., foreman, motor mechanic, printer, seamstress, tool and die maker, electrician)
- Semi-skilled worker (e.g., bricklayer, bus driver, cannery worker, carpenter, sheet metal worker, baker)
- Unskilled worker (e.g., laborer, porter, unskilled factory worker, cleaner)
- Farm worker (e.g., farm laborer, tractor driver)
- Farm proprietor/farm manager

The variable is structured to represent the respondent's self-identified occupational category, based on their most recent job or, in some cases, their current job if they are employed.
These occupational categories are central to the analysis of social stratification in this study. They provide a framework for understanding how individuals from different occupational backgrounds relate to other socio-economic factors such as educational level, income, self-identifying class, and gender. By grouping respondents into specific occupational categories, we are able to compare and analyse the ways in which these different groups experience and perceive their social position. In sum, the occupational groups serve as a fundamental variable in this study, enabling a comprehensive analysis of how various factors of social stratification intersect and influence one another.

3.2 Network modelling and analysis.

In general terms, a network (or graph) is composed of two key components: **vertices** (also known as **nodes**) and **edges**. Formally, a graph is defined as an ordered pair G=(V,E)G = (V, E)G=(V,E), where:

- **V** is the set of **vertices**, which represent the individual units of analysis (in this study, these are the **occupational categories**).
- **E** is the set of **edges**, which represent the connections between the vertices. These connections are unordered pairs of distinct vertices x and y, where x≠y. In simpler terms, edges are the lines that connect the nodes (occupational categories) in the network.

The core idea behind a network is to represent relationships or connections between units. A network simplifies complex systems into two elements: nodes (the entities or positions) and edges (the relationships between them). In this analysis, the nodes represent different occupational categories, while the edges represent the strength of the relationships between these categories.

In this study, the network is built around occupational categories, with the goal of analysing the relationships between these categories based on the variables described previously. The core idea is to represent how occupational positions (the nodes in the network) are related to each other through edges that quantify the strength of these relationships. These relationships are determined based on how similar or different the occupational positions are in terms of these social variables.

To begin, for each occupational category (node), the normalized proportions of the following variables are calculated:

- Educational level (categorized according to ISCED)
- Self-identified class (working class, middle class, upper class)
- Income scale (from lowest to highest income groups)

These proportions are calculated for each variable and then normalized to allow for fair comparison across occupational categories. All data was normalized to produce scales between 0 and 1. The normalized proportions for each occupational category, which represent the relative distribution of variables such as educational level, income, and self-identified class, are referred to as the affinity scores. The affinity score **Aij** measures the degree of alignment between the occupational category and the value of a given variable (e.g., how closely the occupational category aligns with a particular educational level, income group, or self-identified class). In simpler terms, the affinity score quantifies how similar the characteristics of an occupation are to a specific value or category of a variable. Formally:

$$\mathrm{A_{ij}} = \frac{\mathrm{N_i}}{N_{\mathrm{ij}}} \qquad \textbf{(1)}$$

Where:

- $\mathbf{A_{ij}}$ is the affinity score between occupational category i and the value or category j of variable j (e.g., a particular educational level, self-identified class, or income group).
- $\boldsymbol{N}_{\mathbf{ij}}$ is the number of individuals in occupational category iii who belong to the specific category jjj of the variable (e.g., the number of skilled workers who belong to the "middle class").
- $\mathbf{N_i}$ is the total number of individuals in occupational category iii (i.e., the total number of respondents in that occupation).

In the context of a network analysis, weights represent the strength or intensity of the relationships (or connections) between the elements (or nodes) of the network. In this case, the nodes are the occupational categories, and the weights describe how strongly each occupational category is related to the values of the variables being analysed. In the context of this research, the weights are computed to quantify how closely the occupational categories align with the socio-economic profiles defined by the variables of interest (educational level, income, self-identified class).

The weights $\mathbf{W_{ij}}$ are then defined as the inverse of the Euclidean distance between the affinity profiles of an occupational position iii and a value of a variable j. This means that the weights quantify how similar or different the occupational category i is to the value of variable j, with smaller distances (greater similarity) resulting in larger weights. The weight is calculated using the following formula:

$$\mathrm{W_{ij}} = \frac{1}{\mathrm{D_{ij}}} \qquad \mathbf{(2)}$$

Where $\mathbf{D_{ij}}$ is the Euclidean distance between the affinity profiles of occupational category I and the value of variable j, and is defined as:

$$D_{\mathrm{ij}} = \sqrt{\sum_{k=1}^{n} (p_{ik-}\ p_{\mathrm{j}k})2} \qquad \mathbf{(3)}$$

Where:

- $\boldsymbol{p_{ik}}$ is the kth component of the affinity profile for occupational category **i**.
-
- $\boldsymbol{p_{\mathrm{j}k}}$ is the kth component of the affinity profile for the value of variable **j**.
- $\boldsymbol{n}$ represents the number of variables in the analysis (e.g., educational level, self-identified class, income)

Therefore, the network is structured as a weighted graph **G=(V,E,W)** where **V** represents the set of nodes corresponding to occupational categories, and **E** denotes the edges, which indicate the relationships between these occupational categories based on their socio-economic profiles. The weights $\mathbf{W_{ij}}$ on the edges represent the degree of strength between two occupational categories **i** and **j**, derived from their normalized proportions, or affinity scores of educational level, income, and self-identified class.
After the construction of the networks, a series of metrics were calculated in order not only to understand the inherent characteristics of each network but also to facilitate a comparative analysis of their structures. Such an analysis sought to uncover sociological patterns embedded within the networks, offering valuable insights. For this endeavour a series of structural metrics for each network were computed. These metrics included the number of nodes (occupational positions), the number of edges (connections), average degree (indicating overall connectivity), and density (reflecting compactness or sparsity of connections).

Density of a network serves as a measure of connectivity within a graph. It quantifies the extent to which the actual edges present in the graph approach the maximum possible number of edges. Mathematically, it is computed as the ratio of the number of existing edges to the total number of possible edges. A higher density indicates a greater proportion of realized connections among nodes, while a lower density suggests a sparser network with fewer interconnections (McLevey, 2022). This metric provides insights into the level of cohesion and complexity within the graph, informing analyses of its structural integrity and potential functional implications. Formally, density is defined as:

Let's consider the network **G** with nodes n and m edges, then the density **D** of G is calculated as:

$$D = \frac{2m}{n(n-1)} \quad \mathbf{(4)}$$

Where:

- **m** is the number of edges
- **n** is the number of nodes

The average degree of a network is a metric that characterizes the centrality and connectivity of its constituent nodes. Defined as the mean degree across all nodes in the network, it reflects the average number of edges incident upon each node. A higher average degree signifies a denser network structure, indicative of a greater degree of interconnectivity among nodes. Conversely, a lower average degree implies a sparser distribution of edges and potentially a more decentralized topology. Formally, it is defined as:

$$k_{avg} = \frac{2m}{n} \quad \mathbf{(5)}$$

Where:

- **m** is the number of edges
- **n** is the number of nodes

Additionally, a series of analyses were conducted to compare the structures of the networks and identify potential structural similarities. This exploration aimed to discern both similarities and differences in the networks' structure. The primary objective was to identify variations in the network structures of occupational categories based on the selected variables used to construct the weights and edges. Specifically, this approach aimed to explore the network structures when considering different variables: income, self-identified class, and educational level, and to examine potential disparities in the hierarchical organization of occupational positions across various dimensions. One of the key metrics used in this analysis was community detection, implemented using the Louvain algorithm.
The Louvain algorithm identifies communities within a graph by maximizing modularity, a measure of the strength of division of a network into modules. It operates in two main phases: modularity optimization and community aggregation (McLevey, 2022). In the first phase, each node starts in its own community, and nodes are moved between communities to achieve the maximum possible gain in modularity. This process is repeated iteratively until no further improvement is possible. In the second phase, communities are treated as nodes, and the process is repeated, leading to a hierarchical community structure. This method allowed for a detailed examination of how occupational categories cluster based on the chosen variables, revealing patterns of cohesion and division within the socio-occupational networks.

