<u>Cultural Cartographies:</u>
<u>A Web-Analysis of Gaps in Cultural Infrastructure & Data in London's Creative Network</u>

Programme Module	CASA0003 Group Project Data Visualization Report
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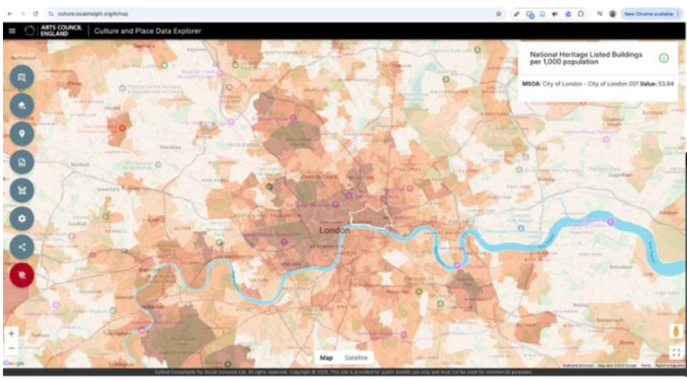
1. Introduction

City Network Concept
This project explores the concept of cultural city networks, focusing on London as a case study. Cultural city networks refer to the interlinked infrastructures, institutions, and spaces through which cultural production, consumption, and participation are facilitated across urban areas. The networked nature of a city's cultural landscape provides crucial insights into access, sustainability, and inclusivity of cultural life. By adopting a spatial-temporal perspective, our web-based analysis seeks to interrogate whether access to London's cultural infrastructure has remained equitable across both space and time. This investigation aims to move beyond static visualisations by incorporating change and transition, acknowledging that the city is not a fixed entity but one in continual flux.



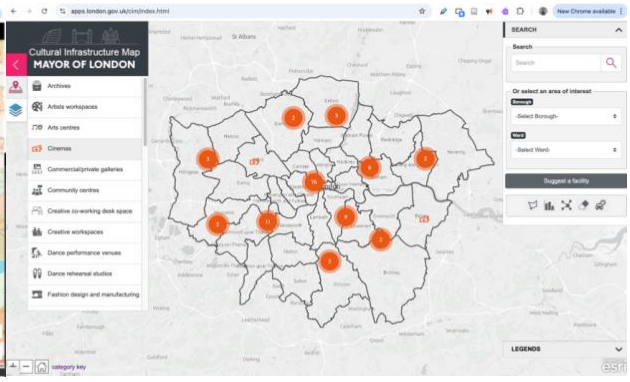


Figure 1 (Right): Mayor of London Cultural Infrastructure Map (london.gov.uk)
Figure 2 (Left): Arts Council England: Culture and Place Data Explorer Map (Localinsight.org, 2024)

Policy and Context
A number of existing digital platforms offer visualisations of London's cultural infrastructure, such as the *Arts Council England: Culture and Place Data Explorer Map* and the *Mayor of London's Cultural Infrastructure Maps* (2018 and 2023). However, these tools primarily present static representations and do not adequately account for transformations in the city's cultural networks over time. This limitation is especially pressing in the context of recent socio-economic and political disruptions—namely the COVID-19 pandemic and lockdowns, Brexit, financial instability, and a sustained period of austerity. Culture in the UK, and particularly in London, has increasingly been designated as "at risk". Studeies already state that the economic impact of COVID-19 on high streets and cultural venues has been uneven, with some areas experiencing significant decline while others showed resilience (Hill and Cheshire, 2022).

Figure 3: Cultural Cartographies Visualizations

The Mayor of London's 2023 data note (We Made That, 2023) highlights the urgency of this issue: between 2018 and 2023, London saw a 10% closure rate in cultural spaces, with a net loss of 2% despite new openings. Spaces of cultural consumption, where the public actively experiences culture, experienced a greater net loss of 3%. While the Greater London Authority (GLA) has collected valuable data, this information has not been extensively studied or visualised beyond summary reporting. This gap underscores the need for our digital project, which leverages this underexplored dataset to illuminate shifts in London's cultural landscape and to assess the equity of cultural access post-COVID and in the wake of wider systemic challenges.

2. Methodology

Data	**Source**
2018 Cultural Infrastructure Data Greater London Authority (GLA)	London Datastore
2023 Cultural Infrastructure Data Greater London Authority (GLA)	London Datastore
Cultural Infrastructure and Creative Economy Data (2022 Report)	World Cities Culture Forum
2017 – 2025 Open Street Map Scraped Data	Overpass Turbo

Table 1: Cultural Cartography Data and Sources

Technical Process
The project began with the Greater London Authority (GLA)'s Cultural Infrastructure Dataset, which provided a foundational but incomplete record of venues. We supplemented this with OpenStreetMap (OSM) data extracted via Overpass Turbo, capturing smaller, community-led spaces often excluded from official datasets.

Data processing involved Excel for initial normalisation (e.g., standardising venue categories, geolocations) and R for deeper cleaning (removing duplicates, resolving inconsistencies). Acknowledging that datasets reflect the biases of their creators, we incorporated principles from Data Feminism, blending quantitative analysis with qualitative insights because "…bodies are missing from the data we collect... (Klein and D'Ignazio, 2020)" from interviews and community engagement to challenge dominant narratives.

