Geographic proximity and artistic style similarity: A network analysis approach

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Abstract

This study investigates the relationship between geographic proximity and artistic style similarity among painters using network analysis. We constructed a network representing 2,887 painters connected through shared artistic styles, weighted by geographic distance between their countries of citizenship. Statistical comparison with random models revealed that painters who share styles exhibit significantly smaller geographic distances (mean difference: 2,321 km, $p < 0.05$) than would be expected by random chance. Our analysis demonstrated dense style-sharing connections within Western Europe and significant transcontinental connections spanning Europe and North America. These findings provide quantitative evidence supporting the importance of geographic proximity in artistic knowledge transfer and stylistic development, with implications for understanding the spatial dynamics of creative communities more broadly. The network analytical approach developed in this study enables systematic examination of spatial patterns across large art historical datasets, bridging qualitative scholarship with quantitative methods.

Key words: network analysis, artistic style, geographic proximity, knowledge transfer, cultural diffusion

1 Introduction

The geography of artistic innovation has long been interesting to art historians and social scientists. From the Italian Renaissance workshops of Florence to the bohemian cafés of 19th-century Paris, artistic styles have historically demonstrated distinct geographic clustering (Plog, 1983). While qualitative art historical scholarship has documented this phenomenon extensively (Baxandall, 1988; Bourdieu, 1993; White & White, 1965), quantitative approaches to measuring and analyzing these spatial patterns remain underdeveloped.

This paper introduces a network analysis approach to investigate the relationship between geographic proximity and artistic style similarity among painters. By constructing a network where artists are connected through shared artistic styles and weighting these connections by geographic distance, we quantitatively test the hypothesis that stylistic similarity correlates with geographic proximity. This approach builds on recent innovations in quantifying artistic networks, such as the "coexhibition networks" that capture the movement of art between institutions (Fraiberger et al., 2018), allowing us to systematically analyze patterns across a large corpus of art historical data.

We apply our methodology to a comprehensive dataset of painters spanning various periods, movements, and geographic regions. Through statistical comparison with random network models, we answer the question *"To what extent is geographic proximity associated with artistic style similarity among painters?"* and find a statistically significant relationship between geographic proximity and style sharing. This analysis contributes to our understanding of how artistic knowledge and innovation diffuse through geographic space, with implications for broader questions of cultural transmission and the spatial dynamics of creative communities.

2 Theoretical background and hypotheses

2.1 Geographic proximity and knowledge transfer

The relationship between geographic proximity and knowledge transfer has been extensively studied across multiple disciplines. Economic geography has established that knowledge spillovers tend to be spatially bounded (Jaffe et al., 1993; Audretsch & Feldman, 1996; Breschi, 2001). This spatial limitation is particularly pronounced for tacit knowledge: skills, techniques, and understandings that are difficult to codify and transmit formally (Polanyi, 1966; Gertler & Wolfe, 2006). Chumnangoon et al. (2021) show that proximity affects knowledge circulation indirectly through cognitive processes. Artistic knowledge, encompassing technical skills, aesthetic sensibilities, compositional principles, and stylistic elements, is predominantly tacit in nature (Kimmel, 1983). Historical evidence suggests that transmission mechanisms depend heavily on physical proximity (Wackernagel, 1981), which helps explain why artists' spatial clustering has been a persistent phenomenon across art history.

2.2 Network perspectives on artistic communities

Social network analysis offers powerful tools for studying artistic communities (Giuffre, 1999; Fraiberger et al., 2018). Network approaches view artists as nodes in relationship webs, revealing structural patterns, influential positions, and diffusion pathways. Artistic style similarity functions as an edge between artists, representing shared aesthetic approaches. These connections form pathways for knowledge and innovation diffusion. Integrating geographic data allows analysis of spatial constraints on these processes (ter Wal, 2009). Taylor (2016) emphasize that artists' social networks, including exchanges, collaborations, and sales, are pivotal in the art world's functioning.

Research has identified several network types influencing artistic careers. "Coexhibition networks" track artists' movement between institutions and measure access to elite venues (Fraiberger et al., 2018). De Silva et al. (2017) show that dealers' network size shapes art market outcomes, with direct links and product specialization predicting connections and prices. Network position correlates with creativity and innovation. Perry-Smith and Shalley (2003) proposed a spiralling model where creativity and network position mutually reinforce each other, with weaker ties generally benefiting creativity. Soda and Bizzi (2012) found network relationships can both positively and negatively affect creativity. Baten (2021) demonstrates that artists seeking inspiration from high-performing peers show better performance themselves.