Following community detection, the modularity of the detected community structure was calculated for each graph. Modularity quantifies the quality of the division of a network into communities by measuring the density of links inside communities compared to links between communities. Modularity is defined as the fraction of the edges that fall within the given groups minus the expected fraction if edges were distributed at random. It can be mathematically expressed as:

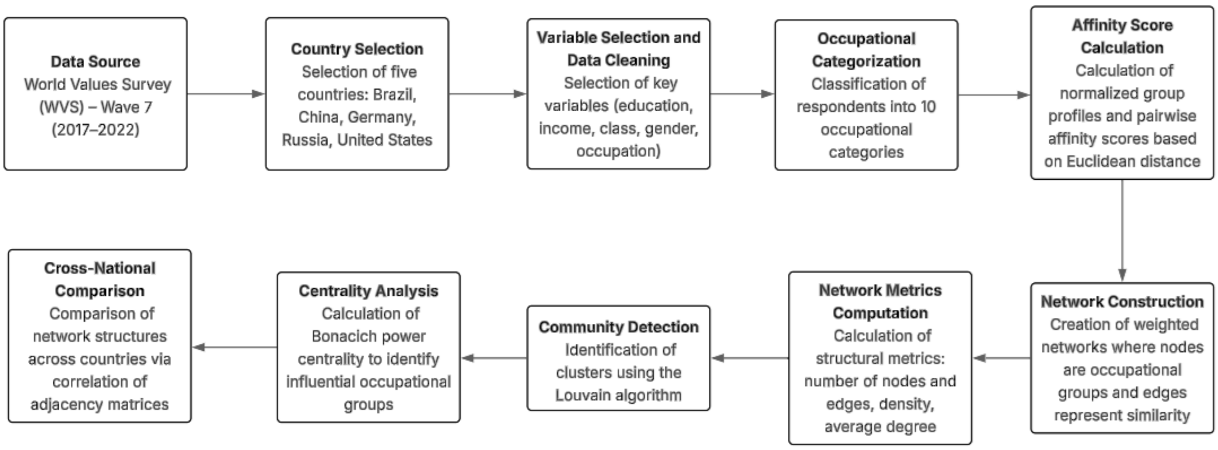
$$Q = \frac{1}{2m} \sum ij \left[A_{ij} - \frac{k_i k_i}{2m}\right] \delta(ci, cj) \quad \mathbf{(6)}$$

Where:

- $\boldsymbol{A_{ij}}$ is the adjacency matrix of the graph (1 if there is an edge between nodes i and j, and 0 otherwise).
- $\boldsymbol{k_i}$ and k_j are the degrees of nodes **i** and **j** respectively.
- **m** is the total number of edges in the graph.
- $\boldsymbol{\delta(ci, cj)}$ is a delta function that equals 1 if nodes **i** and **j** are in the same community and 0 otherwise.
- $\boldsymbol{c_i}$ and $\boldsymbol{c}_i$ are the communities of nodes **i** and **j**

k-core decomposition was utilized to uncover the core structure of the networks. This method identifies maximal subgraphs where each node is connected to at least k neighbours, highlighting nodes that are highly connected and central to the network's cohesion. By focusing on these core components, this analysis sheds light on the network's structural backbone and its most integral nodes. To further analyse network hierarchization, Bonacich power centrality was applied. This measure captures a node's influence by considering both its direct connections and the centrality of its neighbours, making it a powerful tool for identifying patterns of dominance and influence within the network. The following chart summarizes the methodological strategy:

Figure 1: Methodological Design Workflow



4. Results: network analysis of class and occupational structures

The socio-occupational structure of the five countries analysed exhibits both common and specific characteristics. While for each case, there are similarities in the types of occupations present within its workforce, the proportions and emphases placed on specific occupational categories vary significantly which resemble distinct hierarchization patterns of the studied population. Descriptive results for each country are summarized in the following table:

Table 3: Distribution of occupational categories per country

Occupational position	Brazil	China	Germany	Russia	United States
Clerical	16.0%	10.0%	23.7%	9.3%	11.0%
Farm owner, farm manager	0.1%	3.2%	1.2%	0.2%	0.2%
Farm worker	7.7%	12.3%	0.9%	3.6%	0.7%
Higher administrative	1.9%	2.8%	7.8%	3.1%	6.8%
Professional and technical	12.1%	14.3%	14.8%	22.5%	40.1%
Sales	16.7%	15.9%	10.7%	10.5%	9.4%
Semi-skilled worker	11.3%	10.6%	4.7%	17.7%	4.2%
Service	12.6%	11.3%	15.0%	13.6%	12.4%
Skilled worker	9.90%	13.8%	18.70%	13.2%	9.8%
Unskilled worker	11.80%	5.7%	2.50%	6.4%	5.3%

Source: elaborated by author with data from (WVS, 2023).

Firstly, it is possible to observe there are significant variations in the distribution of occupational categories among the listed countries. For instance, in Germany and Brazil, clerical work seems to be more prevalent compared to other countries, with Brazil leading at 16.0% and China following closely at 10.0%. In contrast, Germany has the highest percentage of clerical workers at 23.7%, Another notable observation is the disparity in the distribution of farm-related occupations. China has a relatively higher percentage of farm workers and owners compared to other nations. On the other hand, the United States and Germany have minimal representation in this category.

In terms of professional and technical roles, the United States stands out with a significant percentage of 40.1%, indicating a strong emphasis on specialized skills and expertise within its workforce. This is followed by Russia at 22.5%, suggesting a similar trend in prioritizing professions requiring higher levels of education and training. The distribution of skilled and unskilled workers also varies among the countries, with Germany having the highest percentage of skilled workers at 18.7%. Conversely, China has a lower percentage of skilled workers compared to its counterparts.

In terms of self-identification with a particular social class, the data reveals notable differences and similarities across five diverse countries: The survey respondents were asked to identify themselves within five social class categories: upper class, upper middle class, lower middle class, working class, and lower class. The resulting distribution provides insights into how individuals perceive their socio-economic status within these varied national contexts. This analysis helps to understand the prevailing socio-economic landscape and the proportion of the population that associates itself with each social class in these countries.

In Brazil, the upper class comprises 1.2% of respondents, the upper middle class 12.3%, the lower middle class 34.5%, the working class 45.6%, and the lower class 6.4%. China shows a slightly different distribution, with 0.5% in the upper class, 8.7% in the upper middle class, 30.6% in the lower middle class, 50.2% in the working class, and 10.0% in the lower class. Germany has a higher percentage in the upper middle class, with 20.4%, while 2.3% of respondents identify as upper class, 25.0% as lower middle class, 40.1% as working class, and 12.2% as lower class.

In Russia, 0.8% identify as upper class, 15.0% as upper middle class, 30.0% as lower middle class, 40.0% as working class, and 14.2% as lower class. Lastly, in the United States, the upper class represents 3.5% of respondents, the upper middle class 18.0%, the lower middle class 29.0%, the working class 35.0%, and the lower class 14.5%. These results indicate that the majority of respondents in all five countries identify as belonging to the working or middle classes, with relatively smaller percentages identifying as upper or lower class. Notably, the United States has the highest percentage of respondents identifying as upper class, while China has the highest percentage of respondents identifying as working class.

The evidence suggests that self-perception of social class is shaped by both objective measures and the complex interplay of cultural norms, personal aspirations, and relative social comparisons within the occupational structure and stratification system. In the analysis, the majority of respondents across all five countries identify as belonging to either the working or middle class, with clear variations in alignment between objective socio-economic factors and self-identified class. For example, in the United States, the relatively high proportion of respondents identifying as upper class (3.5%) corresponds to its strong representation of professional and technical roles (40.1%). In contrast, in China, where working-class identification dominates at 50.2%, the data reveal a higher prevalence of farm-related occupations and lower representation in skilled professions. These findings underscore the significant influence of measurable criteria such as income, education, and occupational status in shaping class perceptions.

At the same time, the subjective dimension of class perception emphasizes the role of cultural norms, individual aspirations, and social comparisons. Previous research supports this relational and symbolic view of class identity, highlighting how individuals' self-perceptions often transcend objective measures (Savage et al., 2013). For example, societal expectations and cultural narratives can mediate the extent to which individuals identify with higher- or lower-class positions, even when their socio-economic profiles are similar.

These objective indicators provide a quantitative framework for assessing individuals' socioeconomic status within society which may lead to a higher correspondence between objective socioeconomic characteristics and class identity. On the other hand, the subjective approach recognizes that individuals' perceptions of their own social position are influenced by cultural and social values, as well as by comparisons with others in their social environment. This perspective acknowledges the role of cultural norms, aspirations, and symbolic markers of status in shaping individuals' class identities. To go further into the evidence discussed so far it is necessary to study empirically connections and relationships through the application of network analysis.

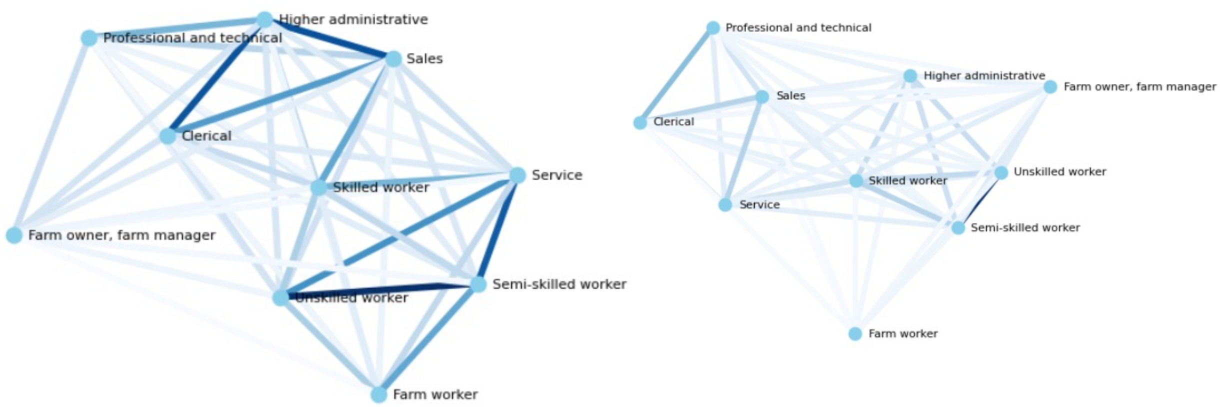
The use of network analysis its aim to explore the affinities between different occupational categories, providing insight into the socioeconomic similarities and differences that shape class. By calculating the affinity values as the inverse of the Euclidean distance between occupational class profiles, it is possible to quantitatively assess the closeness of various roles within the socioeconomic landscape. Higher affinity values indicate greater similarity between the profiles of two occupational classes, reflecting class perceptions among the members of a pair of occupational groups that as an aggregate constitute the network. Ultimately, this analysis seeks to elucidate the relationships between occupational roles and social class, offering a deeper understanding of the factors that contribute to class identity and stratification in society.

