Occupational Inheritance and Kinship: An Empirical Study of Historical Social Elites on Wikidata

Sirui Lai, Liang Wang, Dingqi Yang

***Abstract*—The relationship between occupational inheritance and kinship has often been witnessed in human history. Existing studies often rely on small-scale and regional data, and fail to reveal global and spatiotemporal dynamics of occupational inheritance. In this paper, we conduct an empirical study on a large-scale dataset of historical social elites crawled from Wikidata, consisting of 691,503 validated relationship records involving 334,099 notable people from 3500 BCE to 2020 CE. Based on this dataset, we propose computational approaches to analyze the relationship between occupational inheritance and kinship, by defining the Occupation Connection Index (OCI) measuring pairwise occupation connections under a certain social relationship, and the Occupational Inheritance Index (OII) measuring the overall occupation inheritance across all occupation categories under parent-child relationships only. Subsequently, we reveal the varying impact of kinship over different occupation categories using OCI and also find interesting spatiotemporal patterns of OII reflecting key shifts in occupational inheritance which well align with key historical events and societal changes. Our study sheds light on the potential computational approaches to understanding occupational inheritance and kinship in a systematic manner with empirical evidence, which we believe will inspire further investigations in the field of computational social sciences.**

***Index Terms*—Kinship, Wikidata, Occupational inheritance, Big Data Analytics, Human history.**

I. Introduction

THE study on the relationship between occupational inheritance and kinship provides critical insights into the mechanisms of social stratification and the persistence of privilege across generations [1]. The empirical evidence has been widely used to understand historical and contemporary inequalities, shedding light on how societal structures influence individual opportunities. However, traditional research has been constrained by limited data availability and scope [2]. Specifically, most existing studies rely on small-scale archival records, census data, or manually curated genealogies [3], [4], which often cover limited temporal or geographical spans. This restricted perspective hinders a comprehensive understanding of global patterns and long-term trends in occupational inheritance and kinship networks. Despite recent advancements in computational social science and the availability of large-scale datasets [5], significant gaps remain. Studies employing digital records, network analysis, or large-scale databases have successfully explored phenomena such as cultural clusters [6] and trends [7], urban migration [8], [9], and urban dynamics [10], [11]; comparative computational approaches have also been applied to Wikipedia content to analyze timelines of national histories across language editions [12]. Unfortunately, existing works rarely address occupational inheritance and kinship systematically on a global scale. Moreover, many studies rely on basic statistical analyses or fragmented data that fail to reveal occupational mobility patterns [13]. These limitations highlight the need for a novel computational approach with broader and more detailed datasets to bridge these research gaps.

Against this background, in this paper, we conduct an empirical study on historical social elites on Wikidata, proposing computational approaches to systematically study the relationship between occupational inheritance and kinship. First, we construct a large-scale dataset encompassing over 330K historical elites and their relationships, spanning from 3500 BCE to 2020 CE. Specifically, we crawl the social relationships of social elites on Wikidata, where the social elites are extracted from a cross-verified database of notable people on Wikidata [14]; this database also maintains a well-curated occupation ontology with a three-level hierarchy, providing a unique opportunity to study the relationships between occupational inheritance and social relationships. Second, based on this dataset, we investigate the relationship between occupation categories and kinship by defining an Occupation Connection Index (OCI) that measures the pairwise connection strength between two occupation categories under a certain social relationship (e.g., father). The OCI reveals the varying impact of kinship over different occupation categories, where kinship is essential for maintaining continuity in Culture, Leadership/Politician, and Sports/Games, while in contrast showing low presence in Discovery/Science due to its meritocratic nature; in addition, we also find the specific types of kinship matter across different occupation categories. Third, we investigate the spatiotemporal dynamics of occupational inheritance by defining an integrated Occupational Inheritance Index (OII) measuring the strength of occupational inheritance across all occupation connections under only parent-child relationships. Based on OII, we first study global-scale temporal trends in occupational inheritance and then dig into the regional-scale temporal dynamics; the spatiotemporal dynamics of OII exhibit interesting patterns reflecting shifts in occupational inheritance and mobility, which indeed align with key historical events and societal changes, as evidenced by socioeconomic studies. Our contributions are summarized as follows:

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The code and datasets are available at: https://github.com/UM-Data-Intelligence-Lab/WikiElites

- We investigate the relationship between occupational inheritance and kinship from a data-driven perspective, based on a large-scale dataset of historical social elites crawled on Wikidata.
- We propose computational approaches to understand the relationship between occupational inheritance and kinship, by defining the Occupation Connection Index (OCI) measuring relation-specific pairwise occupation connections and the Occupational Inheritance Index (OII) measuring the overall occupation inheritance across all occupation categories.
- We reveal the varying impact of kinship over different occupation categories using OCI, and also find interesting spatiotemporal patterns of OII reflecting key shifts in occupational inheritance which well align with key historical events and societal changes.

II. Related work

Occupational inheritance refers to the phenomenon where individuals, often within families, tend to pursue and secure jobs that are similar to those held by their parents or other family members [15]. The trend of occupational inheritance is often influenced by various social and economic factors, including access to education, social networks, and cultural expectations, which perpetuate occupational patterns across generations [16].

Previous studies have predominantly utilized census data or manually compiled genealogical records, both of which exhibit limitations in temporal and spatial coverage. Most analyses focus on intergenerational mobility across decades or centuries. Long-term mobility trends in Europe from the 19th to 20th century were explored in [4]. Modalsli [17] documented a substantial increase in intergenerational occupational mobility in Norway from 1865 to 2011, particularly in non-farm occupations. Furthermore, these studies are often restricted to data from one or a few countries, or city-level information [18]. For example, intergenerational class mobility in England, France, and Sweden was examined using data from the early 1970s [19]. Niittykangas and Tervo [20] explored spatial variations in self-employment inheritance in Finland, highlighting the importance of local environments and family background in entrepreneurship. Social mobility in the United States during the 1850s and 1880s was compared between the UK and the US [21], while occupational patterns in Switzerland were analyzed in [22], highlighting the influence of social policies. Scandinavian countries were investigated in [23], emphasizing the role of welfare systems. Cross-national occupational inheritance across thirteen nations was studied in [15]. In Japan, the impact of occupational inheritance on long-term worklessness was examined using post-war data [24]. Studies from India and China further illustrate the spatial limitations of existing research [25]. Beyond the small-scale and regional data used in these existing studies, in this paper, we construct a large-scale dataset encompassing over 330K historical elites and their relationships, spanning from 3500 BCE to 2020 CE, providing a unique opportunity to systematically study the relationships between occupational inheritance and social relationships.