For visualisation, Adobe Illustrator and Photoshop were used to produce infographics, balancing clarity with aesthetic coherence. Collaboration between the two team members was structured around GitHub: one maintained the primary repository, while the other forked and cloned a local copy. Stylistic decisions were iterative—rather than merging conflicting versions, we compared both side-by-side, discussing trade-offs before agreeing on next steps. This ensured transparency and allowed us to critically assess design choices.

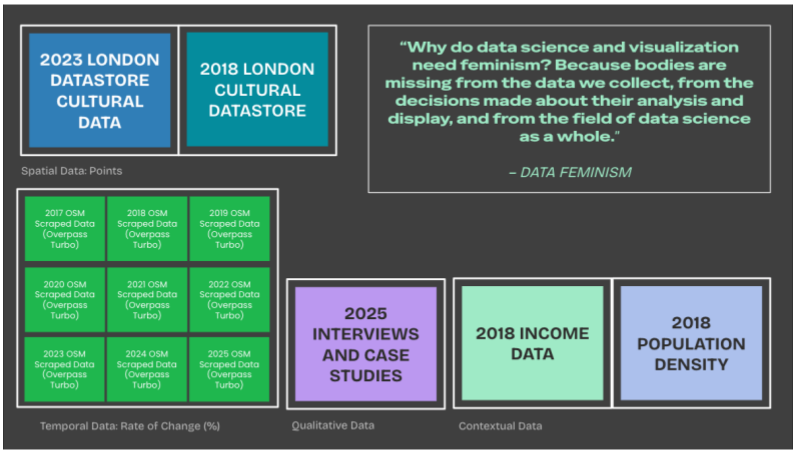


Figure 4: Cultural Cartographies Data Strategy Diagram

Data Strategy

As stated above, our investigation began with the intention of using the Greater London Authority's (GLA) Cultural Infrastructure datasets, which constitute the only verified and authoritative source of cultural data for London. To ensure clarity and accessibility in our visual analysis, we refined our focus to Cultural Consumption spaces—those where the public actively engages with cultural content. This decision aimed to produce manageable insights tailored to stakeholders such as local councils, funding bodies, and members of the public seeking equitable access to cultural infrastructure.

However, significant challenges emerged in the comparability and consistency of the 2018 and 2023 datasets. During the mapping process, we discovered that several datasets had either been removed or had undergone definitional changes between the two periods. This inconsistency meant that the datasets effectively depicted two different cultural networks, limiting the feasibility of drawing robust conclusions about changes over time. Furthermore, concerns about data reliability became apparent when the 2018 dataset reported zero cinemas in the London boroughs of Sutton and Waltham Forest—an error, as multiple cinema venues were verifiably in operation in both boroughs during that year. These inaccuracies necessitated a broader methodological approach to strengthen our findings.

Data Feminism

Recognising the limitations of relying solely on official data, we adopted a Data Feminism framework to expand the scope of our analysis. Data feminism merges intersectional feminism with critical data studies, advocating for the use of both qualitative and quantitative methods to address structural inequalities (Klein and D'Ignazio, 2020). This approach acknowledges that no dataset is neutral and that multiple sources of knowledge must be engaged to create a completer and more equitable picture. Consequently, we supplemented the GLA datasets with alternative sources, including scraped data from OpenStreetMap and Overpass Turbo (covering the years 2017–2025), cultural datasets from the World Cities Culture Forum, and qualitative data from interviews and community engagement.

Although scraped data lacks verification and may not be accurate in absolute terms, it provides the only available proxy for detecting trends over time. To address this, we used the *rate of change* rather than raw values, ensuring the data serves as an indicator rather than an authoritative count. This allowed both the official and scraped datasets to complement one another—each serving distinct but valuable analytical purposes. Lastly, we normalised the data using borough-level population density (per hectare) and weekly household income, enabling a more contextualised interpretation of equitable cultural access across London.

Design Theory
This project applies Munzner and Maguire's (2015, Chapter 2) theoretical framework to guide visualisation design, ensuring techniques align with user needs and data characteristics. Their task taxonomy—categorising visualisation tasks by user goals and data dimensions—helps select appropriate representations while accounting for cognitive biases. Given our varied audience (general public, policymakers, researchers) and heterogeneous datasets, intentional visualisation choices were imperative.

Munzner and Maguire's principles, though often implemented in R, are transferable to HTML-based interactive designs. By integrating HCI theories, we enhanced usability, ensuring visualisations support effective decision-making. This structured approach balanced clarity and analytical depth, catering to diverse user expertise while maintaining accessibility.