In Brazil, the affinity between "Professional and Technical" and "Clerical" occupations is notably high, with a value of 5.4 , suggesting that individuals in these roles share similar socioeconomic traits and class perceptions. In contrast, the affinity between "Professional and Technical" and "Service" occupations is much lower, at 1.4, indicating significant differences in their socioeconomic profiles. The "Professional and Technical" category also shows moderate affinities with "Skilled Worker" (1.9) and "Semi-skilled Worker" (1.4) categories, suggesting some level of similarity. However, the affinity with "Farm Worker" is lower, at 1.2, indicating a closer socioeconomic connection compared to service-related occupations.

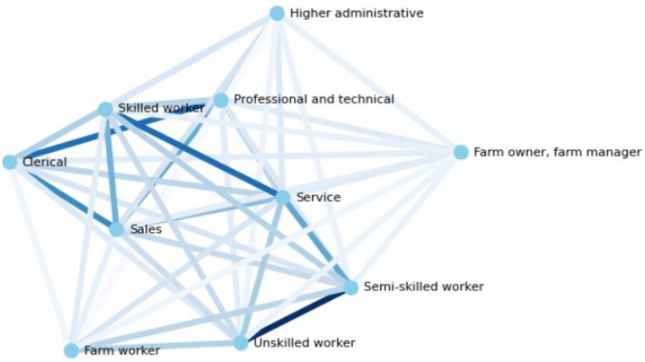
Higher administrative roles in Brazil display a high affinity with clerical occupations, with a value of 7.3, indicating that these two categories share similar socioeconomic characteristics and class perceptions. However, the affinity with service occupations (2.0) and farm worker roles (1.3) is lower, reflecting more significant socioeconomic differences. Sales occupations exhibit a strong affinity with clerical roles (5.3), suggesting similar class perceptions and socioeconomic traits. However, their affinity with service roles is moderate (2.4), and with "Farm Owner, Farm Manager" roles, the affinity is higher at 1.8, indicating notable differences yet some level of socioeconomic overlap.

Figure 2: Self-Perception of Class (Panel A), Educational level (Panel B) and Income levels (Panel C), affinity network for Occupational Categories Affinity Network in Brazil

Panel A **Panel B**



Panel C

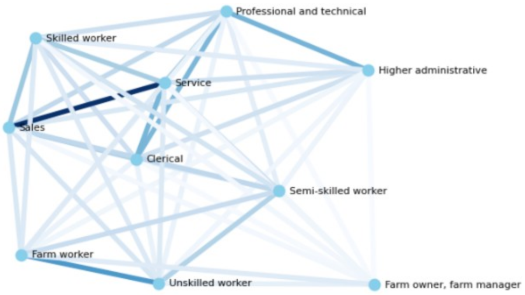


Furthermore, service occupations in Brazil have a moderate affinity with skilled workers (4.4) but a lower affinity with “Farm Owner, Farm Manager” (1.2), . Similarly, skilled workers show a moderate affinity with semi-skilled workers (3.0) but a lower affinity with farm workers (1.9). The highest affinity reflected in the network is between semi-skilled and unskilled workers, at 8.4, suggesting these categories are very similar in socioeconomic traits and class perceptions. Conversely, semi-skilled workers exhibit lower affinity with farm workers (4.9) and “Farm Owner, Farm Manager” (1.2), reflecting more considerable differences. Unskilled workers show moderate affinity with farm workers (3.5) and “Farm Owner, Farm Manager” (1.4), indicating notable socioeconomic differences. Finally, the affinity between farm workers and “Farm Owner, Farm Manager” is relatively low at 1.1, reflecting significant differences in socioeconomic profiles despite both being related to agricultural work, a situation that may be explained by the different positions that these types of workers have regarding the means of production.

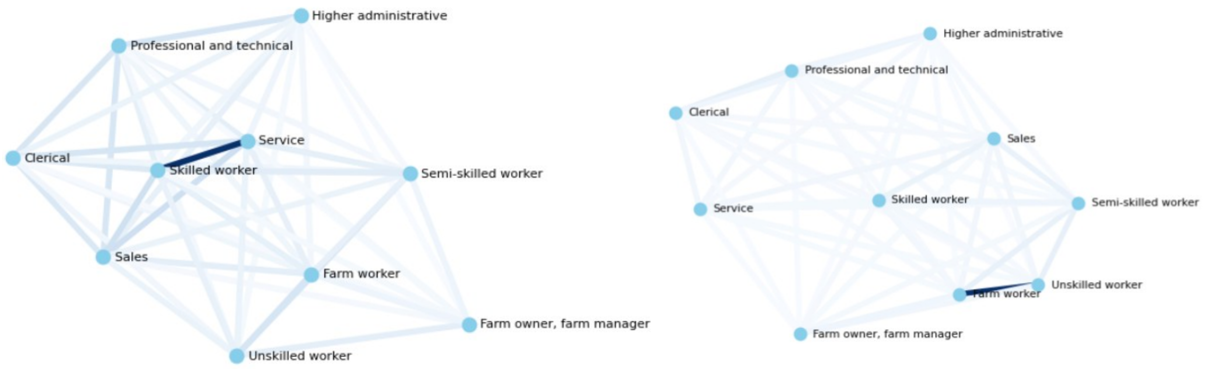
In China, professional and technical occupations demonstrate a notably high affinity with higher administrative roles, with an affinity value of 4.9, suggesting shared socioeconomic traits and class perceptions between these two categories. Conversely, the affinity between professional and technical occupations and service roles is comparatively lower, at 3.3, indicating significant differences in their socioeconomic profiles and class perceptions. Additionally, professional and technical occupations show moderate affinities with skilled workers (3.1) and semi-skilled workers (1.7), implying some level of similarity, while their affinity with farm workers is notably higher, at 2.0, indicating a closer socioeconomic connection compared to service-related occupations.

Figure 3: Self-Perception of Class (Panel A), Educational level (Panel B) and Income levels (Panel C), affinity network for Occupational Categories Affinity Network in China