Occupational inheritance has been extensively studied in sociology and economics, as it reflects the degree of social equity and opportunity in both developed and developing countries [26]. Existing studies have explored a range of factors influencing occupational transmission, including human capital [27], [28], cultural resources [3], and socioeconomic structures [29]. For instance, in rural China, education and skills training have been identified as key drivers of upward mobility [30], while in Italy, children's occupational outcomes remain closely tied to their parents' social status, particularly that of fathers [31]. Mazumder and Acosta [32] measured intergenerational mobility through long-term averages of parental occupation and income. Longitudinal surveys and census data are commonly employed to assess the impact of education on intergenerational mobility. Hilger [33] developed a method using U.S. census data to estimate intergenerational mobility in education. Li [34] utilized the 2015 CGSS database to analyze intergenerational mobility in China, finding that parental education significantly influences children's socioeconomic status. Pujadas-Mora et al. [35] examined intergenerational status transmission among farmers and artisans in 16th-17th century Barcelona using marriage records. While much of this literature focuses on class mobility and typically assesses the upward [36] or downward [37] direction of mobility by examining patterns of capital accumulation, they fail to quantify the extent of this inheritance, which is the main focus of our study.

Traditional analytical approaches mainly employ statistical analysis methods, such as correlation analysis, regression coefficients, and elasticity measures. These methods are designed for static data analysis, focusing on identifying associations rather than capturing the dynamic evolution of mobility across time and space. For instance, Lundberg et al. [38] addressed the challenge of causal identification in multivalued occupational outcomes using generalized treatment effect models. Breen and Karlson [39] proposed a decomposition method for log odds ratios within logistic regression frameworks, enabling the quantification of education's mediating role in intergenerational mobility. Breen [40] further developed statistical models for mobility tables by applying log-linear models and fit diagnostics to evaluate theoretical assumptions against empirical data. In the context of developing countries, where data limitations are more pronounced, Emran and Shilpi [41] advocated for the use of rank-based and intergenerational correlation measures. Nonparametric methods have been proposed to analyze mobility measures, including transition probabilities and upward mobility probability [42]. However, these studies have primarily focused on static methods that identify the causes of occupational mobility, which differs from our current study that tries to quantify their dynamic changes over time and space.

III. Data Collection and Processing

Our data collection is based on the cross-verified database of notable people, 3500BC-2018AD [14]. This database includes 2.29 million notable people from multiple editions of Wikipedia and Wikidata. It contains detailed attributes

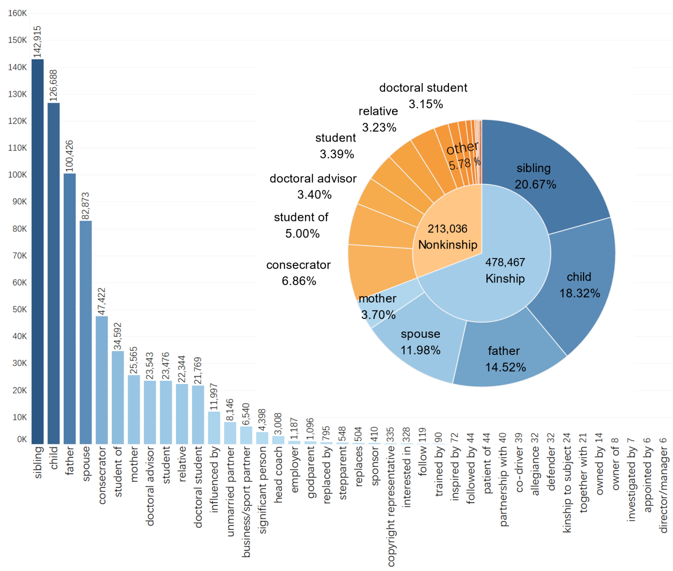

Fig. 1. Statistics of top relationships in our dataset.

Fig. 2. Three levels of occupation ontology. Note that the third-level occupations are not exhaustively shown in this figure, where we only show occupations that involve at least 2000 individuals for better visibility.

such as birth and death dates, nationality, and occupation. Based on this dataset, we first crawl and filter the social relationships among these people on Wikidata, and then also extract the spatiotemporal information to support our study on occupational inheritance and kinship over time and space.

A. Extraction and Refinement of Social Relationships.

We use the entity IDs from the notable people dataset to crawl their social relationships (relations between these entities) on Wikidata. Over 100 types of Wikidata relations were initially crawled. To improve the relevance of the data, we first exclude rare and less informative relations due to their limited significance in the context of this study, such as "named after" (identified as P138 on Wikidata[1]), which does not really refer to social relationships between individuals and only appears less than 122 times. The final dataset retained 40 relations that represent social relationships between individuals, which we have manually checked to ensure the quality. We then filter out the notable people who do not have any of the 40 selected relations and refer to the remaining individuals as "***social elites***" who are the notable people with known social relationships. Figure 1 shows the statistics of top relationships, which are further grouped into kinship-based relationships (e.g., "child") and non-kinship relationships (e.g., "doctoral advisor").

B. Occupation Ontology.

A three-level occupation classification ontology [14] is employed to categorize the occupations of the social elites. Individuals with occupations labeled as "miscellaneous", "other", or a missing entry were excluded to ensure the reliability and specificity of the analysis. As shown in Figure 2, the third-level occupations represent the most detailed classification and are grouped into 10 second-level categories, which are then further grouped into 4 top-level categories (culture, leadership, discovery/science, and sports/games).