3. Complete Website Design Decisions

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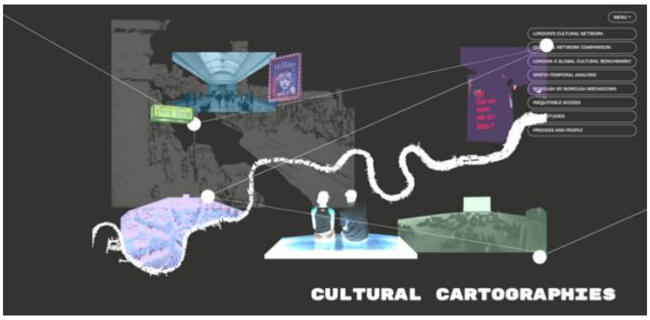
	

Figure 5: Cultural Cartography's Website Landing Page

Design and Interactivity
The website employs a scroll-through narrative structure, guiding users through visualisations and information in a deliberate sequence to enhance comprehension and engagement. While this linear flow encourages exploration, a collapsible menu and navigation buttons in the top-right corner provide flexibility, allowing users to jump between sections as desired. To minimise visual clutter during data interaction, the collapsible menu enhances focus on the content. A vibrant dark theme—also referred to as a "neon UI"—has been adopted, characterised by high-contrast, high-saturation neon hues on a dark background.

The landing page is designed to make a strong first impression. It features a bold title that functions almost as a logo, accompanied by a custom collage that introduces the core theme of the site. This visual includes symbolic network nodes and connecting lines—suggesting cultural connectivity—overlaid with the iconic shape of the Thames River and recognisable London cultural landmarks, immediately situating the project within its geographic and thematic context.

Subsequent sections are designed to gradually unfold the narrative. Each section pairs concise, explanatory text with appropriate data visualisations—ranging from static comparisons to interactive elements—that highlight trends, correlations, or insights relevant to the research focus. The textual content acts as a guide, helping users interpret visual data and understand its implications in the wider cultural context.

Throughout, the website strikes a deliberate balance between interactivity, animation, and data visualisation as art. This mixed approach is intended to maintain user engagement, offering pathways for exploration without overwhelming visitors with dense information or excessive technical detail. By weaving together storytelling, design, and interactivity, the website aspires to create an accessible yet thought-provoking platform for exploring London's cultural data landscape.

Typography and spacing have been carefully chosen to support readability and tone. The two main typefaces—Bricolage Grotesque for headlines and EB Garamond for body text—create a dynamic but legible visual hierarchy, aligning with the balance between innovation and clarity that the site aims to achieve. Generous spacing between sections ensures a visually digestible experience while maintaining overall coherence across pages.

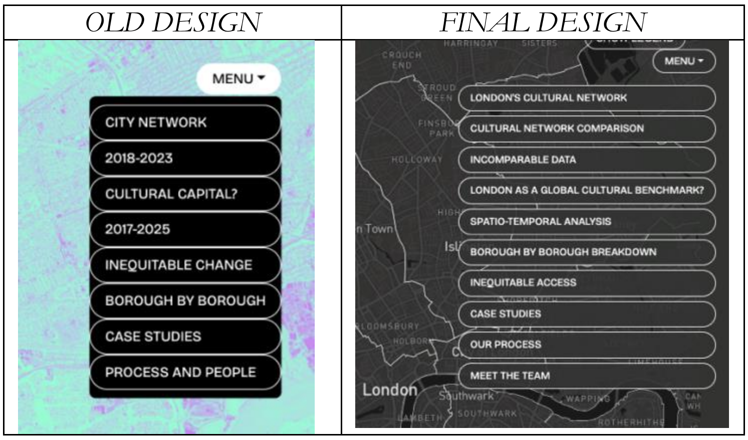


Figure 6: Drop Down Menu Design Iterations

Challenges and Discussion
One of the key decisions in this project was to structure each visualisation as a separate .html file and embed them into the main index.html. This modular approach offered better flexibility in chaining different visualisations and allowed for smoother collaboration, as components could be worked on independently without breaking the full layout.

However, this also introduced several challenges. Aligning and styling the various charts and visualisations so they fit seamlessly within the website's structure required a lot of tweaking. Ensuring consistent dimensions, responsive behavior, and smooth transitions between sections was a highly iterative and time-consuming process. The goal was for the experience to feel cohesive and intentional rather than fragmented.

Creating smooth and logical transitions between the website's sections was particularly challenging. Much of this work involved mapping out a clear narrative structure that would make sense to users, guiding them step-by-step through the data story. This part of the process took many rounds of discussion and revision during team meetings to arrive at a final storyline that felt both informative and intuitive.

From a technical standpoint, the project had its limitations. The final website is not fully optimised—there are noticeable performance issues, especially regarding loading times and efficiency. With more time and a wider scope, optimising scripts, compressing media, and improving responsiveness would be essential next steps.

Maintaining consistency in visual design—fonts, spacing, button styles, and colour palettes—also proved to be an unexpectedly tedious task. Each design decision needed to reinforce the clarity of the message while also fitting into a unified aesthetic system.

Despite the challenges, the iterative process of prototyping, testing, and refining was deeply valuable. It highlighted how even small design decisions can have a significant impact on usability, user experience, and the effectiveness of data storytelling.