Panel A



Panel B **Panel C**



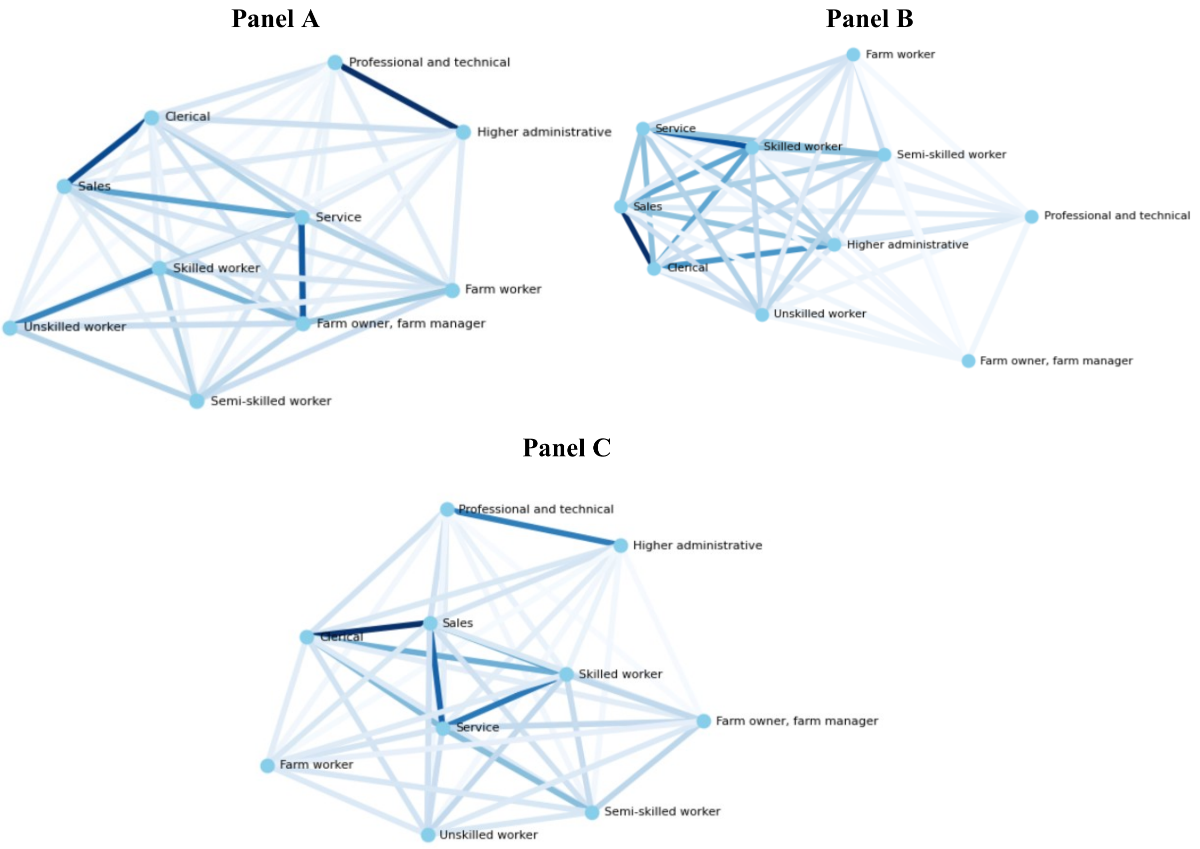
Higher administrative roles in China exhibit a high affinity with clerical occupations, with a value of 2.4, indicating shared socioeconomic characteristics and class perceptions. However, the affinity with service occupations (2.1) and farm owner, farm manager roles (1.0) is lower, reflecting more significant socioeconomic differences. Clerical roles also demonstrate a strong affinity with sales occupations (4.4), suggesting similar class perceptions and socioeconomic traits. However, their affinity with service roles is notably higher, at 5.0, and with skilled worker roles, the affinity is 4.2, indicating some differences yet some level of socioeconomic overlap.

Sales occupations in China show a strong affinity with service roles (6.1), indicating shared socioeconomic characteristics and class perceptions. However, their affinity with skilled worker roles is slightly lower, at 5.7, and with farm owner, farm manager roles, the affinity is 1.4, indicating notable differences yet some level of socioeconomic overlap. Service occupations exhibit a remarkably high affinity with skilled worker roles, at 25.1, suggesting considerable closeness and tightness of the network between these occupational categories. However, their affinity with semi-skilled worker roles is 3.2, and with farm owner, farm manager roles, the affinity is 1.4, indicating notable differences in socioeconomic profiles.

Skilled worker roles in China show moderate affinities with semi-skilled worker roles (3.5) but a lower affinity with farm worker roles (3.0), suggesting some similarities in socioeconomic traits with the former and notable differences with the latter. Semi-skilled worker roles demonstrate a remarkably high affinity with unskilled worker roles, at 4.7. However, their affinity with farm worker roles is lower, at 2.8, and with farm owner, farm manager roles, the affinity is 2.2, indicating notable differences. Unskilled worker roles show a moderate affinity with farm worker roles (4.9) and farm owner, farm manager roles (3.2). Finally, the affinity between farm worker roles and farm owner, farm manager roles is relatively low, at 2.2, reflecting significant differences in socioeconomic profiles despite both being related to agricultural work.

Professional and technical occupations in Germany display a notably high affinity with higher administrative roles, with an affinity value of 8.5. This suggests a strong correlation in socioeconomic backgrounds and class identities between these two categories. In contrast, the affinity between professional and technical occupations and clerical roles is significantly lower, at 2.1, indicating substantial differences in their socioeconomic profiles and class perceptions. Additionally, professional and technical occupations demonstrate relatively low affinities with sales (1.7) and service roles (1.5), suggesting distinct socioeconomic characteristics compared to these occupational categories. The affinity with skilled worker roles is even lower, at 1.0, indicating a notable divergence in class perceptions and socioeconomic traits between professional and technical occupations and skilled workers. Similarly, professional and technical occupations exhibit low affinities with semi-skilled (1.0), unskilled (0.9), and farm worker roles (1.7), further highlighting significant differences in class perceptions and socioeconomic backgrounds.

Figure 4: Self-Perception of Class (Panel A), Educational level (Panel B) and Income levels (Panel C), affinity network for Occupational Categories Affinity Network in Germany



Higher administrative roles in Germany demonstrate a strong affinity with clerical occupations, with an affinity value of 2.5, indicating a shared socioeconomic background and class perceptions between these two categories. However, the affinity with service roles (1.7) and farm worker roles (1.3) is notably lower, indicating significant differences in socioeconomic profiles. Clerical roles exhibit a strong affinity with sales roles (7.8), suggesting similar class perceptions and socioeconomic traits. Additionally, clerical roles display moderate affinities with service (3.4) and farm owner, farm manager roles (2.4), indicating some differences yet some level of socioeconomic overlap.

Sales roles in Germany show a strong affinity with service roles (5.1), indicating shared socioeconomic characteristics and class perceptions. However, their affinity with skilled worker roles is relatively low, at 2.0, indicating notable differences in socioeconomic profiles.

The affinity with farm owner, farm manager roles is slightly higher, at 3.0, suggesting some socioeconomic overlap. Service roles exhibit a remarkably high affinity with farm owner, farm manager roles, at 7.3, suggesting considerable similarities in socioeconomic traits and class perceptions. However, their affinity with skilled worker roles is moderate (3.2), indicating some differences in socioeconomic profiles.

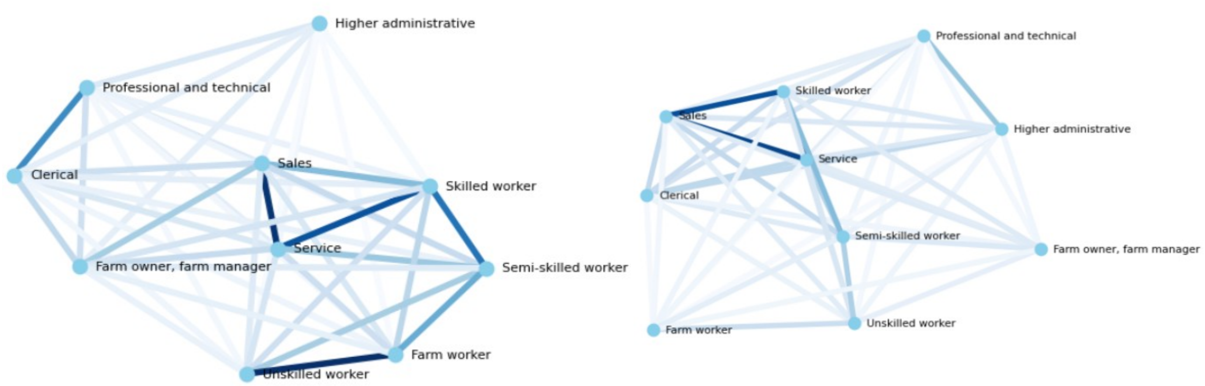
Skilled worker roles in Germany show moderate affinities with semi-skilled worker roles (3.4) but a notably higher affinity with unskilled worker roles (6.0), suggesting considerable similarities in socioeconomic traits and class perceptions with the latter. The affinity with farm worker roles is relatively low, at 2.2, indicating significant differences in socioeconomic profiles. Semi-skilled worker roles demonstrate a moderate affinity with unskilled worker roles (3.2) and farm worker roles (2.6), indicating some similarities in socioeconomic traits with both categories. However, their affinity with farm owner, farm manager roles is notably higher, at 3.1, suggesting notable socioeconomic overlap.

Unskilled worker roles in Germany show a moderate affinity with farm worker roles (1.7) and farm owner, farm manager roles (2.7), indicating some socioeconomic differences between these categories. The affinity between farm worker roles and farm owner, farm manager roles is relatively high, at 3.9, reflecting notable similarities in socioeconomic profiles despite differences in occupational roles.

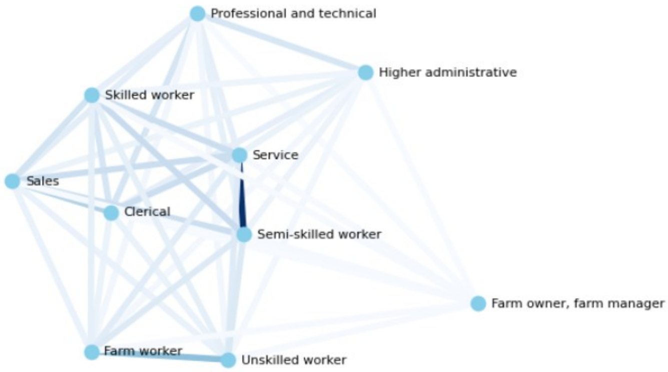
In Russia, higher administrative roles demonstrate a moderate affinity with clerical occupations, with an affinity value of 2.5, indicating a modest correlation in socioeconomic backgrounds and class perceptions between these two categories. Conversely, the affinity with service roles (1.6) and farm worker roles (0.7) is notably lower, indicating significant differences in socioeconomic profiles. Professional and technical occupations exhibit a moderate affinity with higher administrative roles, with an affinity value of 3.3, suggesting a modest correlation in socioeconomic backgrounds and class perceptions between these two categories. Conversely, the affinity between professional and technical occupations and clerical roles is notably lower, at 1.9, indicating significant differences in their socioeconomic profiles and class perceptions.