The strength of network analysis lies in its ability to model complex interdependencies while maintaining methodological rigor. By representing artistic communities as networks with geographic attributes, we can systematically test hypotheses about spatial clustering that would be difficult to address through conventional art historical methods alone (Kaufman & Gabler, 2004).

2.3 Spatial patterns in artistic production

Artistic production historically clusters in specific locations—Florence during the Renaissance, Paris in the late 19th century, New York in the mid-20th century

(Florida, 2003; Currid, 2008). These clusters may emerge through multiple mechanisms: institutional infrastructure (academies, museums, galleries), patronage networks, labor market pooling, or knowledge spillovers (Scott, 1997). Currid and Williams (2010) demonstrate that cultural events systematically concentrate in specific urban areas, forming significant clusters with measurable effects. The clustering of similar styles within these broader artistic centres represents a more specific phenomenon. Style clusters may emerge through what Allen (1983) terms "collective invention," where interactions among multiple painters give rise to distinct artistic movements and periods of intense creativity. This process depends on both the exchange of tacit knowledge facilitated by geographic proximity and the establishment of creative communities with shared aesthetic goals.

Based on the theoretical frameworks, we formulate the following hypothesis:

> **H1:** Painters who share artistic styles exhibit significantly smaller geographic distances between them than would be expected by random chance.

The hypothesis can be formally expressed as follows: Let $\bar{d}_E$ represent the mean geographic distance between artists who share styles and $\bar{d}_R$ represent the mean geographic distance between random pairs of artists. We hypothesize that:

$$\bar{d}_E < \bar{d}_R \tag{1}$$

3 Methodology

3.1 Data

This study employs the PainterPalette dataset (Péter, 2023). The original dataset encompasses 10,361 artists with 29 distinct attributes, including biographical information, artistic style classifications, locations of activity, occupations, artistic influences, professional relationships, and quantitative data on artistic output across various styles. For our network analysis, we primarily utilized artist names, citizenship data, and style classifications.

We excluded artists lacking citizenship data (14% of the original dataset) or style classifications (69% of the original dataset). We retained only known styles when "unknown" appeared alongside identifiable classifications, and removed artists with exclusively "unknown" styles. This resulted in 2,887 artists (28% of original dataset) with complete information on citizenship and artistic style. We grouped the 91 individual styles into 13 broader categories based on art historical relationships and stylistic similarities. The complete classification of all 91 styles into these 13 categories is presented in Table 3 in Appendix A1. Moreover, historical political entities no longer existing as sovereign states were mapped to their modern geographic equivalents based on territorial continuity and political succession principles, following established historical geographic conventions (Princeton University, 2025). The 319 original citizenships were reduced to 86 in our final dataset, with successor states assigned for complex historical entities (e.g., Austria for Austria-Hungary, Russia for the Soviet Union). Colonial territories were mapped to current independent nations, ancient civilizations to modern nations encompassing their historical regions, and Wikidata identifiers and URLs to "Unknown." The complete mapping appears in Table 4 (Appendix A2). Each country was represented by its capital city's coordinates from the World Capital GPS dataset (Kaggle, 2025), as capitals typically serve as cultural and administrative centres (Heilbrun, 1992). Code replication instructions can be found in Appendix B.

3.2 Network construction

3.2.1 Artistic similarity network definition

To analyze the relationship between geographic proximity and artistic style similarity, we first constructed a bipartite graph $B = (U, V, E_B)$ where U represents the set of artists, V represents the set of artistic styles, and $E_B \subseteq U \times V$ represents the associations between artists and their styles. Formally, an edge $(u, v) \in E_B$ exists if artist $u \in U$ employs artistic style $v \in V$. We then projected this bipartite graph onto the artist node set to create a unipartite graph $G = (U, E, \mathbf{A})$ where artists are connected if they share at least one artistic style, and $\mathbf{A}$ represents a set of edge attributes. For each pair of artists $i, j \in U$, we defined the set of shared styles as $S_{ij} = \{v \in V : (i, v) \in E_B \wedge (j, v) \in E_B\}$. An edge between artists i and j exists in G if their shared style set is non-empty:

$$E = \{(i, j) : S_{ij} \neq \emptyset, i, j \in U, i \neq j\} \tag{2}$$

For each edge $(i, j) \in E$, we calculated the following edge attributes:

$$s_{ij} = S_{ij} \quad \text{(the set of shared style categories)} \tag{3}$$

$$c_{ij} = |S_{ij}| \quad \text{(the number of shared style categories)} \tag{4}$$

The number of shared style categories c_{ij} provides a measure of stylistic similarity strength between artists in the projected network.