[1]https://www.wikidata.org/wiki/Property:P138

C. Spatiotemporal Information.

We also extract the spatiotemporal information of the social elites to support the comparative study on occupational inheritance and kinship over time and space. For the temporal information, we extract the birth and death dates of individuals and exclude the entries lacking birth dates. For individuals born on or after 1900 with missing death dates, we assumed they were alive. For the spatial information, we extract the nationality of the social elites and then map the nationalities to countries. For individuals with multiple nationalities, we simply consider that they belong to the corresponding countries, and contribute equally to the countries in our spatiotemporal analysis later. Moreover, as nationalities/countries are often associated with different names in history, we map their historical names to current names and use current country boundaries in our spatial analysis. For example, "Russian Empire", "Tsardom of Russia", "Grand Duchy of Moscow" are clubbed under Old Russia and mapped to the current boundaries of Russia for the purpose of visualization on modern maps.

D. Evolution of Relationship and Occupational Categories.

Figure 3 illustrates the distribution of occupation types and social relationships across five historical periods [14]: Ancient History (before 500), Post-Classical History (501–1500), Early Modern Period (1501–1750), Mid Modern Period (1751–1900), and Contemporary Period (1901–present). The number of social relationship instances shows a significant increase from Ancient History to the Contemporary Period, with kinship relationships consistently outnumbering non-kinship ones throughout all periods. In Ancient History, societies were primarily organized around kinship, with professions often inherited within families. Non-kinship relationships were less prominent, reflecting a community-centric structure. During Post-Classical History, there was a slight increase in non-kinship relations. This period saw the rise of feudal systems and guilds, where occupations began to diversify beyond

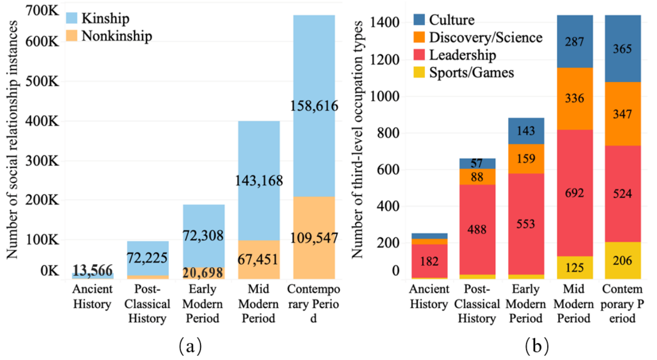

Fig. 3. Evolution of social relationship instances and occupation types across five historical periods. (a) Kinship and Nonkinship relationship instances. (b) Third-level occupation types grouped by four major categories. Due to the stacked bar chart format, specific numbers for smaller categories with fewer than 10000 instances in (a) or 50 types in (b)are not shown for better visibility.

		Culture	Discovery/ Science	Leadership/ Politician	Sports/Games
Culture	kinship	51.96	5.16	5.77	1.66
	nonkinship	30.18	2.30	1.19	0.85
Discovery/ Science	kinship	5.19	17.02	4.17	0.54
	nonkinship	2.02	58.38	1.59	0.28
Leadership/ Politician	kinship	5.80	4.19	64.20*	1.08
	nonkinship	0.90	1.56	18.73	<u>0.11</u>
Sports/ Games	kinship	1.65	0.54	1.07	61.58
	nonkinship	0.56	0.28	0.13	23.80

Fig. 4. OCI (in %) under kinship and non-kinship at the top-level occupation categories. An asterisk marks the maximum value; an underline marks the minimum value.

familial lines, though kinship still played a significant role. The evolution of relationship categories reflects broader societal changes, from kinship-dominated ancient societies to the diverse and complex contemporary period.

Regarding third-level occupation types, there is a clear diversification over time. The mid-modern period saw a surge in discovery/science occupations, reflecting the era's emphasis on exploration and innovation. For example, in the periods before the Middle Ages, the field of "Discovery/Science" was primarily composed of philosophers, historians, and linguists. These roles played a crucial part in the early development of human knowledge, focusing on understanding the world through philosophical inquiry, documenting historical events, and studying languages. Starting from the Middle Ages, however, the focus of "Discovery/Science" began to shift significantly. This period witnessed the emergence of more specialized scientific roles such as physicians, mathematicians, physicists, biologists, and astronomers. These professions marked the beginning of systematic scientific exploration and the development of various scientific disciplines. Leadership became increasingly dominant from the Post-Classical Period onward. This trend reached its peak in the Mid Modern Period, where 692 distinct leadership occupation types were recorded—an increase from 182 in Ancient History. The decline in leadership occupations during the Contemporary Period is largely attributed to the reduced presence of nobility. By the contemporary period, sports/games emerged as a significant category, indicating society's growing focus on leisure and entertainment. This evolution underscores the dynamic nature of occupational landscapes across different historical contexts.

IV. Occupation Categories and Kinship

In this section, we investigate the relationship between occupation categories and kinship. Specifically, we first introduce an Occupation Connection Index (OCI), which measures the pairwise connection strength between two occupation categories under a certain social relationship (e.g., Kinship), and then reveal several interesting findings by comparing the OCI between different occupation categories across different social relationships.

A. Occupation Connection Index

Let A denote a relationship matrix between occupation categories, where each entry $a_{i,j}$ represents the count of the total relationships from individuals with a source occupation $s = i$ to individuals with a destination occupation $d = j$; similarly, $a^r_{i,j}$ denote the same count under a specific relation r. Subsequently, the (empirical) conditional probability of seeing the destination occupation $d = j$ given the source occupation $s = i$ under the relation r can be computed as:

$$P^r(d = j|s = i) = \frac{a^r_{i,j}}{\sum_j a_{i,j}} \tag{1}$$

Similarly, the (empirical) conditional probability of seeing the source occupation $s = i$ given the destination occupation $d = j$ can be computed as:

$$P^r(s = i|d = j) = \frac{a^r_{i,j}}{\sum_i a_{i,j}} \tag{2}$$

Subsequently, the occupation connection index is defined as the harmonic mean of the two conditional probabilities:

$$\text{OCI}^r_{i,j} = \frac{2}{\frac{1}{P^r(d=j|s=i)} + \frac{1}{P^r(s=i|d=j)}} = \frac{2a^r_{i,j}}{\sum_i a_{i,j} + \sum_j a_{i,j}} \tag{3}$$

Note that due to the directed social relationships (e.g., child), OCI is asymmetry referring to the occupational connection from a source occupation $s = i$ to a destination occupation $d = j$ under a given relation r.