Figure 5: Self-Perception of Class (Panel A), Educational level (Panel B) and Income levels (Panel C), affinity network for Occupational Categories Affinity Network in Russia

Panel A **Panel B**



Panel C



Sales roles in Russia show a strong affinity with service roles (6.8), indicating shared socioeconomic characteristics and class perceptions. However, their affinity with skilled worker roles is relatively high, at 6.6, indicating some notable similarities in socioeconomic profiles. The affinity with farm owner, farm manager roles is slightly lower, at 1.5, suggesting some socioeconomic overlap. Clerical roles exhibit a moderate affinity with sales roles (2.4), suggesting some similarities in class perceptions and socioeconomic traits. Additionally, clerical roles display moderate affinities with service (2.5) and farm owner, farm manager roles (1.0), indicating some differences yet some level of socioeconomic overlap.

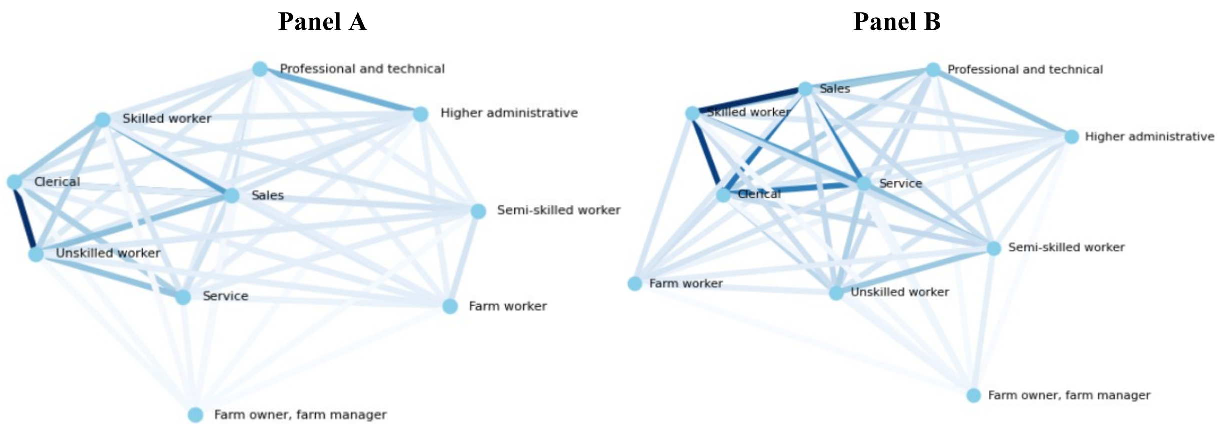
Service roles in Russia exhibit a remarkably high affinity with skilled worker roles, at 7.4, suggesting considerable similarities in socioeconomic traits and class perceptions. However, their affinity with semi-skilled worker roles is moderate (2.7), indicating some differences in socioeconomic profiles. Skilled worker roles show moderate affinities with semi-skilled worker roles (3.6) but a notably lower affinity with unskilled worker roles (1.7), suggesting considerable similarities in socioeconomic traits with the former and notable differences with the latter. The affinity with farm worker roles is relatively low, at 1.0, indicating significant differences in socioeconomic profiles. Semi-skilled worker roles demonstrate a moderate affinity with unskilled worker roles (2.9) and farm worker roles (1.3), indicating some similarities in socioeconomic traits with both categories. However, their affinity with farm owner, farm manager roles is slightly higher, at 1.6, suggesting some socioeconomic overlap.

Unskilled worker roles in Russia show a moderate affinity with farm worker roles (2.1) and farm owner, farm manager roles (1.2), indicating some socioeconomic differences between these categories. Finally, the affinity between farm worker roles and farm owner, farm manager roles is relatively low, at 0.9, reflecting notable differences in socioeconomic profiles despite both being related to agricultural work. Sales roles in Russia show a strong affinity with service roles (6.8), indicating shared socioeconomic characteristics and class perceptions. However, their affinity with skilled worker roles is relatively high, at 6.6, indicating some notable similarities in socioeconomic profiles. The affinity with farm owner, farm manager roles is slightly lower, at 1.5, suggesting some socioeconomic overlap. Clerical roles exhibit a moderate affinity with sales roles (2.4), suggesting some similarities in class perceptions and socioeconomic traits. Additionally, clerical roles display moderate affinities with service (2.5) and farm owner, farm manager roles (1.0), indicating some differences yet some level of socioeconomic overlap.

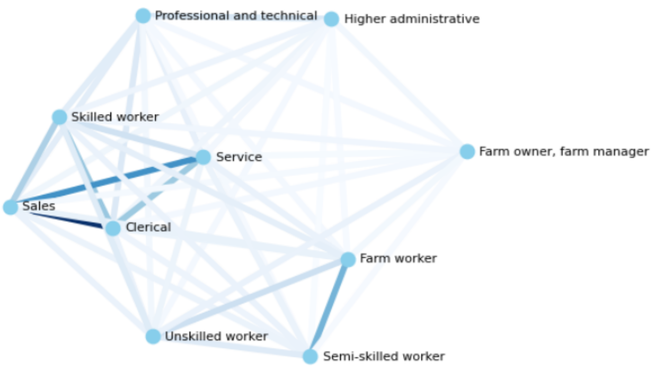
Service roles in Russia exhibit a remarkably high affinity with skilled worker roles, at 7.4, suggesting considerable similarities in socioeconomic traits and class perceptions. However, their affinity with semi-skilled worker roles is moderate (2.7), indicating some differences in socioeconomic profiles. Skilled worker roles show moderate affinities with semi-skilled worker roles (3.6) but a notably lower affinity with unskilled worker roles (1.7), suggesting considerable similarities in socioeconomic traits with the former and notable differences with the latter. The affinity with farm worker roles is relatively low, at 1.0, indicating significant differences in socioeconomic profiles. Semi-skilled worker roles demonstrate a moderate affinity with unskilled worker roles (2.9) and farm worker roles (1.3), indicating some similarities in socioeconomic traits with both categories. However, their affinity with farm owner, farm manager roles is slightly higher, at 1.6, suggesting some socioeconomic overlap. Unskilled worker roles in Russia show a moderate affinity with farm worker roles (2.1) and farm owner, farm manager roles (1.2), indicating some socioeconomic differences between these categories. Finally, the affinity between farm worker roles and farm owner, farm manager roles is relatively low, at 0.9, reflecting notable differences in socioeconomic profiles despite both being related to agricultural work.

In the United States, clerical roles exhibit a remarkably high affinity with sales roles, boasting an affinity value of 13.6. This indicates strong similarities in class perceptions and socioeconomic traits between these two categories. Additionally, clerical roles show considerable affinities with service roles (5.6) and skilled worker roles (5.7), suggesting shared socioeconomic backgrounds and class perceptions. However, their affinities with semi-skilled worker roles (1.5), unskilled worker roles (1.7), farm worker roles (1.6), and farm owner, farm manager roles (1.1) are notably lower, indicating significant differences in socioeconomic profiles.

Figure 6: Self-Perception of Class (Panel A), Educational level (Panel B) and Income levels (Panel C), affinity network for Occupational Categories Affinity Network in United States



Panel C



Sales roles in the United States demonstrate strong affinities with service roles (8.8) and skilled worker roles (5.0), reflecting shared socioeconomic characteristics and class perceptions. However, their affinities with semi-skilled worker roles (1.6), unskilled worker roles (1.7), farm worker roles (1.7), and farm owner, farm manager roles (1.0) are relatively lower, suggesting some differences in socioeconomic backgrounds. Service roles exhibit a remarkably high affinity with skilled worker roles, at 3.3, indicating considerable similarities in socioeconomic traits and class perceptions. However, their affinities with semi-skilled worker roles (1.6), unskilled worker roles (1.5), farm worker roles (1.6), and farm owner, farm manager roles (0.9) are notably lower, indicating significant differences in socioeconomic profiles.

Skilled worker roles in the United States demonstrate moderate affinities with semi-skilled worker roles (1.7) but a notably higher affinity with unskilled worker roles (2.3), suggesting considerable similarities in socioeconomic traits with the former and notable differences with the latter. The affinity with farm worker roles is relatively moderate, at 2.0, indicating significant differences in socioeconomic profiles. Semi-skilled worker roles exhibit a remarkably high affinity with farm worker roles, at 6.8, indicating considerable similarities in socioeconomic traits and class perceptions. However, their affinities with unskilled worker roles (2.4) and farm owner, farm manager roles (1.0) are relatively lower, suggesting some differences in socioeconomic profiles.mUnskilled worker roles in the United States show a moderate affinity with farm worker roles (3.5) and farm owner, farm manager roles (1.6), indicating some socioeconomic differences between these categories. Finally, the affinity between farm worker roles and farm owner, farm manager roles is relatively moderate, at 1.1, reflecting notable differences in socioeconomic profiles despite both being related to agricultural work.