3.2.2 Spatial representation and distance calculation

Each artist $i \in U$ was associated with their country of citizenship C_i. For each pair of connected artists $(i, j) \in E$ in the network, we calculated the great-circle distance d_{ij} between their respective countries' capitals using the Haversine formula:

$$d_{ij} = 2r \arcsin \left(\sqrt{\sin^2 \left(\frac{\phi_j - \phi_i}{2} \right) + \cos(\phi_i) \cos(\phi_j) \sin^2 \left(\frac{\lambda_j - \lambda_i}{2} \right)} \right) \tag{5}$$

where $r = 6371$ km is Earth's radius, ϕ_i and ϕ_j are the latitudes, and λ_i and λ_j are the longitudes of the respective capital cities in radians. We also defined a binary indicator b_{ij} for whether two artists are from the same country:

$$b_{ij} = \begin{cases} 1 & \text{if } C_i = C_j \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

Both the geographic distance d_{ij} and the same-country indicator b_{ij} were stored as additional edge attributes, completing our multi-attributed edge set:

$$\mathbf{A}_{ij} = (s_{ij}, c_{ij}, d_{ij}, b_{ij}) \tag{7}$$

Figure 1 illustrates our network construction methodology.

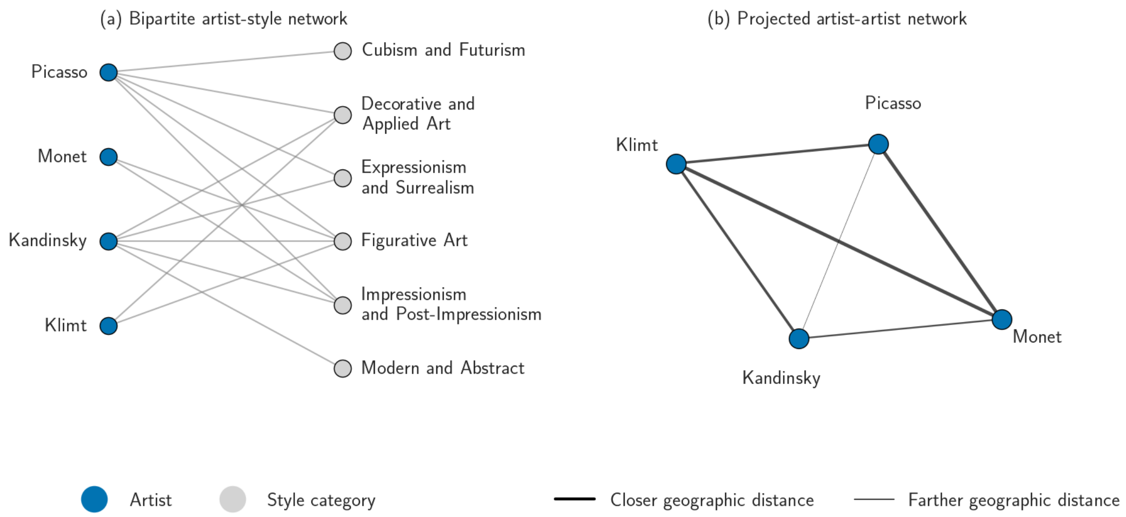

Figure 1: Network construction process. (a) The bipartite artist-style network connects artists and their styles. (b) The projected artist-artist network transforms these relationships into connections between artists, where edges indicate shared artistic styles. Edge thickness represents geographic proximity.

3.3 Analytical approach

To determine whether the observed geographic clustering of artistic styles was statistically significant, we compared our observed network to a random null model. Let $G = (U, E, \mathbf{A})$ be our observed network as defined previously, and let $D_E = \{d_{ij} : (i,j) \in E\}$ be the set of geographic distances in this network.

We constructed a null model by generating a random network $G_R = (U, E_R)$ with the same number of edges as G but with edges formed between randomly selected pairs of artists, independent of their artistic styles. Random artist pairs were sampled without replacement from the set of all artists with known geographic locations. For each edge $(i,j) \in E_R$, we calculated the geographic distance d_{ij}^R using the same Haversine formula described earlier. Let $D_R = \{d_{ij}^R : (i,j) \in E_R\}$ be the set of distances in this random model.