4. Webpage Specific Design Decisions

OLD DESIGN	*FINAL DESIGN*
	

Figure 7: City Networks Information Visualization Infographic

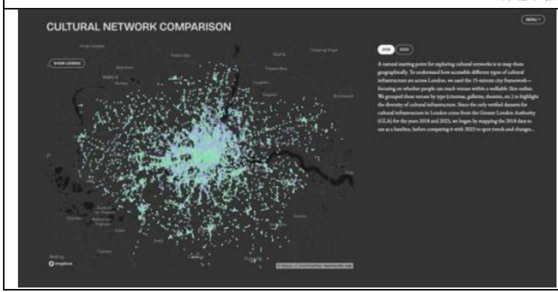
Visualization Name:	City Networks Information Visualizations
Contributor:	Maheer
Data Used:	World Cities Culture Forum
Data Type:	Items and Attributes
Attribute Type:	Quantitative
Ordering Type:	Sequential
Dataset Type:	Table
Visualization Method:	Stylised Static Collage Chart
Graph/Chart:	Bar Chart, Pie Chart and Line Graph

Table 2: City Networks Information Visualization Infographic – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity
The visualisations employ clean, simple graphs collaged against iconic London cultural landmarks, such as Shakespeare's Globe, the National Gallery, and the National Theatre, creating a visually engaging juxtaposition. Eye-catching statistics are highlighted using colour-filled styles, which Javed, McDonnel, and Elmqvist (2010) argue are particularly effective for trend discrimination and value identification. This approach effectively showcases proportions, extremes, and trends, ensuring clarity while maintaining aesthetic appeal.

Challenges and Discussion
A key challenge was balancing interactivity with simplicity. The team debated whether to prioritise interactive features or static, stylised designs, ultimately opting for clarity over complexity. To ensure data inferability, raw figures were displayed in text form, mitigating potential misinterpretation.

FINAL DESIGN



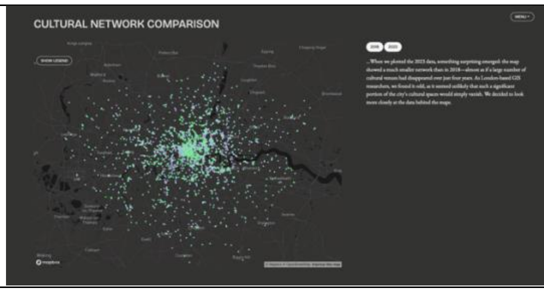


Figure 8: 2018 vs 2023 Spatial Network Map

Visualization Name:	2018 vs 2023 Spatial Network Map
Contributor:	Hania
Data Used:	2023 and 2018 Cultural Infrastructure Data Greater London Authority (GLA)
Data Type:	Items and Links
Attribute Type:	Categorical
Ordering Type:	Cyclical
Dataset Type:	Geometry
Visualization Method:	Maps
Graph/Chart:	Network Map

Table 3: 2018 vs 2023 Spatial Network Map – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity
This visualisation presents a Spatial Network Map of Greater London, comparing cultural infrastructure data from 2018 and 2023. All identified cultural sites were included to provide a comprehensive overview of the city's cultural landscape before refining the investigation's focus. Cultural sites are represented as colour-coded pins according to their typology (e.g., theatre, cinema, gallery). To simulate a networked urban model aligned we employed the "15-minute city" which emphasizes proximity to essential services, including cultural amenities such as museums, theaters, and community centers, which are integral to urban life (Akrami, Sliwa & Rynning 2024). We achieved this by connecting pins of the same typology within a 1km radius, forming undirected, cyclical network structures (Lee et al., 2006). This approach illustrates localised cultural clusters while accommodating the study's need for flexible, interconnected relationships rather than hierarchical tree structures.

The connections between nodes use variable line thickness, a method proven most effective for communicating additional attributes in network diagrams (Holten and Wijk, 2009). This design choice enhances the visualisation by emphasising cluster density and connectivity strength. A toggle feature allows users to switch between the 2018 and 2023 datasets, enabling clear comparison and highlighting areas of cultural growth or decline. This functionality is crucial for observing the spatial implications of network shrinkage and identifying boroughs most affected by changes over time. By integrating these analytical and visual techniques, the map provides insights into the density, accessibility, and evolution of London's cultural resources.

Challenges and Discussion
We considered connecting all cultural sites irrespective of typology but ultimately chose to distinguish networks by cultural type. This decision enables users to identify specific cultural deserts and assess the balance of cultural provision across London. Given the density and volume of data, the networks are presented in a static format. While this limits close-up interaction and detailed spatial analysis, the visualisation effectively communicates its primary purpose: to illustrate the significant reduction in cultural infrastructure between 2018 and 2023. This approach ensures clarity in highlighting the overall decline in London's cultural network over time.

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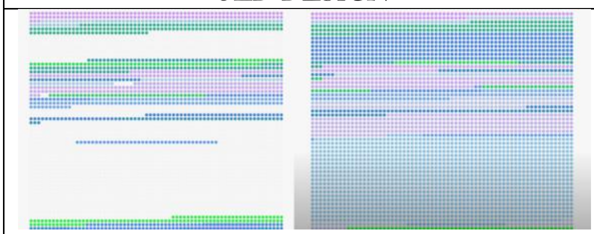	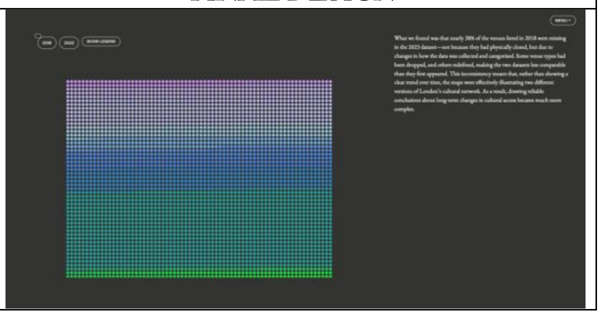