Comparing the social class affinities among various occupational categories across Brazil, China, Germany, Russia, and the United States reveals both intriguing differences and notable similarities. In Brazil, there's a pronounced affinity between professional and technical occupations and clerical roles, indicating shared socioeconomic backgrounds and class perceptions. This trend is echoed in China, where professional and technical roles exhibit high affinities with higher administrative positions, suggesting similar socioeconomic traits. However, in the United States, clerical roles show a remarkable affinity with sales occupations, indicating a unique pattern compared to other countries. Across all five countries, sales roles demonstrate strong affinities with service roles, reflecting shared socioeconomic characteristics and class perceptions in the service sector. Additionally, service roles exhibit a remarkably high affinity with skilled worker roles, indicating considerable similarities in socioeconomic traits across these occupational categories.

Interestingly, while semi-skilled worker roles in Brazil and Russia show a remarkably high affinity with farm worker roles, suggesting considerable similarities in socioeconomic traits, this trend is less prominent in China, Germany, and the United States. This divergence may stem from variations in industrial structures and agricultural practices among these countries. Furthermore, the affinity between clerical roles and sales occupations is notably high in Brazil, China, and the United States, indicating similar class perceptions and socioeconomic backgrounds in these sectors. However, this trend is less pronounced in Germany and Russia, where clerical roles exhibit stronger affinities with skilled worker roles.

In terms of disparities, the affinity between professional and technical occupations and service roles is notably lower in China compared to other countries, suggesting significant differences in socioeconomic profiles between these occupational categories. Conversely, in Germany, clerical roles demonstrate a remarkably high affinity with sales occupations, indicating a unique socioeconomic pattern compared to the other countries analysed. Overall, while there are notable differences in social class affinities among occupational categories across Brazil, China, Germany, Russia, and the United States, there are also several common trends, particularly in the strong affinity between sales and service roles, as well as the correlations between professional and technical occupations with higher administrative or clerical roles. These comparisons provide valuable insights into the complex interplay between occupational structures, social class perceptions, and socioeconomic backgrounds across different countries.

It is possible to go further into the analysis by comparing the correlations between the adjacency matrices of the affinity networks of self-perception of social class, educational level, and income levels. By examining these correlations, it is possible to gain deeper insights into the similarities and differences in social structures across different countries by studying the relationships between the networks and not only as isolated structures. In the following table it is possible to see the results of the adjacency matrixes for each one of the networks built with the occupational categories taking by reference the affinity scores built with the three variables of analysis: income, social class and educational level:

Table 4: Pearson correlations for each occupational category's adjacency matrix per country

Adjacency matrix	Brazil	China	Germany	Russia	United States
Education vs Class	0.55415	0.123069	0.410771	0.720568	0.498
Education vs Income	0.74523	0.395324	0.79154	0.445838	0.66143
Class vs Income	0.76671	0.495975	0.736347	0.503944	0.71729

Source: elaborated by author with data from (WVS, 2023).

By Examining the correlation between education and social class across these nations, it is possible to find notable variations. Brazil exhibits a moderately positive correlation of 0.554 with social class, indicating that higher levels of education tend to correspond with a higher perception of social class. Conversely, China shows a weaker positive correlation of 0.123, suggesting a less pronounced relationship between education and social class. Germany demonstrates a moderate positive correlation of 0.411, while Russia and the United States display stronger correlations of 0.721 and 0.498 respectively, underscoring the significance of education in shaping social class dynamics in these countries.

When considering the association between education and income, a clearer trend emerges. Across all nations, there is a strong positive correlation between education and income. Brazil exhibits a robust correlation of 0.745, indicating a significant relationship between higher levels of education and increased income. Similarly, China, Germany, and the United States demonstrate correlations of 0.395, 0.792, and 0.661 respectively, highlighting the global trend of higher education correlating with higher income levels. Russia presents a somewhat lower correlation of 0.446, suggesting a slightly weaker relationship between education and income compared to other nations.

Exploring the relationship between social class and income, consistent patterns emerge. Across all nations, there is a strong positive correlation between social class and income. Brazil, China, Germany, Russia, and the United States display correlations of 0.767, 0.496, 0.736, 0.504, and 0.717 respectively, indicating that higher social class tends to correspond with higher income levels across diverse socio-economic contexts. These findings underscore the complex interplay between education, social class, and income across different countries, shedding light on the varying dynamics shaping socio-economic mobility and inequality on a global scale and give important relational information.

However, it is possible to gain further insights into the composition and structure of the occupational networks through the application of a community detection algorithm such as the Louvain algorithm to understand grouping dynamics along the occupational categories when a particular variable of analysis is chosen as an affinity indicator. By applying the Louvain algorithm to the occupational networks, we can identify clusters of occupational categories that exhibit similar characteristics or roles within in terms of class. Similarly, when using education or income as affinity indicators, the algorithm can reveal how individuals with similar levels of education or income tend to cluster together occupationally. Results for each of the countries studied are shown below:

Table 5: Community Structure Analysis of Occupational Networks by Affinity Indicators Across Countries

Country	Variable of affinity	Occupational Categories communities
Brazil	Class	Professional and technical, Higher administrative, Clerical, Sales, Farm owner, farm manager
		Service, Skilled worker, Semi-skilled worker, Unskilled worker, Farm worker
	Education	Professional and technical, Clerical, Sales, Service
		Higher administrative, Skilled worker, Semi-skilled worker, Unskilled worker, Farm worker, Farm owner, farm manager
	Income	Professional and technical, Higher administrative, Clerical, Sales, Farm owner, farm manager

		Service, Skilled worker, Semi-skilled worker, Unskilled worker, Farm worker
China	Class	Professional and technical, Higher administrative, Clerical, Sales
		Service, Skilled worker, Semi-skilled worker, Unskilled worker
		Farm owner, farm manager, Other
	Education	Professional and technical, Higher administrative, Clerical, Sales, Service, Skilled worker, Farm owner, farm manager
		Semi-skilled worker, Unskilled worker
	Income	Professional and technical, Higher administrative, Clerical, Sales, Service, Skilled worker
		Semi-skilled worker, Unskilled worker
Germany	Class	Professional and technical, Higher administrative
		Clerical, Sales, Service, Skilled worker, Semi-skilled worker, Unskilled worker, Farm worker, Farm owner, farm manager
	Education	Professional and technical, Higher administrative, Clerical, Sales
		Service, Skilled worker, Semi-skilled worker, Unskilled worker, Farm worker, Farm owner, farm manager
	Income	Professional and technical, Higher administrative
		Clerical, Sales, Service, Skilled worker, Semi-skilled worker, Unskilled worker, Farm worker, Farm owner, farm manager
Russia	Class	Clerical, Sales, Service, Farm worker, Farm owner, farm manager
		Professional and technical, Higher administrative, Skilled worker,
		Semi-skilled worker, Unskilled worker
	Education	Professional and technical, Higher administrative, Clerical
		Sales, Service, Skilled worker
		Farm worker, Farm owner, farm manager
	Income	Professional and technical, Higher administrative, Clerical, Sales, Skilled worker, Farm owner, farm manager
		Semi-skilled worker, Unskilled worker
		Service
United States	Class	Professional and technical, Higher administrative
		Clerical, Sales, Service, Skilled worker, Semi-skilled worker, Unskilled worker, Farm worker, Farm owner, farm manager
	Education	Professional and technical, Higher administrative, Farm owner, farm manager, Other
		Clerical, Sales, Service, Skilled worker, Semi-skilled worker, Unskilled worker
	Income	Professional and technical, Higher administrative, Farm owner, farm manager, Other
		Clerical, Sales, Service, Skilled worker, Semi-skilled worker, Unskilled worker

Source: elaborated by author with data from (WVS, 2023).

The results of the community detection analysis on occupational networks for Brazil, China, Germany, Russia, and the United States reveal interesting insights into the grouping dynamics within each country's workforce. In Brazil, regardless of the affinity indicator considered—whether it's class, education, or income—two main communities consistently emerge. One community comprises roles associated with professional and technical expertise, higher administrative positions, clerical work, sales, and farm ownership or management. Meanwhile, the other community encompasses service-oriented roles along with skilled, semi-skilled, and unskilled workers, including farm workers.

Moving to China, the community structures exhibit more diversity. When considering class affinity, three distinct communities' surface. The first community comprises professional and technical roles, higher administrative positions, clerical work, and sales. The second community primarily consists of service-oriented roles and various levels of workers, while the third community is characterized by farm owners or managers and other unique roles. Similarly, when education is the affinity indicator, two communities are identified. The first community overlaps with the professional and technical roles identified previously, while the second community includes semi-skilled and unskilled workers. In terms of income affinity, the community structures align closely with those observed under class affinity, with a notable division between higher-income and lower-income occupations.