The statistical significance of the difference in mean distances was assessed using a two-sample t-test at a significance level of $\alpha = 0.05$:

$$t = \frac{\bar{d}_E - \bar{d}_R}{\sqrt{\frac{s_E^2}{n_E} + \frac{s_R^2}{n_R}}} \tag{8}$$

where $\bar{d}_E$ and $\bar{d}_R$ are the mean distances in the observed and random networks respectively, s_E^2 and s_R^2 are their variances, and $n_E = |E|$ and $n_R = |E_R|$ are the number of edges in each network.

Additionally, we calculated Cohen's d to quantify the effect size:

$$d = \frac{\bar{d}_E - \bar{d}_R}{\sqrt{\frac{(n_E-1)s_E^2+(n_R-1)s_R^2}{n_E+n_R-2}}} \tag{9}$$

Cohen's d provides a standardized measure of the magnitude of the difference between the observed and random distance distributions. We interpret the effect size according to conventional guidelines: $|d| < 0.2$ indicates a small effect, $0.2 \leq |d| < 0.8$ a medium effect, and $|d| \geq 0.8$ a large effect (Cohen, 1988, 1992).

4 Results

4.1 Network structure and properties

Table 1 presents the key structural properties of the artist style-sharing network. It consists of 2,887 artists (nodes) connected by 896,769 edges representing shared artistic styles. The network has a density of 0.215, meaning that 21.5% of all possible connections exist. On average, each artist shares stylistic connections with 621 others, while the most connected artist shares styles with 2,011 others. The network exhibits a high global clustering coefficient of 0.738, suggesting that artists tend to form densely connected communities. The average path length of 1.73 indicates a "small world" structure, where any two artists in the network are connected through fewer than 2 intermediaries on average. The network consists of 61 connected components, with 84.3% of artists belonging to the largest connected component. This high connectivity suggests that artistic styles form a largely interconnected system of influence, with very few isolated stylistic islands.

Network Metric	**Value**
Number of artists (nodes)	2,887
Number of connections (edges)	896,769
Network density	0.251
Average degree	621.246
Maximum degree	2,011
Global clustering coefficient	0.738
Average path length	1.73
Number of connected components	61
Size of largest component (% of nodes)	2,433 (84.3%)

Table 1: Metrics of the artist style-sharing network

4.2 Geographic overview of artistic style sharing

Figure 2 presents the geographical distribution of artists and the style-sharing connections between them. Each node corresponds to a country, and the size of each node is proportional to the square root of the number of artists from that country. Edges connecting the nodes represent shared artistic styles between countries, with the thickness of these lines logarithmically scaled to show the number of style connections. We observe dense clusters of style-sharing in Western Europe, particularly in France, Germany, Italy, and the United Kingdom, reflecting these regions' historical importance as artistic centres. In addition, we note transcontinental connections spanning Europe and North America, demonstrating the global spread of artistic styles despite geographic barriers.