Figure 9: Missing Data Dot Diagram

Visualization Name:	Missing Data Dot Diagram
Contributor:	Hania
Data Used:	2023 and 2018 Cultural Infrastructure Data Greater London Authority (GLA)
Data Type:	Items and Attributes
Attribute Type:	Categorical
Ordering Type:	Sequential
Dataset Type:	Table
Visualization Method:	Categorical/ Hierarchical
Graph/Chart:	Network Map

Table 4: Missing Data Dot Diagram – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity
The goal behind this visualisation was to create something original and clean rather than relying on pre-made chart templates. The dot diagram was intentionally kept minimalistic, with a single purpose: to highlight the disappearance of data between two time points—specifically, the absence of entries in the 2023 dataset compared to 2018.

Unlike traditional charts where colour differentiation aids in comparing categories, this visualisation purposefully uses subtle and non-distinct colours. This design choice reinforces the core message: the emphasis is not on contrasting data types but on drawing attention to the missing or incomplete data.

Challenges and Discussion
An important design consideration was whether to include a legend. Initially, it was unclear if one was necessary, as the visualisation's simplicity could speak for itself. However, upon reflection, it became apparent that some level of explanatory detail improves user understanding—especially for audiences unfamiliar with the dataset. Therefore, a minimal legend was included to provide necessary context without overwhelming the design.

Interactivity also underwent several iterations. The first version used a single toggle button that switched between 2018 and 2023 views (e.g. "Switch to 2023" → "Switch to 2018"). While this method was efficient, it caused uncertainty about the currently displayed year. To resolve this, two separate buttons were introduced—one for each dataset—with active highlighting to clearly indicate which view the user is seeing. This change significantly improved clarity and user experience, especially when navigating between the datasets.

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	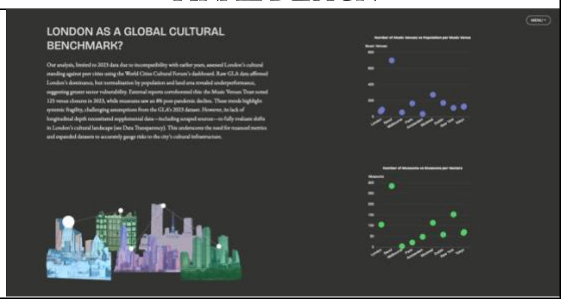

Figure 10: Normalised Cultural Access in Global Leading Cities: Music and Museum Availability

Visualization Name:	Normalised Cultural Access in Global Leading Cities: Music and Museum Availability
Contributor:	Maheer
Data Used:	World Cities Cultural Form
Data Type:	Items and Attributes
Attribute Type:	Categorical
Ordering Type:	Sequential
Dataset Type:	Table
Visualization Method:	Categorical/ Hierarchical
Graph/Chart:	Bar Graph to Scatter plot

Table 5: Global Leading Cities – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity
We initially used bar charts to display the volume of cultural assets per city, as their clear alignment aids perceptual comparison (Yau, 2011) and effectively highlights proportional differences (Munzner, 2015). However, once the data was normalised, a dot/ scatter plot better represented the multivariate nature of our dataset (Yau, 2012, Chapter 7), allowing users to observe shifts in normalised values more precisely.

Challenges and Discussion
While the graphs revealed general trends, they lacked sufficient visual impact to be the page's focal point. To maintain engagement, we introduced a "city skyline collage", which risked diverting attention from the charts. However, since the bar charts were primarily conversation-starters rather than the main analytical focus, this trade-off was justified.

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	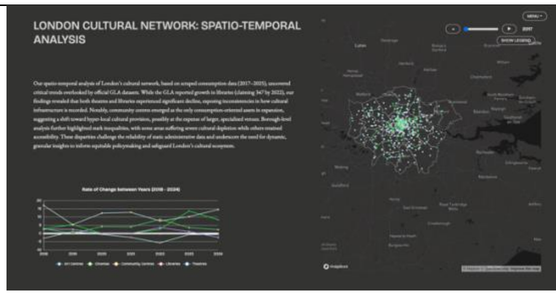

Figure 11: Spatio-Temporal Change in Cultural Consumption Assets in London (2017–2025)

Visualization Name:	Spatio-Temporal Change in Cultural Consumption Assets in London (2017–2025)
Contributor:	Maheer and Hania
Data Used:	OSM Scraped Data
Data Type:	Items and Attributes
Attribute Type:	Categorical
Ordering Type:	Sequential
Dataset Type:	Table and Geometry
Visualization Method:	Time Series and Maps
Graph/Chart:	Dot Plot Map and Line Graph

Table 6: Global Leading Cities – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity

The visualisation combines an interactive time-toggle map with a line graph to simultaneously present spatial and temporal trends. Initial prototypes incorporated 3D map pins, as research indicates consistent dimensionality minimises comparative distortion (Levy et al., 1996), though subsequent testing confirmed 3D elements offer no interpretative advantage (Siegrist, 1996). The final design employs 2D representations for clarity, paired with a line graph specifically chosen over bar charts due to its superior capacity for visualising temporal progression (Zacks & Tversky, 1999). This dual approach allows users to correlate geographic distribution with rate-of-change patterns.