Our design choices have the following benefits. First, compared to directly using the count of relationships $a^r_{i,j}$, the conditional probabilities eliminate the biases incurred by the overdominance issue of some occupation categories having a large number of individuals, which is evidenced by the statistics of the occupation ontology as shown in Figure 2. Second, the harmonic mean balances the two empirical conditional probabilities by considering their reciprocal. In particular, it penalizes a low value in either of the two probabilities; in other words, it prioritizes the cases of high values in both probabilities simultaneously, therefore highlighting the significance of the occupational connection from a source occupation $s = i$ to a destination occupation $d = j$.

B. Impact of Kinship on Occupation Connection

Based on our defined OCI, we investigate the impact of kinship on different occupation connections. Specifically, we first study the OCI between each directed pair of the top-level occupations under both kinship and non-kinship relationships and then conduct in-depth analyses on the breakdown over the detailed kinship.

1) Varying Impact of Kinship over Different Occupation Categories: Figure 4 shows the comparison between kinship and non-kinship over different occupation pairs. First, we observe that within the same occupation (intra-occupational connection), kinship connections show higher OCI values compared to non-kinship in most cases (Culture, Leadership/Politician, and Sports/Games), where the only exception is Discovery/Science (more discussion below). For instance, in the Leadership/Politician category, kinship connections account for 64.20% of OCI, which is much higher than the 18.73% observed for non-kinship connections. This suggests that family-based networks are essential for maintaining continuity in these fields. In contrast, Discovery/Science shows a markedly different pattern, where non-kinship dominates intra-occupational connection. The OCI for non-kinship relationships reaches 58.38%, significantly surpassing the 17.02% observed for kinship. This suggests that the scientific field prioritizes individual merit and collaborative networks over familial connections, reflecting its meritocratic nature.

In addition, we also observe that inter-occupational connections are generally weak, particularly across unrelated occupation categories. For example, the OCI from Leadership/Politician to Sports/Games is low, with kinship (1.08%) and non-kinship (0.11%). This indicates that individuals associated with politicians, whether family members or non-relatives, are unlikely to engage in the sports industry, reflecting the limited interaction between these two fields.

2) Types of Kinship Matter: In kinship-dominated occupation categories such as culture, politics, and sports, as shown in Figure 4, kinship may exacerbate inequalities by limiting opportunities for individuals without such connections. To further understand the impact of different kinship, Figure 5 shows a breakdown on the detailed kinship: child, spouse, sibling, father, and mother across different occupation categories. We have the following findings.

Politician. Children of politicians have a high likelihood of becoming politicians themselves. There is a lower prevalence of mother relationships compared to father relationships. Fathers usually play a more important role in the political socialization process within the family than mothers [43], [44]. The influence of fathers in political careers can be attributed to the transfer of political knowledge, networks, and resources within the family [45]. Additionally, siblings of politicians are frequently found to be politicians, indicating that political influence and opportunities are often shared within families. Many related studies have revealed this phenomenon. For example, a strong link between individuals and their parents concerning party affiliation has been found [46], and this transmission persists over generations and across siblings; meanwhile, politicians often come from families with a history of political involvement [47], further supporting the idea that

		Culture	Discovery/ Science	Leadership/ Politician	Sports/Games
child	Culture	11.12	1.17	1.06	0.28
	Leadership/Politician	2.17	1.43	18.56	0.50
	Discovery/Science	1.71	4.83	1.18	0.21
	Sports/Games	0.36	0.11	0.20	11.17
spouse	Culture	18.01	0.96	1.15	0.71
	Leadership/Politician	1.14	0.42	6.56	0.12
	Discovery/Science	0.95	3.33	0.42	0.06
	Sports/Games	0.70	0.07	0.12	8.59
sibling	Culture	11.90	1.35	1.43	0.31
	Leadership/Politician	1.43	1.17	20.52	0.25
	Discovery/Science	1.36	4.10	1.16	0.16
	Sports/Games	0.32	0.16	0.25	30.85
father	Culture	8.11	1.54	1.89	0.32
	Leadership/Politician	0.72	1.06	14.97	0.18
	Discovery/Science	0.89	4.44	1.30	0.09
	Sports/Games	0.19	0.19	0.44	9.78
mother	Culture	2.81	0.15	0.25	0.03
	Leadership/Politician	0.34	0.11	3.60	0.02
	Discovery/Science	0.28	0.32	0.12	0.01
	Sports/Games	0.09	0.01	0.05	1.20

Fig. 5. OCI (in %) breakdown over 5 types of kinship.

political influence and opportunities are frequently shared within families.

Sports. The analysis of athletic occupations revealed that siblings of athletes are often athletes themselves. This pattern suggests that athletic talent and career paths may be significantly influenced by family dynamics and shared environments. Factors such as genetic predisposition [48], access to training resources, and familial support, including parental support and sibling interactions [49], often play a crucial role in the development of athletes.

Science Occupations. As shown in Figure 5, science occupations exhibit a comparatively lower reliance on kinship ties across all relationship types. For instance, the proportions of child (2.41%), sibling (2.05%), and father (2.22%) relationships are consistently lower than those observed in leadership/politician and sports occupations. This trend suggests that occupational inheritance in the scientific domain, particularly within academia, is less dependent on familial connections. Instead, it appears to be driven by meritocratic factors such as education, skills, and professional mentorship. A key explanation for this pattern lies in the prominence of teacher-student relationships within the academic field, where the most significant relationships are those of “doctoral advisor” and “doctoral student”. Prior studies have shown that teachers play a crucial role in the career advancement of scientists [50], [51], influencing their research productivity, network access, and professional opportunities.

V. Measuring Occupational Inheritance

The above analysis reveals the varying impact of kinship across pairwise occupation connections, which motivates us to further study occupational inheritance and analyze its spatiotemporal dynamics over time and space. To this end, in this section, we further propose an integrated metric, the Occupational Inheritance Index (OII), quantifying the strength of occupational inheritance across all occupation connections, which serves as the foundation for studying the spatiotemporal dynamics of occupation inheritance.