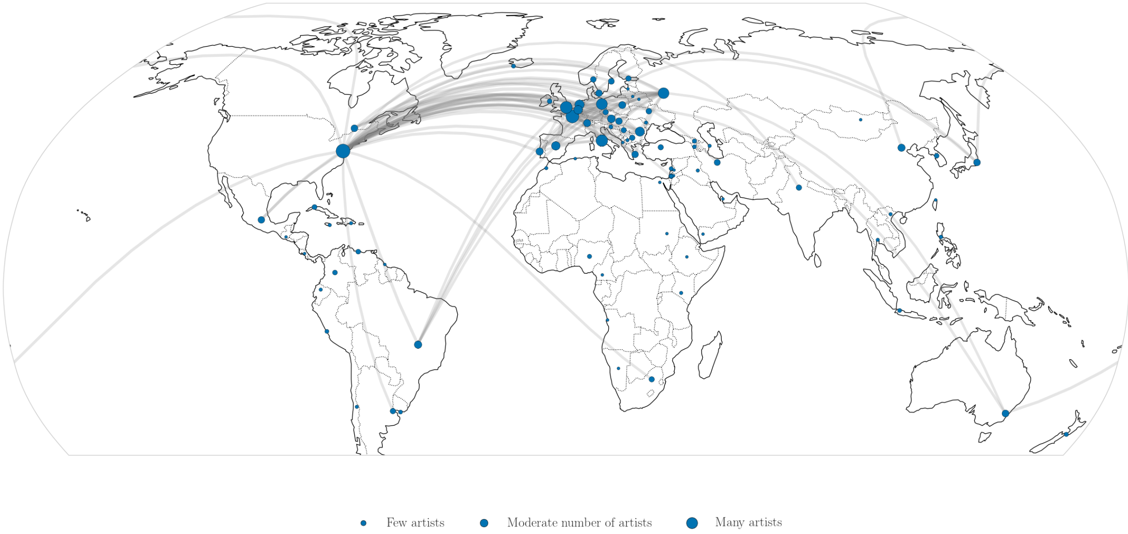

Figure 2: Global distribution of artists and their international shared style connections. Node size represents the number of artists, while grey edges indicate shared artistic styles between countries.

4.3 Statistical analysis of geographic distance and style sharing

Our analysis reveals a statistically significant relationship between geographic proximity and artistic style similarity. As shown in Table 2, the mean geographic distance between artists who share styles (4,516 km) is 2,321 km less than the mean distance between random artist pairs (6,837 km). This difference is statistically significant ($p < 0.05$), demonstrating that artists who share stylistic approaches tend to be geographically closer than would be expected by random chance. The effect size (Cohen's $d = 0.5379$) indicates that this effect is medium in magnitude. Further, Figure 3 visualizes that the distributions of distances for both style-sharing and random pairs exhibit similar bimodal patterns, with peaks at approximately 0-1,000 km (likely representing intra-continental distances) and 6,000-8,000 km (likely representing inter-continental distances). The leftward shift of the style-sharing distribution indicates the tendency toward smaller distances.

Metric	Style-sharing pairs	Random pairs
Mean distance (km)	4,516	6,837
Difference in means (km)	2,321	
t-statistic	-477	
p-value	0.000	
Effect size (Cohen's d)	0.5379	

Table 2: Statistical comparison of geographic distances between style-sharing and random artist pairs. The mean difference is 2,321 km and statistically significant.

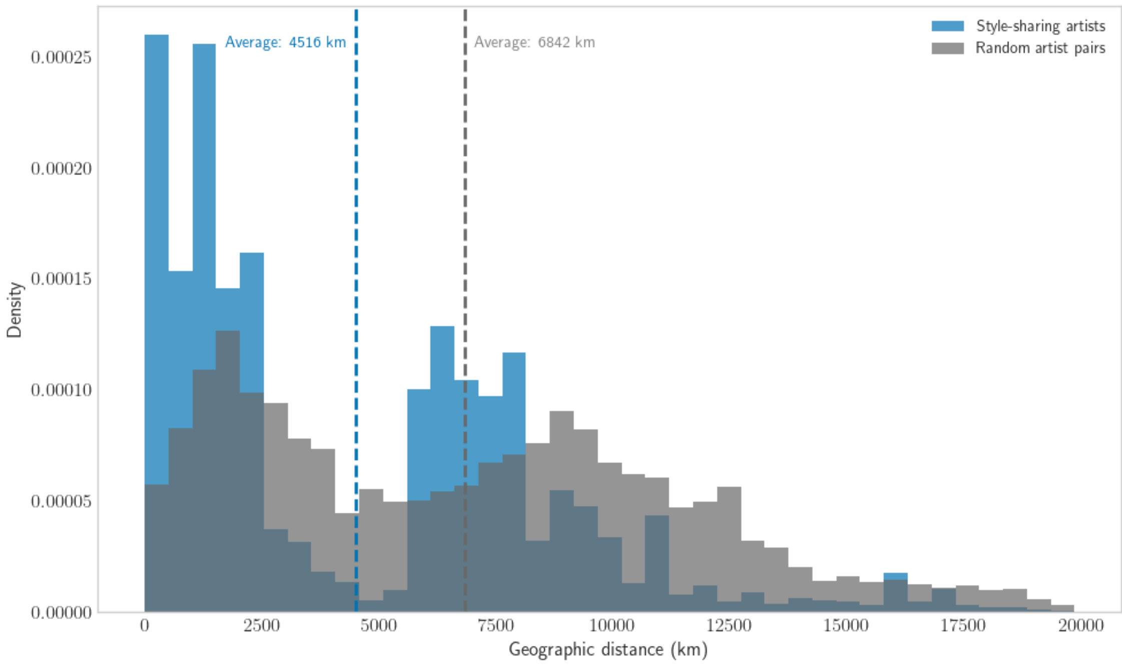

Figure 3: Distribution of geographic distances between artist pairs in the style-sharing network compared to randomly connected artist pairs. The x-axis shows distance in kilometres, and the y-axis shows density. The leftward shift in the style-sharing distribution demonstrates the tendency for artists sharing styles to be geographically closer than random pairs.