Challenges and Discussion

While the map initially appeared ineffective at displaying temporal changes at city-scale, user testing revealed these became perceptible when zooming into local areas. Reducing the default map size successfully encouraged this exploratory zoom behaviour. Additionally, implementing a collapsible legend improved interface cleanliness without compromising functionality. The solution effectively balances immediate readability with deeper analytical potential, though requires user engagement to reveal its full interpretive value.

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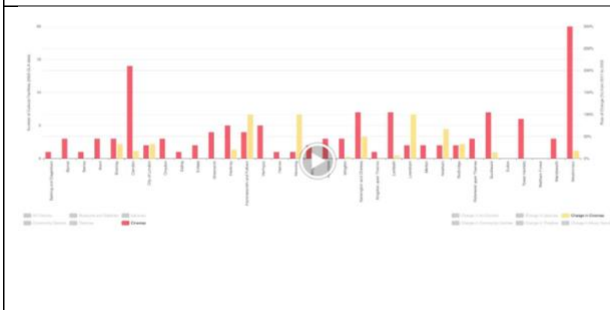	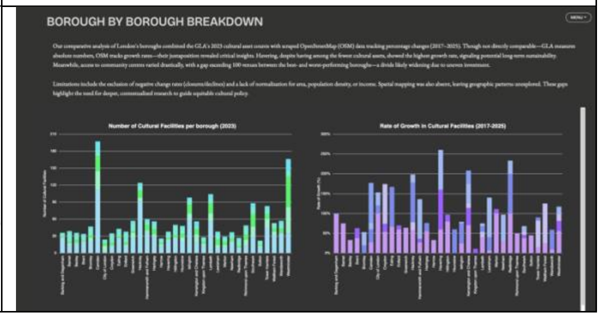

Figure 12: Cultural Consumption Volume and Rate of change per Borough (2017–2025) in London

Visualization Name:	Cultural Consumption Volume and Rate of change per Borough (2017–2025) in London
Contributor:	Maheer
Data Used:	OSM Scraped Data and GLA Data
Data Type:	Items and Attributes
Attribute Type:	Categorical
Ordering Type:	Sequential
Dataset Type:	Table
Visualization Method:	Hierarchical/ Categorical
Graph/Chart:	Stacked Bar Graph

Table 7: Cultural Consumption Volume and Rate of change per Borough (2017–2025) in London – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity

The visualisation employs stacked bar charts to compare both the volume of cultural consumption assets and their rate of change across London boroughs. Initially presented as a single bar graph with paired bars per borough, the design evolved into two parallel bar charts to improve trend observation and readability. Interactive toggles enable users to filter by specific cultural typologies. This approach aligns with empirical evidence demonstrating bar charts' superiority over alternative shapes like circles or cubes in comparative tasks (Croxton, 1932) and quantitative judgement (Zacks & Tversky, 1999; Shah & Freedman, 2009), justifying their selection over less precise options like pie charts.

Challenges and Discussion
A key limitation emerged in representing negative growth rates, as bar charts cannot naturally display negative values. While this visualisation effectively captures current asset distribution and positive growth, subsequent charts were specifically designed to address declining rates, ensuring comprehensive analysis of borough-level cultural changes. This phased approach maintains clarity while accommodating the full spectrum of temporal trends.

FINAL DESIGN

Figure 13: Inequitable Access Data Visualizations

Visualization Name:	Rate of change in Libraries per London Borough (2017-2025)
Contributor:	Maheer
Data Used:	OSM Scraped Data
Data Type:	Items and Attributes
Attribute Type:	Categorical
Ordering Type:	Sequential
Dataset Type:	Table
Visualization Method:	Categorical/ Hierarchical and Geometric
Graph/Chart:	Horizontal Bar Graph and Thematic Map

Table 7: Inequitable Access Data Visualizations – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity
The analysis of community centres employed the same visualization approach as previous datasets, transitioning from bar graphs to categorical dot plots when normalizing against population density. This maintained consistency in representing absolute counts versus normalized values. For cinema and library access mapped against income data, we implemented a thematic map-to-bar chart transition. Horizontal bar charts effectively displayed both positive and negative rates of change, with colour coding (informed by Light and Bartlein's 2004 work on map perception) clearly distinguishing high- and low-performing boroughs. This dual visualization approach allowed users to first grasp spatial patterns before examining detailed quantitative comparisons.

Challenges and Discussion
Initial designs featured automatic transitions between visualizations, but user testing revealed this hindered interpretation. Since the maps only displayed raw values on hover, we implemented manual toggle controls to let users pace their analysis. This change respected varying user needs - some requiring time to extract precise figures while others preferred quicker overviews. The solution balanced analytical depth with accessibility, though required careful UI design to ensure the toggle functionality was immediately apparent to all users.