A. Occupational Inheritance Index

Different from OCI, which measures the strength of pairwise occupation connections under a given social relationship, we now shift our focus to capture broader patterns of inheritance across the entire occupational structure, and track its dynamics over time and space. We define the Occupational Inheritance Index (OII) to measure the strength of occupational inheritance across all occupation connections under only parent-child relationships (i.e., father, mother, child). Specifically, let A_I denote the parent-child relationship matrix between occupation categories, where each entry $a^I_{i,j}$ represents the count of the parent-child relationship from individuals with a source occupation $s = i$ to individuals with a destination occupation $d = j$. We borrow the idea of Pointwise Mutual Information (PMI) from information theory, measuring the association between two events by comparing the probability of two events occurring together to what this probability would be under the independent assumption of these events [52]. In the context of our problem, the PMI of two occupations is computed as:

$$\begin{aligned} \mathrm{PMI}_{i,j} &= \log \frac{P(i,j)}{P(i) \cdot P(j)} = \log \frac{\frac{a^I_{i,j}}{T}}{\frac{\sum_i a^I_{i,j}}{T} \cdot \frac{\sum_j a^I_{i,j}}{T}} \\ &= \log \frac{a^I_{i,j} T}{\sum_i a^I_{i,j} \cdot \sum_j a^I_{i,j}} \end{aligned} \tag{4}$$

where $P(i,j)$ refers to the joint probability of two occupations, and $P(i) \cdot P(j)$ refers to the joint probability under independent assumption. T refers to the total number of parent-child relationships in A_I. Subsequently, the OII is computed as the weighted average of PMI over A_I:

$$\mathrm{OII} = \sum_{i,j} \mathrm{PMI}_{i,j} \cdot w_{i,j} \tag{5}$$

where the weights $w_{i,j}$ represent the frequency of the parent-child relationship. Finally, the OII measures the overall strength of occupational inheritance across all occupation connections, where a high value indicates a strong occupational inheritance and vice versa. In the following, we first study the global-scale temporal trend of occupational inheritance, followed by the regional-scale temporal analysis.

B. Global-Scale Temporal Trends in Occupational Inheritance

By incorporating temporal data, we can observe the overall trends in occupational inheritance over different historical periods. In this analysis, social elites are aligned yearly, and an individual is included to compute the OII for a specific year if the individual were alive in that year, determined by (birth year $\leq$ year $\leq$ death year). This analysis allows us to identify significant shifts and patterns in occupational inheritance, providing insights into how societal changes have influenced career paths across generations.

To address potential biases caused by uneven sampling across historical periods, where data before 1700 are relatively limited and records are abundant in recent years, we adopt a bootstrapping method with fixed sample size. For each year, we apply uniform random sampling with replacement to select a fixed number of parent–child pairs and compute OII 500 times for each sample size to obtain mean OII values and corresponding 95% confidence intervals. Figure 6 compares results based on sample sizes of 100 and 1,000 per year. These values were chosen to represent small and large sample regimes, respectively, allowing us to assess the robustness of the OII trajectory across different levels of data availability. As expected, the smaller sample size yields wider confidence intervals due to higher variance. However, the overall temporal pattern, including the timing and shape of major peaks and troughs, is closely aligned between the two settings. This consistency demonstrates that the OII is a weighted average and is not mechanically influenced by sample size, supporting our focus on temporal dynamics rather than absolute values.

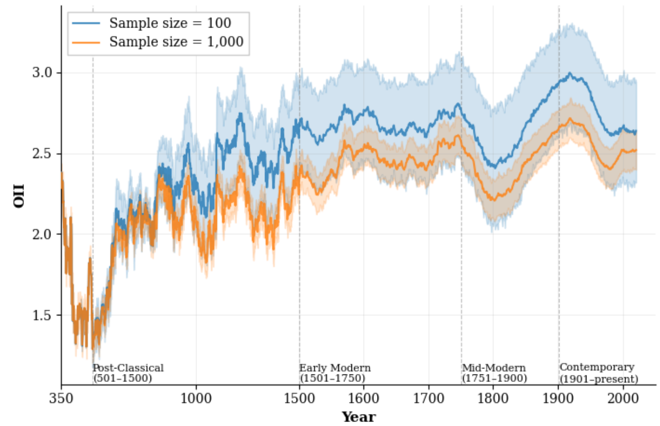

Fig. 6. Global-scale temporal trends in occupational inheritance over historical periods, 350–2020.The shaded region denotes the 95% confidence interval based on 500 bootstrapped OII curves.

Figure 6 shows the trends in occupational inheritance across four historical periods [14]: Post-Classical History (501–1500), Early Modern Period (1501–1750), Mid-Modern Period (1751–1900), and Contemporary Period (1901–present). The results show a gradual increase in occupational inheritance during the Post-Classical Period. Furthermore, in each subsequent transitional phase between periods, the OII exhibits a consistent pattern of rising and then declining. These patterns align with major historical and socioeconomic transitions.

1) Post-Classical History to Early Modern Period: The observed increase in occupational inheritance during this period reflects the influence of rigid societal structures. Feudal systems linked occupations to family lineage through religious and noble hierarchies, with clergy and aristocrats inheriting roles [53]. The guild systems in Europe further reinforced these patterns by limiting access to specific professions to those with family ties to existing guild members. The Black Death (1347–1351) [54] significantly impacted this trend. Labor shortages due to the plague heightened the reliance on kinship ties for economic survival, as families sought to maintain their livelihoods through established occupations.

The Early Modern Period saw a continuation of the upward trend in occupational inheritance. The Renaissance (14th–17th centuries) [55] played a pivotal role during this phase, especially in Europe. Elite families consolidated wealth and power through patronage systems and controlled professions linked to arts, science, and trade [56]. Despite its cultural emphasis on individual merit, the Renaissance often reinforced familial privilege by restricting access to knowledge and professional networks.

2) Early Modern to Middle Modern Period: A significant decline in occupational inheritance occurred from the late 17th to the 18th century. This trend corresponds to several transformative events: The Enlightenment (17th–18th centuries) [57]: Promoted merit-based advancement and questioned traditional hierarchies, reducing the reliance on kinship for career progression. This decline coincided with the First Industrial Revolution (1760–1840), which introduced mechanized production and new industrial jobs [58]. These changes disrupted traditional family-dominated occupations, as skills and labor became more valued than lineage in emerging sectors.