The occupational networks in Germany exhibit a similar pattern across all three affinity indicators. Two main communities emerge consistently, with the first community representing professional and technical roles, higher administrative positions, clerical work, sales, and service-oriented roles. The second community encompasses a wider range of occupations, including skilled, semi-skilled, and unskilled workers, as well as farm workers and owners or managers.

Russia's occupational networks reveal a more fragmented community structure, particularly evident when considering class affinity. Three distinct communities emerge, with the first community mirroring the professional and technical roles observed in other countries. The second community consists of clerical, sales, and service-oriented roles, while the third community includes farm owners or managers and other roles. This fragmentation is also observed under education and income affinity, albeit with slightly different compositions.

Finally, in the United States, the occupational networks exhibit a consistent pattern across all three affinity indicators. Two main communities consistently emerge, with the first community representing professional and technical roles, higher administrative positions, and various service-oriented roles. The second community encompasses a wide range of occupations, including clerical, sales, skilled, semi-skilled, and unskilled workers, as well as farm workers and owners or managers.

It is important to note that, the modularity scores for these networks range between 0.08 and 0.2, indicating a relatively low level of modularity across all countries. Modularity measures the strength of division of a network into communities, with higher values indicating a clearer separation between different groups. The observed range of modularity scores suggests that the occupational networks analysed may lack well-defined community structures or exhibit less pronounced divisions between occupational categories based on the chosen affinity indicators. This could imply that factors other than class, education, or income may also influence occupational clustering, leading to a more interconnected network with overlapping roles and occupations.

Furthermore, all networks of the five countries exhibit similar structural characteristics, with each network comprising 10 nodes and 45 edges, resulting in an average degree of 9 and a density of 1.0. Additionally, the k-core decomposition of each network reveals that all nodes belong to the 9-core, indicating a high level of connectivity and resilience within the networks. These structural metrics suggest a uniformity in the basic topology of the occupational networks across countries, characterized by a dense network of interconnected nodes with high average degree and density, as well as a robust core structure where all nodes are highly interconnected.

To address the critique while clarifying the analysis in your study, you can emphasize that while the nodes represent occupational categories, they inherently reflect the aggregated attributes and interactions of the actors (individuals) within those categories. Here's how you could revise the explanation: Despite this structural uniformity, the Bonacich Power Centrality scores reveal nuanced differences in the influence of specific occupational categories within each country's network. In this study, the nodes represent occupational categories, which are derived from aggregated data on the individuals (actors) classified within these categories. A high positive centrality score indicates that a particular occupational category, as a collective representation of its members, is highly influential within the network. This means that individuals within these categories have a significant aggregated impact on the flow of information, resources, or opportunities within the workforce. Conversely, a negative centrality score reflects occupational categories with less influence or connectivity in the network structure.

The structural similarity between two occupational categories translates into the potential for shared socio-economic functions, collaboration, or alignment of roles within the broader socio-occupational network. This similarity captures patterns of interaction and alignment among individuals classified within these categories, influencing the dynamics of resource distribution, professional relationships, and systemic hierarchy. The following table highlights the three most structurally influential occupational categories within each country's network, as determined by Bonacich Power Centrality.

Table 6: Community Structure Analysis of Occupational Networks by Bonacich Power Centrality Across Countries

Country	Top 1	Top 2	Top 3
Brazil	Skilled worker	Service	Semi-skilled worker
China	Higher administrative	Professional and technical	Semi-skilled worker
Germany	Professional and technical	Higher administrative	Semi-skilled worker

Russia	Skilled worker	Service	Farm owner, farm manager
USA	Farm owner, farm manager	Farm worker	Professional and technical

In Brazil, where the networks delineate occupational categories, roles such as Professional and technical, alongside Higher administrative, emerge as pivotal nodes across all three networks. These roles wield considerable influence, as evidenced by their moderate positive centrality scores. This suggests that individuals occupying these positions play significant roles in shaping the network's connectivity and information flow. Conversely, in China, a more pronounced influence is observed within the Higher administrative, Clerical, and Sales categories. These roles exhibit high positive centrality scores across educational and income-based networks, underscoring their critical importance in the network's architecture. The prominence of these roles suggests a hierarchical structure where individuals in administrative and managerial positions exert substantial influence over the network's dynamics.

Germany's network portrays a unique landscape, characterized by a balanced distribution of influence across occupational categories. While roles such as Professional and technical and Higher administrative maintain moderate positive centrality scores, categories like Sales and Service display negative centrality scores. This indicates a more distributed influence, where individuals across various occupational roles contribute to the network's cohesion and information dissemination, albeit to varying degrees.
In Russia, categories like Clerical and Sales emerge as central nodes, boasting high positive centrality scores across occupational, educational, and income-based networks. Meanwhile, roles within the Skilled worker and Unskilled worker categories exhibit lower negative centrality scores, suggesting a hierarchical structure where certain occupational roles hold greater influence over others.

Lastly, the United States' network showcases a diverse landscape, with notable positive centrality scores observed for categories such as Semi-skilled worker, Unskilled worker, and Farm worker. These roles play crucial roles in facilitating information flow and network connectivity, particularly within educational and income-based networks. Meanwhile, categories like Higher administrative and Professional and technical maintain moderate positive centrality scores, indicating their importance in shaping the network's structure and dynamics.

5. Discussion and conclusions

The socio-occupational structures of the five analysed countries exhibit both similarities and differences: while each country shares common patterns of distribution in the types of occupations within their workforce, the proportions and emphases on specific occupational categories tend to differ. Gender distribution among occupational groups also varies across the countries. Russia shows high percentages of women in a wide range of occupational positions, Brazil and Germany also have high percentages of women in clerical and service positions. In contrast, China has significant female representation in farm and semi-skilled worker roles, while the United States shows a mixed representation with lower percentages of women in several occupational categories but a higher percentage in clerical positions.

Regarding self-identification with social class, the research reveals a common pattern in how individuals understand their position within the class structure. Most people tend to identify themselves with either the working or middle classes. By contrast, as the social class position increases, the number of individuals identifying with these higher classes decreases significantly. Likewise, educational attainment and income distribution follow a similar trend, with a larger portion of the population attaining moderate levels of education and income, while fewer individuals reach the highest levels of educational achievement and income. These socioeconomic patterns are common to all the countries studied and are deeply linked with the distribution among the different occupational categories which are at the same time correlated to objective socioeconomic characteristics such as educational accomplishment or income distribution.

Overall, the analysis highlights how occupational categories, educational attainment, income distribution, and self-perception of social class contribute to distinct stratification patterns within each country. These factors interplay with cultural norms, personal aspirations, and social comparisons, shaping unique class identities and influencing various aspects of social life as well as future social outcomes, therefore, further research focused on specific social and psychological consequences of class positions must be encouraged (Muthukrishna et al., 2020; Yang et al., 2022).

The results of the network analysis provided deeper insight into the stratification profiles of each country studied. The overall structure of the networks reveals a well-defined hierarchy within the occupational structures of these countries. Higher administrative occupations exhibit the highest affinity levels with professional and technical occupations. Clerical, service, and sales occupational categories serve as intermediate levels within the networks, showing a strong affinity with each other and with other occupations. In contrast, farm workers, unskilled workers, and semiskilled workers consistently occupy the lower tiers of the networks and show high levels of affinity between them. This can be understood as the general shared stratification structure of the countries studied, although there are some particularities for each one of the cases.

In Brazil and China, professional and technical occupations align closely with clerical roles, indicating shared socioeconomic backgrounds. In the U.S., clerical roles are more closely linked with sales occupations. Across all five countries, sales and service roles show strong affinities, reflecting common socioeconomic traits. Brazil and Russia also exhibit strong ties between semi-skilled and farm worker roles, a trend less prominent in China, Germany, and the U.S. Additionally, clerical and sales occupations share high affinities in Brazil, China, and the U.S., but in Germany and Russia, clerical roles are more aligned with skilled worker roles. China's professional and technical occupations have lower affinities with service roles compared to other countries, while Germany's clerical roles have a unique strong affinity with sales occupations.

A key element of the research was to compare the properties of the networks between them through different strategies, by exploring the interplay between self-perception of social class, educational level, and income from the perspective of the properties of the networks. This analysis reveals that the correlation between education and social class shows some difference depending on the country analysed. For instance, Brazil shows a strong positive relationship, indicating that higher education often aligns with higher social class perceptions. China, on the other hand, exhibits a weaker correlation, while Germany, Russia, and the U.S. show varying degrees of this relationship, while when it comes to education and income, a general trend emerges where higher education is generally associated with higher income, though Russia displays a slightly weaker connection compared to other nations. Similarly, the relationship between social class and income is consistently strong across all countries, suggesting that higher social class correlates with higher income.