FINAL DESIGN

Figure 14: Collage-style map of London highlighting case study boroughs

Visualization Name:	Cultural Cartographies Case Study Map
Contributor:	Maheer
Data Used:	London Shapefile
Data Type:	Positions and Links
Attribute Type:	Categorical
Ordering Type:	Cyclic
Dataset Type:	Geometry
Visualization Method:	Map
Graph/Chart:	Interactive Thematic Map (collage)

Table 8: Cultural Cartographies Case Study Map – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity
The case studies mark a shift towards intersectional analysis, combining quantitative data with qualitative insights from community engagement, interviews, and policy research. To reflect this methodological transition, we employed more illustrative visualisations created in Adobe Illustrator and Photoshop, moving beyond purely data-driven formats. These bespoke graphics helped communicate complex socio-cultural relationships that standard charts could not capture.

Challenges and Discussion
While we successfully coded borough shapes as interactive buttons to navigate case studies, we ultimately prioritised narrative flow. Given the website's story-driven structure—where the sequence of engagement was carefully designed—we introduced a more guided, human-centred interaction. This involved using hand-drawn elements and team figures to personalise the user journey, subtly reinforcing the project's participatory ethos. The solution balanced exploratory functionality with intentional storytelling, ensuring users absorbed insights in a coherent, impactful order.

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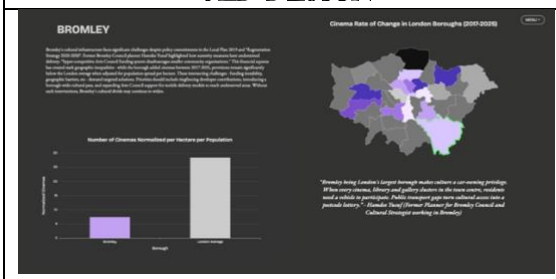
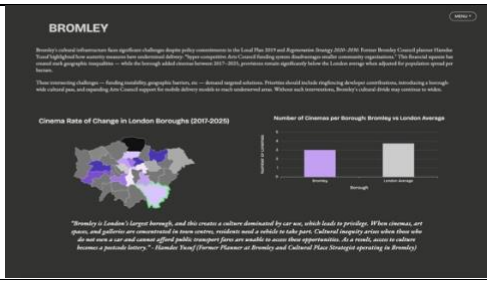
	

Figure 15: Bromley Cultural Case Study Web Page

Visualization Name:	Bromley Cultural Case Study
Contributor:	Maheer
Data Used:	GLA and OSM
Data Type:	Attributes, Items and Positions
Attribute Type:	Quantitative
Ordering Type:	Sequential
Dataset Type:	Table and Geometry
Visualization Method:	Hierarchical
Graph/Chart:	Thematic Map and Bar Chart

Table 9: Bromley Cultural Case Study – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity
The case studies employ an intersectional approach, combining quantitative and qualitative visualisation methods while maintaining intentional simplicity. Following Yau's (2012) principles of effective data filtering, the analysis compares selected boroughs against London averages rather than overwhelming users with all 32 boroughs simultaneously. The visual treatment deliberately highlights Bromley's unique positive growth through stylised channels and markers (Munzner & Maguire, 2015), while using standard bar chart transitions to enable direct volume comparisons where most relevant.

Challenges and Discussion
While the current visualisations successfully communicate core insights, a more expansive project scope could have incorporated Bromley's geographical significance as London's largest borough through additional layered maps. Ward-level analysis of cultural venue access would have provided valuable granularity, though such detail was deemed excessive for a snapshot case study format. This tension between analytical depth and communicative clarity remains an important consideration for future iterations of the research.

RAW MAP	*FINAL DESIGN*
	

Figure 16: Hackney Cultural Case Study Web Page

Visualization Name:	Hackney Cultural Case Study
Contributor:	Maheer
Data Used:	OSM, GLA and Community Engagement
Data Type:	Items, Attributes and Words
Attribute Type:	Quantitative and Categorical
Ordering Type:	Sequential
Dataset Type:	Tables and Words
Visualization Method:	Qualitative and Hierarchical
Graph/Chart:	Word Cloud Map, Bar Graph and Pie Chart.

Table 10: Hackney Cultural Case Study – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity
We opted for two static visualizations to maintain simplicity, particularly as the qualitative community engagement map was already information dense. The original participatory map was carefully redesigned for visual appeal while preserving all handwritten contributions to avoid editorial bias. For proportional representation of Hackney's cultural assets, we selected a pie chart over bar charts, as research demonstrates pie charts maintain interpretability with multiple segments (Spence & Lewandowsky, 1991), unlike bar charts which suffer declining effectiveness with additional components (Eells, 1926).

Challenges and Discussion
The qualitative data represents only a specific temporal snapshot (27th May 2025, 9-11:30am), while quantitative data inherently lacks contextual depth about cultural quality. However, their combination provides compensatory strengths - the quantitative breadth offsets qualitative temporal limitations, and qualitative insights mitigate quantitative reductionism. This methodological synergy offers a more nuanced understanding than either approach could achieve independently, despite their respective constraints.