3) Middle Modern Period to Contemporary Period: A slight recovery is observed in the latter half of the 19th century, during the Second Industrial Revolution (1870–1914) [59], industrial elites and business families consolidated their power by securing exclusive access to education and professional opportunities [60]. These practices began to restore occupational inheritance, particularly in rapidly growing fields like engineering and finance.

As observed through historical periods, the long-term trends in occupational inheritance provide a foundational understanding of the socio-economic dynamics that have shaped intergenerational mobility over centuries. However, these trends are not uniform across regions and time. Variations in economic systems, cultural practices, and historical events have produced significant spatial and temporal disparities in occupational inheritance. To gain a more detailed understanding of these patterns, it is essential to move beyond a purely temporal perspective and explore how regional differences and localized factors interact with broader historical trajectories.

VI. Spatiotemporal Analysis of Occupational Inheritance

We further explore the spatiotemporal dynamics in occupational inheritance, focusing on the influence of economic transformations and historical events. By analyzing the Occupational Inheritance Index (OII) across regions, we aim to understand how industrialization, economic changes, and significant global disruptions, such as wars, have shaped occupational inheritance over time. Unlike the global-scale trends discussed earlier, the data in this section represent the entire living population of each country for a specific year. This approach ensures a more precise examination of the changes surrounding key historical events.

A. Social Stratification: Observation and Evidence from the Industrial Revolutions

The Industrial Revolution, spanning two transformative periods, profoundly reshaped economic and occupational structures across societies. The First Industrial Revolution

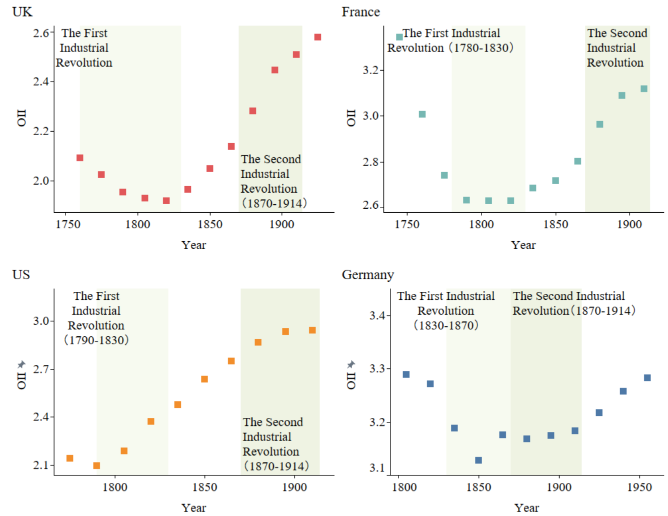

Fig. 7. OII trends in four countries during the Industrial Revolution with data points for each fifteen-year interval.

(around 1760–1830, [58]) marked the transition from agrarian economies to mechanized industries, characterized by the widespread introduction of machinery and factory-based production. In contrast, the Second Industrial Revolution (1870–1914, [59]) expanded on this foundation, driven by advancements in electricity, chemical engineering, and large-scale manufacturing.

During these periods, occupational inheritance patterns reflected the different stages of society's adaptation to industrialization. While the First Industrial Revolution disrupted traditional roles, leading to instability in occupational inheritance, the Second Industrial Revolution fostered a more stable and continuous occupational structure as societies adjusted to the new industrial framework. This study analyzes how these distinct stages of industrial development influenced intergenerational occupational inheritance, as measured by the Intergenerational Occupational Inheritance Index (OII), across four industrialized nations: the United Kingdom (UK), the United States (US), France, and Germany.

Each of these four countries experienced two industrial revolutions, marking reference lines according to the country's respective entry time. Given the temporal continuity of the two industrial revolutions, it is meaningful to analyze them together, as they represent different stages of the same transformative process. The First Industrial Revolution began in the UK in the late 18th century, around the 1760s. The revolution then spread to other countries in the following decades: France around the 1780s, the US by the 1790s, and Germany after the 1830s [61].

As shown in Figure 7, a shared characteristic among all four countries is the decline in OII during the initial stages of industrialization, indicating that mechanization and the rise of emerging industries disrupted traditional occupational structures. This can be attributed to the disruptive nature of early industrialization. Traditional artisanal and agricultural occupations were replaced by factory-based jobs [62], leading to instability in occupational inheritance. The societal shift toward urbanization and wage labor eroded the reliance on family-based occupations. The Second Industrial Revolution focused on advanced technologies like electricity, steel production, and chemical industries, which enhanced and expanded existing industries rather than replacing entire sectors like agriculture and handicrafts. Despite technological advancements and economic growth, the wealth generated was unevenly distributed [63]. The rise of monopolies and large corporations further concentrated wealth [64], [65] leading to increased social inheritance. All four countries experienced an increase in OII, reflecting improved and strengthened intergenerational occupational inheritance.

The UK, as the birthplace of the Industrial Revolution, saw significant resource concentration in the hands of industrialists and capitalists. The rapid industrialization led to the accumulation of wealth among factory owners and investors [66], while the working class faced harsh living and working conditions [67]. Its OII provides a clear example of this trend, which dropped significantly during the First Industrial Revolution but began recovering in the subsequent phase, showing a stabilization in occupational structures as industrialization progressed. France and the US, having industrialized later, benefited from observing and adapting the UK's experiences. Consequently, while these countries also experienced an initial decline in OII, their occupational structures stabilized more quickly. In particular, US began industrializing shortly after achieving national stability. By promptly adopting British technologies and practices, it avoided a sharp early decline in OII and instead experienced rapid growth during its industrialization phase. Germany entered the industrialization process last among the four countries and experienced the two revolutions in close succession. It underwent a rapid transformation in occupational structure and achieved a relatively smooth transition into the Second Industrial Revolution.

B. Impact of Conflicts: Observation and Evidence from Wars

To assess the impact of large-scale conflicts on occupational inheritance, we examine the two World Wars as historical case studies. For each country, we define the extent of wartime disruption by two factors: whether it was a battlefield and whether it emerged as a victor or a defeated power provided by [68], [69]. We then analyze changes in the OII across countries with different wartime experiences.