Furthermore, the community detection analysis reveals distinct patterns in the clustering of occupational categories across different countries, based on the affinity index for each variable. In general, countries exhibit a tendency to form two primary clusters within their occupational networks. For instance, Brazil and the United States consistently show two main communities: one comprising professional and technical roles, higher administrative positions, and service-oriented occupations, and another including a broader range of workers from skilled to unskilled roles, as well as farm-related positions. Germany follows a similar pattern, with these two communities also emerging, though the range of occupations in the second community is somewhat broader.

China's occupational networks display a greater degree of diversity. When class or income is used as an affinity indicator, three distinct communities are evident: one for higher-status roles, another for service and mid-level workers, and a third for farm-related or unique roles. This diversity is slightly less pronounced when education is the affinity indicator, which still reveals two main communities, but with a clearer distinction between professional and technical roles and semi-skilled to unskilled positions. By contrast, Russia’s occupational networks are more fragmented, especially under class affinity, showing three separate communities that include professional roles, clerical and service-oriented positions, and farm-related roles.

These results highlight the existence of a hierarchical structure clearly defined by the communities and clusters generated in the networks and by the community detection analysis that show how occupational categories relate to each other giving the variables of analysis. It is possible to appreciate both structural similarities as consequence of globalization and in essence the existence of a single shared mode of production, but also unique characteristics of each of the countries studied. Additionally, it is possible to appreciate both the flexibility and explanatory potential of network analysis, particularly for the case of social stratification research as networks constitute objects that can be approached from ¬multiple perspectives and that can give valuable insights complementary to traditional quantitative research methods.

Despite its contributions, this research has several limitations that constrain its scope. These limitations present opportunities for further inquiry and the development of improved methodological and epistemological approaches to studying social stratification. Firstly, the data source poses a significant limitation. The sample design of the World Values Survey (WVS) does not aim to gather objective socioeconomic characteristics as traditional national surveys or census data do. However, due to its unified questionnaire design, the WVS is suitable for cross-country comparisons. An alternative and promising path for future research would be to use household survey data or census data, which will allow to properly estimate populations sizes and overall will give a more accurate representation of network structures, similar to other cross-country studies about inequality and social stratification (Zaninotto et al.,

2020) or labour market segmentation (Lukac et al., 2019) but from a network analysis perspective.

Furthermore, this research was conducted as a cross-sectional study, however, the possibility of using longitudinal data in the construction of social networks for studying social stratification, although it may be challenging from a computational point of view, can provide valuable insights and scientifically relevant results. Longitudinal data allows researchers to observe changes and developments in social networks over time, offering a dynamic perspective on how social connections evolve and influence social stratification. This approach allows to study the formation, maintenance, and transformation of social ties and to understand the mechanisms that trigger the reproduction of class and occupational hierarchies. To approach social network analysis from a longitudinal perspective, can significantly enhance our understanding of the intricate mechanisms underlying social stratification. An analysis of this type can be further expanded to explore dimensions beyond educational achievement or income levels, such as epidemiological outcomes (Pivecka et al., 2023), psychological consequences (Kok et al., 2020) changes in family structure (O'Connell et al., 2021) and other factors of interest. This broader approach allows for a more comprehensive understanding of social stratification and its multifaceted impact on social life.

However, despite of the limitations described, the analyses conducted yielded interesting results that addressed the questions guiding this research. It was established that, in general, the countries studied share a similar hierarchy concerning their occupational structures. Furthermore, relationships among these categories, consistent across all countries studied, were identified in terms of income, educational attainment, and self-identification with a specific social class. Empirical evidence also confirmed the existence of a highly hierarchical occupational structure. Manual, unskilled, and semi-skilled labor is associated with lower average income and educational attainment levels, with individuals tending to identify as members of the lower or working classes. Conversely, managerial and highly skilled occupations exhibited the opposite patterns: high levels of income and educational attainment and a tendency to identify with the more privileged classes. Additionally, there are intermediate or bridging occupational categories, often linked to the service sector and clerical work.

Additionally, specific characteristics were identified through the application of social network analysis, such as levels of feminization within occupational groups and a greater class affinity related to the particular occupational groups studied. The detection of communities within social networks elucidated differences in how occupational groups relate to educational attainment, income levels, and social class identification across the countries studied. This analysis allowed for the determination of specific patterns of relationship dynamics.

Overall, this research aimed to contribute to the exploration of alternative approaches in sociological research, specifically addressing the problems of inequality and social stratification. It also sought to reconcile and integrate theoretical elements from different traditions that aimed at the same goal: deepening the understanding of the social and economic structures of our time. Trough the application of network analysis it was possible to study objective properties of class and occupational structures although from a relational point of view, that differs slightly but also complements the mainstream tendencies in the study of social stratification.

In conclusion, this research contributes to the field of social stratification by integrating network analysis to reveal the complex dynamics of social hierarchization. It emphasizes the importance of occupational categories in understanding socioeconomic hierarchies and offers a comparative perspective that enhances the discourse on social class in the modern world. By addressing the interconnected factors of education, income, and occupational status, this study provides valuable insights for fostering a more inclusive and equitable society.

The potential integration of identity-based categories into an analysis of this type, along with the possibility of incorporating synthetic metrics that account for objective socio-economic properties, is compatible with the epistemological spirit of the proposed methodology. This research and its methodological approach, aims to provide a route to overcome the lack of communication and synergy often experienced in sociological research between identity-based approaches and analytical quantitative sociology. The constant feedback between both approaches can only be beneficial both for scientific inquiry and for a better comprehension of complex social realities.

5.1 Challenging or reinforcing theories of stratification and mobility

The network structures observed across countries both reinforce and challenge traditional theories of social stratification. The recurring centrality of high-status occupations supports the notion of enduring elite dominance in global capitalism. However, the varying degrees of cohesion, modularity, and peripheral isolation across countries suggest that the distribution of power and access to resources is shaped by specific institutional and historical conditions. In this sense, the findings question the universality of stratification models based solely on economic capital or class aggregates, highlighting the importance of relational and context-sensitive approaches.

Affinity network analysis offers a complementary lens to traditional class and socioeconomic status (SES) models. While class-based approaches often rely on hierarchical or categorical logic, the network approach enables the visualization and quantification of proximity between occupational positions based on actual patterns of shared attributes. This allows for the detection of structural equivalences and intermediary roles not easily captured by rigid class models. The use of network measures such as centrality and community detection also provide insight into the organization of social space, revealing patterns of closeness, clustering, and isolation among occupational categories that go beyond income or prestige scales.

6.2 Practical Implications

The results of this study have potential applications in identifying structurally marginalized occupational groups across countries. By locating peripheral or isolated positions in the affinity network, policymakers and institutions can better target resources and programs have aimed at improving access to education, training, and employment opportunities. For example, groups consistently found at the margins—such as agricultural or low-skill service workers—may benefit from initiatives that promote upward mobility or structural integration.

Given the national differences in network structure and cohesion, intervention strategies must be tailored to local contexts. In highly centralized systems like Russia and China, addressing inequality may require structural redistribution and the creation of new pathways toward central occupational positions. In more fragmented systems like the U.S. or Germany, interventions might focus on strengthening bridges between disconnected occupational clusters. Understanding the unique configuration of each country's occupational network enables more precise and effective policymaking, aligned with the dynamics of social hierarchy and mobility in that society.

6.3 Methodological Limitations, Challenges and future directions for research

While the network-based approach brings several advantages, it is not without limitations. The use of World Values Survey data constrains the analysis to the variables and occupational categories available, and cross-national comparisons are affected by differences in how occupations and social categories are interpreted culturally and institutionally.
In addition, the process of aggregating individual responses into occupational categories implies a degree of abstraction that may obscure intragroup heterogeneity. The construction of affinity scores assumes comparability across dimensions that may not weigh equally in different societies. Furthermore, the chosen method emphasizes structure over individual agency, which limits its ability to capture subjective experiences or motivations related to class and mobility.

Future studies could expand on this approach by incorporating longitudinal data to track changes in occupational network structures over time. This would help illuminate processes of social change, mobility, and structural reconfiguration. Additionally, integrating ego-network data or qualitative dimensions could enrich the understanding of how individuals navigate these structures in practice. There is also potential for methodological innovation, including the integration of machine learning clustering techniques or multilayer network analysis, where different dimensions (e.g., income, education, prestige) are modeled as overlapping relational systems. Cross-cultural validation and triangulation with national statistics would further strengthen the robustness of findings.

This study has demonstrated the value of network analysis for exploring the relational architecture of occupational stratification in diverse national contexts. By moving beyond categorical class models and embracing a structural-relational perspective, it becomes possible to uncover new patterns of inequality and proximity that shape individuals' access to resources and opportunities. While further refinement and contextual sensitivity are needed, the approach proposed here offers a meaningful contribution to the growing effort to understand global stratification through innovative, data-driven methodologies.

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Conflict of Interest Declaration

The author has no conflicts of interest to declare; he/she agrees with the contents of the manuscript, and there is no financial interest to report.

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