5 Discussion

5.1 Findings and contributions

Our findings provide empirical evidence for the relationship between geographic proximity and artistic style similarity. The significant difference in geographic distance between style-sharing artists compared to random pairs (2,321 km, $p < 0.05$, Cohen's $d = 0.5379$) confirms our hypothesis that painters sharing styles tend to be geographically closer. This quantifies spatial clustering in artistic styles while offering methodological insights into how artistic knowledge diffuses through space. The observed spatial patterns reveal that while our network demonstrates connectivity across regions (shown by the distance distribution with peaks at both intra-continental and inter-continental distances), the significant pull toward smaller distances indicates proximity remains an important facilitator of stylistic exchange. This aligns with Meyners et al. (2017)'s argument that spatial proximity mitigates differences between artists, and supports Boschma (2005)'s framework where geographic proximity complements other dimensions in knowledge transfer.

Our findings contribute to innovation geography more broadly. The network structure, characterized by high clustering coefficient (0.738) and dense connectivity (density 0.215), demonstrates how artistic knowledge functions as "collective invention" (Allen, 1983), where interactions generate distinct movements. This relates to Nakamura and Saito (2023)'s finding that influencer-guided transmission better explains artistic style evolution than community-guided models, suggesting the importance of key individuals in style diffusion. The historical implications are significant. Major artistic centres in our visualization match documented historical art capitals, with Western Europe showing particularly dense style-sharing connections. Yet numerous intercontinental edges indicate artistic influences regularly transcended distances, confirming Currid and Williams (2010)'s observations about cultural events concentrating in specific nodes while maintaining broader influence networks. This pattern resonates with Zheng et al. (2024)'s finding that while spatial proximity is not necessary for maintaining artistic networks, it remains crucial for enhancing artists' influence and prestige. These findings have theoretical implications for understanding creative economies, suggesting that even as digital technologies increasingly facilitate remote collaboration, the geographic dimension of creativity remains significant. Policy implications include the potential value of supporting artistic clusters and mobility programs that facilitate face-to-face knowledge transfer among artists, potentially creating conditions for new artistic innovations through strategic geographic connections.

5.2 Limitations and future research

Our study faces several methodological and data-related constraints. Representing artists by their country of citizenship simplifies the complex spatial dynamics of artistic careers, as artists might be mobile throughout their lives. Our static analytical approach does not account for temporal dynamics in both artistic styles and geographic locations. Hence, future research could include time-series analysis examining how the relationship between proximity and style has evolved across different periods, tracking artists' movements between artistic centres and their stylistic evolutions. Further, the aggregation of 91 individual styles into 13 broader categories, while necessary for analysis, may obscure nuanced patterns and artificially increase network connectivity. Further examination could include style-specific geographic analysis and investigate whether different artistic movements show varying degrees of geographic clustering. Lastly, our methodology assumes contemporary national boundaries and capital cities as proxies for historical artistic centres, which may inadequately represent historical geographic realities, particularly for artists active before the modern nation-state system. More complex spatial modelling approaches could incorporate multiple dimensions of proximity, including social, cognitive, and institutional, to develop a more comprehensive model of artistic influence networks.

6 Conclusion

Our study provides empirical evidence for the relationship between geographic proximity and artistic style similarity. Through network analysis of 2,887 painters spanning diverse historical periods and regions, we established that artists who share stylistic approaches tend to be geographically closer than would be expected by random chance (mean difference: 2,321 km, $p < 0.05$). This finding quantifies the spatial clustering of artistic styles documented in qualitative art historical scholarship, suggesting that physical proximity was an important facilitator of stylistic exchange despite global artistic diffusion. By integrating geographic data into style-sharing networks, we provide a framework for examining spatial patterns across large datasets, enabling quantitative testing of hypotheses that traditional art historical methods struggle to address at scale. The geography of artistic innovation revealed by our analysis contributes to broader discussions of cultural transmission, creative communities, and knowledge spillovers, with potential applications for understanding contemporary creative economies in an increasingly digital world.