World War I (1914–1918) involved over 30 countries [70], while World War II (1939–1945) saw participation from more than 100 countries [71]. France and Russia were battlefield nations in both World Wars and suffered extensive destruction. In contrast, Switzerland and Sweden remained neutral, experiencing minimal direct impact from the conflicts.

Figure 8 illustrates fluctuations in the Occupational Inheritance Index (OII) across France, Russia, Switzerland, and Sweden during both World Wars. France and Russia showed similarly sharp decreases in OII after each conflict. These periods coincided with widespread infrastructure damage, economic instability, and social upheaval. Significant changes in occupational structures were observed during the same time. In contrast, Switzerland and Sweden experienced increases in OII

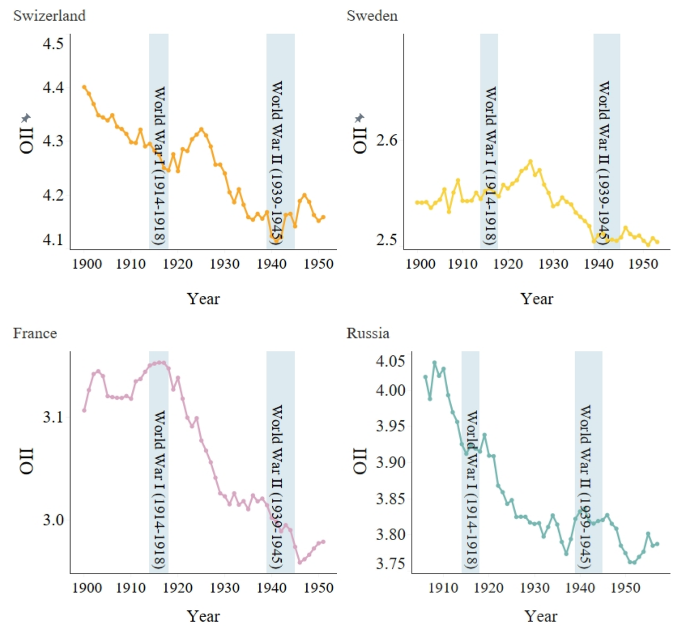

Fig. 8. Comparison between Neutral and Battlefield Countries during the Two World Wars

after both wars, while overall fluctuations remained relatively stable. These patterns coincided with periods of economic loss and upheaval in occupational systems during and after the conflicts.

1) Economic Losses: Wars devastate economies by destroying infrastructure, disrupting trade, and depleting resources. The GDP of countries involved in World War saw significant declines [72], particularly in those that were primary battlefields. In France, wealth inheritance represented approximately 20–25% of national income between 1820 and 1910, but fell below 5% by 1950 due to the socioeconomic disruptions caused by two world wars [73]. This sharp decline reflects the erosion of intergenerational wealth transmission, as wartime destruction, inflation, and post-war taxation policies significantly reduced the ability of elite families to preserve and pass on their assets. While this does not directly equate to occupational inheritance, it suggests a broader destabilization of traditional elite structures, potentially increasing social mobility in the short term but also contributing to economic uncertainty and inequality. Economic collapse was accompanied by widespread unemployment and poverty, alongside a weakening of the institutional foundations of elite professions and a decline in occupational inheritance, as reflected in reduced intergenerational occupational continuity in postwar societies. Neutral countries such as Switzerland and Sweden experienced relatively stable occupational inheritance during the World Wars. Their neutrality avoided direct wartime devastation, preserving their economic infrastructure and institutional stability. their inheritance dynamics were shaped by endogenous policy shifts rather than exogenous shocks. In Switzerland, inheritance flows remained relatively stable [74], with the wealth-income ratio oscillating around 500% throughout most of the 20th century [75]. The decline in inheritance flows in Sweden, meanwhile, was driven by domestic reforms, including welfare

TABLE I
REGRESSION COEFFICIENTS OF GDP GROWTH BY COUNTRY

Country	Coefficient	P-value	Standard Error
Australia	5.91	0.393	6.81
Canada	8.76	0.543	14.23
China	2.57	0.835	12.23
France	-8.76	0.044	4.17
Germany	-17.85	0.046	8.98
Italy	-20.59	0.004	6.69
Japan	7.43	0.171	5.30

expansion and progressive taxation [76].

2) Upheaval in the Occupational Systems: Wars disrupt occupational hierarchies through population displacement, institutional breakdown, and changes in labor market structures. In France and Russia, large-scale conflicts coincided with significant transformations in social structures, marked by the decline of traditional elite roles and the emergence of new professions such as industrial labor and bureaucratic administration. These shifts altered established career trajectories and affected the Occupational Inheritance. Casualty rates were disproportionately concentrated among lower-income groups [77], disrupting community cohesion and weakening occupational continuity. After World War II, many veterans struggled to re-enter the labor market due to skill mismatches and psychological trauma [78], contributing to a measurable decline in the OII. The occupational system was reshaped by forced migrations, the Holocaust, and the imposition of communist policies [79], which dismantled prewar professional structures and redefined occupational pathways. In contrast, countries that remained neutral during major conflicts tended to preserve their occupational structures more effectively. The absence of direct wartime destruction allowed for the maintenance of institutional continuity, including educational systems, professional associations, and labor market stability.

C. Modern Economic Events and Regional Variations

In the late 20th and early 21st centuries, global economic events such as the dot-com bubble (1995–2001) [80] and the global financial crisis (2007–2008) [81] produced divergent OII trends across major economies. We use GDP growth rate data from the World Bank national accounts and OECD National Accounts data files[2] to study its influence on the OII. To examine the relationship between GDP growth and OII, we estimate the following regression model:

$$\text{GDP Growth}_i = \beta_0 + \beta_1 \cdot \text{OII}_i + \varepsilon_i \tag{6}$$

where GDP Growth$_i$ is the annual GDP growth rate of country i, OII$_i$ denotes the Occupational Inheritance Index, β_0 is the intercept, β_1 is the estimated coefficient measuring the effect of OII$_i$ on GDP growth, and ε_i is the error term.