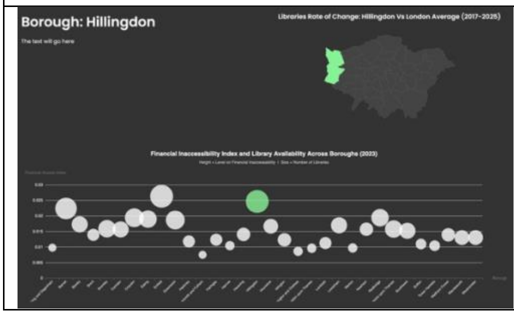
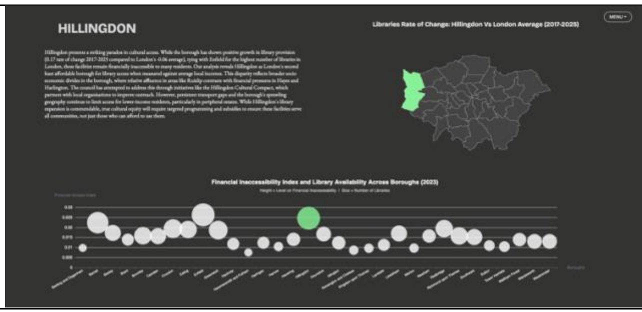
OLD DESIGN	*FINAL DESIGN*
	

Figure 17: Hillingdon Cultural Case Study Web Page

Visualization Name:	Hillingdon Cultural Case Study
Contributor:	Maheer
Data Used:	GLA and OSM and Office for National Statistics
Data Type:	Items, Attributes and Positions
Attribute Type:	Quantitative and Categorical
Ordering Type:	Sequential
Dataset Type:	Tables and Geometry
Visualization Method:	Hierarchical and Map
Graph/Chart:	Thematic Map and Dot Plot

Table 11: Hillingdon Cultural Case Study – Visualization Analysis and Design (2014) Taxonomy

Design and Interactivity
While line graphs were initially considered, research warns they risk misinterpretation when representing non-temporal relationships (Gattis & Holyoak, 1996), making them unsuitable for our case. Though dot plots effectively reveal multivariate correlations (Harrison et al., 2014; Kay & Heer, 2016), we addressed potential misinterpretation of clustered points (Cleveland et al., 1982) by adopting a wider format to visually separate data points. This balanced the need for correlation visibility with clarity.

Challenges and Discussion
A significant limitation emerged in Hillingdon, where no community members provided qualitative input, preventing intersectional analysis of the borough's cultural network. This highlights the inherent constraints of self-collected qualitative data, where participation gaps can create blind spots in otherwise

mixed-methods research. The absence underscores both the value and fragility of community-engaged methodologies in cultural mapping.

6. Conclusion

Findings and Application

This investigation does not seek to provide definitive conclusions but rather to initiate a critical discussion about London's shifting cultural infrastructure. As the research moved from verified datasets to scraped and qualitative data, its purpose evolved—rather than forming a basis for policy, it became a tool to interrogate the reliability of cultural data and the strategic decisions that rely on it. While the findings cannot be used to directly inform policy due to the unverified nature of some datasets, they expose significant gaps in how London's cultural landscape is monitored and managed. Most strikingly, there has been no updated cultural strategy for London since Culture for All Londoners was published by the Mayor of London in December 2018—an alarming lapse given the city's rapid demographic and economic changes. Existing research demonstrates persistent disparities in cultural participation, with engagement among socially disadvantaged groups remaining over 75% but still below the national average, heavily influenced by unemployment, educational attainment, and income levels (Renton et al., 2012). Furthermore, austerity measures have disproportionately impacted deprived areas, where annual spending on culture has fallen by 7.5% compared to 4.5% in more affluent neighbourhoods (Fahy et al., 2023). The recent 2024 Cultural Planning Framework for the City of London, while a positive development, applies only to the Square Mile, highlighting the uneven distribution of strategic efforts to sustain and develop culture across the capital.

The transparency of this project's data is intended to enable researchers, cultural organisations at risk, funding bodies, and local authorities to generate their own visualisations using updated datasets. However, this reproducibility is constrained by the fact that many areas outside London lack equivalent data quality or cultural infrastructure. The key takeaway is that the Mayor of London must take three urgent steps: first, implement consistent, comparable data collection to prevent the deterioration of dataset usability; second, critically evaluate the GLA's existing data before using it to shape a new cultural strategy; and third, adopt a more strategic, borough-specific approach to cultural risk and investment to address entrenched inequalities in access and provision.

Limitations

This study has several important limitations that must be acknowledged. The reliance on scraped data alongside GLA datasets means that accuracy cannot be guaranteed—a more robust approach would integrate GIS mapping, surveys, and in-person verification, though such methods were beyond the scope of this project. The qualitative data gathered during a two-hour community engagement session in Hackney provided some local insights but could not capture the full diversity of voices across different demographics. Additionally, the analysis was conducted at the borough level, which lacks the granularity needed for targeted interventions, particularly in large and underserved boroughs such as Bromley. Finally, during engagement sessions, participants challenged the very definition of 'cultural consumption' used in this research, pointing out that the mere existence of a cultural venue does not equate to accessibility or meaningful use. These limitations highlight the need for more rigorous, inclusive, and hyper-local data collection in future studies—without it, any new cultural strategy for London risks perpetuating the same blind spots around equity and sustainability.

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