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A Appendix A: Data

A.1 Artistic style categorization

Style category	Included styles
Figurative Art	Neo-Figurative Art, American Realism, Naturalism, Hyper-Realism, Photorealism, Classical Realism, Contemporary Realism, Realism
Impressionism & Post-Impressionism	Neo-Impressionism, Pointillism, Post-Impressionism, Fauvism, Impressionism
Expressionism & Surrealism	Neo-Expressionism, Expressionism, Surrealism, Abstract Expressionism, Fantastic Realism, Magic Realism, Figurative Expressionism
Modern & Abstract	Abstract Art, Modernism, Minimalism, Neo-Minimalism, Geometric, Op Art, Abstract Expressionism, Neo-Geo, Post-Minimalism, Neoplasticism
Renaissance & Classical	Proto Renaissance, Classicism, Early Renaissance, High Renaissance, Renaissance, Baroque, Neo-Rococo, Neo-Baroque
Cubism & Futurism	Cubism, Synthetic Cubism, Analytical Cubism, Cubo-Expressionism, Mechanistic Cubism, Cubo-Futurism, Futurism
Pop & Contemporary Art	Pop Art, Neo-Pop Art, Street art, Graffiti Art, New media art, Contemporary, New European Painting
Social & Political Art	Social Realism, Socialist Realism, Feminist Art, Postcolonial art, Environmental (Land) Art, Junk Art, Excessivism
Decorative & Applied Art	Art Deco, Rococo, Biedermeier, Art Nouveau (Modern), Neo-Romanticism, Fiber art, Mail Art
Other Styles	Sumi-e (Suiboku-ga), Shin-hanga, Gongbi, Ukiyo-e, Zen, Mosan art, Joseon Dynasty, Safavid Period, Ming Dynasty, Mannerism (Late Renaissance), Mannerism
Dada & Conceptual	Dada, Conceptual Art, Art Informel, Performance Art, Automatic Painting, Existential Art, Stuckism, Transavantgarde
Decorative & Stylized	Synthetism, Cloisonnism, Rayonism, Lyrical Abstraction, Tonalism, Pictorialism, New Realism
Others	Kitsch, Neo-Byzantine, Neo-Concretism, Neo-Dada, Neo-Futurism, Superflat, Stuckism, Queer art, Precisionism

Table 3: Complete classification of all 91 artistic styles by category. Style categorization based on art historical relationships and stylistic similarities.

A.2 Historical country mapping

Historical political entity	Modern equivalent
Europe	
Western Europe	
Prussia; Brandenburg-Prussia; Kingdom of Prussia; Anhalt-Köthen; Duchy of Anhalt; Electorate of Bavaria; Kingdom of Bavaria; Duchy of Holstein; Electorate of Hesse; Landgraviate of Hesse-Kassel; Frankfurt; Free Imperial City of Nuremberg; Grand Duchy of Baden; Grand Duchy of Mecklenburg-Schwerin; Duchy of Nassau; Duchy of Saxe-Meiningen; Kingdom of Saxony; Kingdom of Hanover; Hamburg; Lübeck; Principality of Reuss-Gera; Principality of Waldeck and Pyrmont; Weimar Republic; German Empire; German Reich; Holy Roman Empire; West Germany; German Democratic Republic; Solms-Braunfels; Kingdom of Württemberg; Roman Catholic Diocese of Halberstadt; Goths; Swedish Pomerania; Prince-Bishopric of Fulda	Germany
Italian Republic; Kingdom of Naples; Kingdom of Sicily; Kingdom of the Two Sicilies; Kingdom of Sardinia; Duchy of Savoy; Republic of Venice; Republic of Genoa; Republic of Florence; Florence; Duchy of Florence; Grand Duchy of Tuscany; Duchy of Ferrara; Duchy of Mantua; Duchy of Milan; Duchy of Modena and Reggio; Duchy of Urbino; Republic of Siena; Papal States; Cremona; Lordship of Bologna; Province of Bologna; Kingdom of Lombardy–Venetia; Kingdom of Italy; Signoria di Correggio; Ancient Rome; Prince-Bishopric of Trent	Italy
Kingdom of England; England; Kingdom of Scotland; Scotland; Kingdom of Great Britain; British Empire; United Kingdom of Great Britain and Ireland; Cornwall; Wales	United Kingdom
Kingdom of Ireland	Ireland
Kingdom of France; French constitutional monarchy; Francia; Duchy of Burgundy; County of Burgundy; Republic of Mulhouse; Duchy of Lorraine	France
Kingdom of the Netherlands; United Kingdom of the Netherlands; Dutch Republic; Batavian Republic; Batavian Commonwealth; Kingdom of Holland; County of Holland; Northern Low Countries; Seventeen Provinces; Low Countries	Netherlands
Southern Netherlands; Austrian Netherlands; Belgian Netherlands; Habsburg Netherlands; Spanish Netherlands; County of Flanders; Duchy of Brabant; Burgundian Netherlands; Prince-Bishopric of Liège	Belgium
Three Leagues; Prince-Bishopric of Basel; Republic of Geneva	Switzerland