The regression results reported in Table I reveal a statistically significant negative association between the Occupational Inheritance Index (OII) and GDP growth in France, Germany, and Italy. Specifically, the estimated coefficient $\hat{\beta}_1$ is negative and significant at the 5% level ($p < 0.05$), suggesting that

[2]https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG

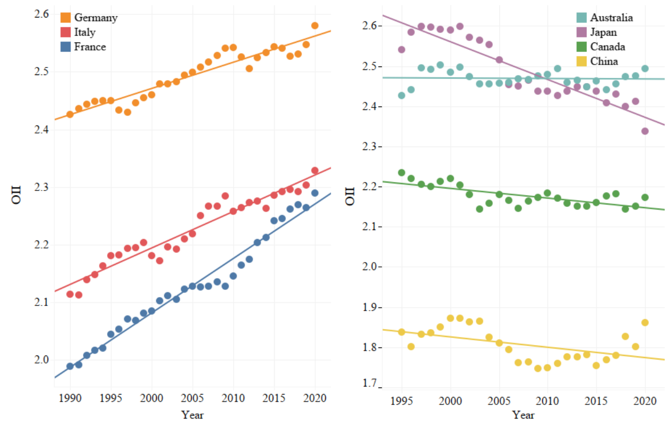

Fig. 9. Historical Trends in OII with Economic Event 1990-2020

higher levels of occupational inheritance are linked to lower economic growth in these countries. This finding implies that entrenched occupational structures may constrain economic dynamism, potentially by limiting intergenerational mobility and reducing the efficient allocation of human capital. In contrast, the relationship between OII and GDP growth is not statistically significant in Australia, Canada, China, and Japan. This heterogeneity suggests that the economic implications of occupational inheritance are context-dependent and may be moderated by institutional, cultural, or developmental factors. For instance, in countries with more flexible labor markets or stronger social safety nets, the adverse effects of occupational persistence may be mitigated.

These variations highlight the differentiated impact of economic transformations on occupational inheritance. Nations with robust industrial bases and stable recovery mechanisms demonstrate less variability, while those undergoing rapid transitions or crises show pronounced fluctuations. For instance, Germany with strong industrial sectors and effective policy responses, managed to maintain relatively stable OII values despite economic upheavals [82]. In contrast, countries like China, which experienced significant economic restructuring and rapid industrialization, saw more pronounced changes in occupational inheritance patterns [83]. This spatiotemporal perspective provides a nuanced understanding of how economic, historical, and geographic factors interact to shape long-term trends in occupational inheritance.

VII. Discussion and Limitations

A. Data Bias

Although our study reveals interesting findings on the relationship between occupational inheritance and kinship, we also acknowledge the potential data bias. First, the notable people on Wikidata may not be representative of the entire population, as they primarily consist of individuals who have achieved significant social, political, or cultural prominence. This overrepresentation of elites and historically significant figures can result in a biased picture of occupational inheritance across all societal strata. We acknowledge this data bias by emphasizing the term "historical social elites" in this study.

Potential countermeasures to mitigate such data bias include integrating multiple biographical datasets beyond Wikidata and developing bias-correction models aligning with census-based benchmarks. We leave these as our future work.

In addition, Western bias is another concern, stemming from the reliance on seven European-language editions of Wikipedia, which may lead to an overrepresentation of Western individuals. Despite this limitation, the dataset still provides a meaningful global perspective, as approximately 30 percent of individuals were identified through non-English language editions. Temporal bias may also affect the data, as more recent figures are better represented than those from earlier historical periods, which can distort long-term trends. Similarly, spatial bias arises from data sparsity in small regions, where only a limited number of social elites are recorded, increasing variance and widening confidence intervals. As a countermeasure, our bootstrapping sampling method mitigates both temporal and spatial biases to some extent. Despite these potential data biases, our study still offers valuable insights into global-scale and long-term occupational inheritance patterns using a computational approach with empirical evidence, which we believe will inspire further investigations in the field of computational social sciences.

B. Interpretation and Complementarity of OCI and OII

This study introduces two complementary indices, the occupation connection index (OCI) and the occupational inheritance index (OII), to capture different dimensions of occupational structure and inheritance of kinship. OCI provides a descriptive statistic of the most prevalent pair occupation. In contrast, OII offers a more inferential perspective by focusing on the overall picture by measuring the conditional co-occurrence of occupations within parent-child relations. However, each index has distinct strengths and limitations that must be considered in its application. OCI is sensitive to the number of occupational categories and can suffer from dilution effects when applied to fine-grained classifications, which limits its usefulness for temporal or cross-sectional trend analysis. OII, while highly sensitive to changes over time and robust to sampling variation, produces values that are context-dependent. As such, comparisons between countries, periods, or relational types should be made with caution, with an emphasis placed on relative trends rather than absolute scores. Building on these characteristics, OCI can be applied to map kinship networks and identify dominant occupation pairs, thereby uncovering micro-level structural patterns. OII can then be used to analyze longitudinal and comparative trends, capturing inheritance dynamics across time and socioeconomic contexts. Combining both indices enables multilevel interpretation: OCI reveals localized pairwise connections, while OII uncovers broader intergenerational persistence. These considerations highlight the importance of aligning methodological choices with research questions to ensure meaningful interpretation and valid conclusions.

VIII. Conclusion

This paper investigates the relationship between occupational inheritance and kinship over human history. We present an empirical study on a large-scale dataset of historical social elites crawled from Wikidata. We introduce computational approaches to systematically analyze the relationship between occupational inheritance and kinship. Specifically, we first propose the Occupation Connection Index (OCI) measuring pairwise occupation connections under a certain social relationship, and then the Occupational Inheritance Index (OII) measuring the overall occupation inheritance across all occupation categories under parent-child relationships only. Subsequently, analyses using OCI reveal the varying impact of kinship over different occupation categories, and analyses using OII show interesting spatiotemporal patterns reflecting key shifts in occupational inheritance that well align with key historical events and societal changes. We hope our study paves the way to understanding the complex interplay between occupational inheritance and kinship from a computational perspective and will inspire further studies in the field of computational social sciences.

In the future, we will further investigate the data bias issues as we acknowledged in this study, and also explore further data to be integrated with Wikidata.

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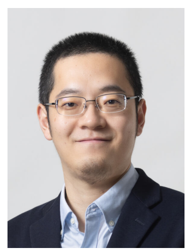

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