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Table 4 – continued from previous page

Historical political entity	**Modern equivalent**
Kingdom of Denmark	Denmark
Southern Europe	
Kingdom of Spain; Crown of Castile; New Castile; Kingdom of Aragon; Crown of Aragon; Kingdom of León; Kingdom of Granada; Principality of Catalonia; Hispanic Monarchy	Spain
Kingdom of Portugal	Portugal
Classical Athens; Delian League; Second Athenian League; Sparta; Third Hellenic Republic; Kingdom of Greece	Greece
Central and Eastern Europe	
Archduchy of Austria; Austrian Empire; Habsburg monarchy; Austria-Hungary; Cisleithania	Austria
Kingdom of Hungary	Hungary
Congress Poland; Second Polish Republic; Polish People's Republic; Polish–Lithuanian Commonwealth	Poland
Kingdom of Serbia; Principality of Serbia; Kingdom of Yugoslavia; Yugoslavia; Socialist Federal Republic of Yugoslavia; Federal People's Republic of Yugoslavia; Kingdom of Serbs, Croats and Slovenes	Serbia
Kingdom of Romania; Romanian People's Republic; Socialist Republic of Romania; Wallachia	Romania
Livonia Governorate; Latvian Socialist Soviet Republic	Latvia
Ukrainian People's Republic; Ukrainian State; West Ukrainian People's Republic; Cossack Hetmanate	Ukraine
Belarusian People's Republic	Belarus
Grand Principality of Finland	Finland
Principality of Montenegro	Montenegro
First Republic of Armenia; Armenian Soviet Socialist Republic; Armenian Kingdom of Cilicia	Armenia
Azerbaijan Democratic Republic	Azerbaijan
Protectorate of Bohemia and Moravia; Second Czechoslovak Republic; Czechoslovakia	Czech Republic
North Macedonia	Macedonia
Russian Empire; Soviet Union; Russian Socialist Federative Soviet Republic; Tsardom of Russia; Grand Principality of Moscow	Russia
Americas	
British North America; Lower Canada; Province of Canada	Canada
New Spain	Mexico
Colonial Brazil	Brazil
Viceroyalty of Peru	Peru

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Table 4 – continued from previous page

Historical political entity	**Modern equivalent**
Asia	
East Asia	
Qing dynasty; Ming dynasty; Song dynasty; Northern Song dynasty; Southern Song dynasty; Tang dynasty; Yuan dynasty; Later Zhou dynasty; Republic of China (1912–1949); People's Republic of China; Szechwan Military Government; Wey	China
Empire of Japan; Tokugawa shogunate; Ashikaga shogunate	Japan
Joseon; Korea; Korea under Japanese rule	South Korea
South Asia	
British Raj; Dominion of India; Mughal Empire; Kingdom of Thiruvithamkoor; Kota State	India
Southeast Asia	
Dutch East Indies	Indonesia
Middle East and Western Asia	
Ottoman Empire; Byzantine Empire	Turkey
Jalayirid Sultanate; Abbasid Caliphate	Iraq
Safavid Iran; Interim Government of Iran; Zand dynasty	Iran
French mandate of Lebanon	Lebanon
State of Palestine	Palestine
Northern Cyprus	Cyprus
Africa	
Ancient Egypt; Republic of Egypt	Egypt
French protectorate of Tunisia	Tunisia
Union of South Africa; Zulu Kingdom	South Africa
Oceania	
Colony of New South Wales	Australia
Colony of New Zealand	New Zealand
Other	
statelessness; Q118177298; Q25934646; Q3715870; http://www.wikidata.org/.well-known/genid/a1a64316e3d270ec704ff940f674a446	Unknown

Table 4: Mapping of historical political entities to modern countries. This mapping follows established historical geographic conventions based on territorial continuity and political succession principles. Historical political entities were mapped to modern nation-states to facilitate spatial analysis of artistic influence networks.