

Information Visualisation Practices in the Digital Humanities

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The increasing availability of Humanities data is a powerful driver of information visualisation projects in the Digital Humanities (DH). While several efforts in defining taxonomies, project classifications and best practices in several domains exist, only a few contributions focus on how DH effectively address the epistemological potential of data visualisations in Humanities research. In this article, we present an analysis of 186 DH web projects, which have been described in terms of (1) narrative strategies; (2) scientific domains; (3) charting solutions; (4) interactive capabilities and (5) critical approaches to visualise uncertainty and interpretation. Our findings reveal a field still characterised by a naïve reuse of visualisation and interaction choices, with a strong preference for out-of-the-box solutions and a general reluctance or impossibility to provide customised visualisations that better frame humanistic enquiries. The research provides a new foundation for critical reflection and decision-making for digital humanists who intend to maximise the potential of design choices in information visualisation and narrativity within forthcoming projects.

CCS Concepts: • **Human-centered computing** → **Information visualization**; • **Applied computing** → **Arts and humanities**; • **General and reference** → **Surveys and overviews**;

Additional Key Words and Phrases: Information Visualisation, Digital Humanities, Data Storytelling, Uncertainty, Interaction

ACM Reference format:

Tommaso Battisti and Marilena Daquino. 2026. Information Visualisation Practices in the Digital Humanities. *ACM J. Comput. Cult. Herit.* 19, 2, Article 36 (June 2026), 32 pages.
<https://doi.org/10.1145/3814606>

1 Introduction

The intersection of **Digital Humanities (DH)** and information visualisation offers opportunities to explore the complexities of Humanities data, address epistemic issues, foster dissemination and enable research-oriented processes.

While such aspects have generated vibrant discussions in the literature [13, 24, 27, 37, 64, 88, 92, 93], design choices of DH practitioners remain rather underexplored. A few notable works focus on single domains (e.g., musicology [43]) or specific case studies (e.g., visualisation of **Cultural Heritage (CH)** collections [93]), but a clear outlook on the landscape of DH practices is missing. Nonetheless, being able to appreciate strengths,

Tommaso Battisti is responsible for Sections 2–6. Marilena Daquino is responsible for Sections 1 and 7. Both authors are responsible for Section 8.

Project funded by the European Union—NextGenerationEU under the National Recovery and Resilience Plan (NRRP) (J33C23002070002), Investment I.4.1—Borse PNRR Patrimonio Culturale.

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ACM 1556-4711/2026/6-ART36

<https://doi.org/10.1145/3814606>

gaps and promising approaches would foster awareness in the Humanities community and promote effective dissemination projects based on data-driven analyses.

This research aims to provide an overview of current information visualisation practices in web-based DH projects, highlighting characteristics and emerging criticalities characterising the interplay between visualisation techniques, narrative structures and interactive approaches. The study broadens the domain and the scope of previous research and extends our prior work [9] reporting on narrative strategies, critical perspectives and coping methods for common issues related to the representation of humanities data. Results show a naïve reuse of visualisation and interaction approaches, with a strong preference for out-of-the-box solutions and a general reluctance or impossibility to provide customised visualisations that better frame humanistic enquiries.

The remainder of the article is the following. In Section 2, we provide definitions to clarify the theoretical foundations of the survey. In Section 3, we present an overview of existing taxonomies, contributions and previous surveys. In Section 4, we outline our **Research Questions (RQs)**, and in Section 5, we describe the materials and methods of the analysis. We present results in Section 6, discussed and compared to prior studies in Section 7, showing limitations and novel research directions.

2 Definitions

Visualisation Techniques. In our study, visualisations are computer-supported visual representations of abstract data [18] that fulfil Kosara’s criteria [48]: (1) being based on non-visual data; (2) generating an image from the data as the primary means to communicate them and (3) producing a readable and recognisable result. Although these principles apply to both information and scientific visualisation, our focus is on information visualisation techniques. These are deliberately constructed visual representations of abstract data designed to support understanding and reasoning about the underlying information [23, 61], with meaning emerging through the interrelation between glyphs and symbols [32, 47]. While our analysis also considers non-interactive data visualisations included in projects’ websites, we exclude representational formats such as tables [42], lists, slideshows, grids and mosaics [93].

Interactions and Interaction Categories. For the purpose of the analysis, we define “interaction as actions from users that cause visible changes in the visualisation” [50, p. 1149]. By adopting the perspective of user “allowable actions” [22], we evaluate the interactive capabilities of a visualisation system (i.e., the range of actions users can perform), focusing on those that act or cause changes in the visual representation. We group these actions into *interaction categories* according to the type of action they enable (e.g., selection, filtering, other modifications).

Narrativity. Storytelling involves structuring pieces of evidence through rhetorical strategies [84] while drawing on both explicit and implicit knowledge [73]. A story encompasses presented and inferred events within a narrative [14], incorporating facts, data and other elements essential to the plot [6], while narrativity refers to how a story is conveyed, the arrangement of its elements to construct specific perspectives [14]. In this study, we use the term *narrative* to encompass meaningful sequences of story pieces, often visualised and accompanied by authorial commentaries [52, 60]. These can take the form of “author-driven” data stories—strictly organising story elements to support specific messages [52, 85] within an author-defined plot [81]—or more “reader-driven” experiences, where users actively manipulate the narrative during exploration [75]. For the purposes of the analysis, we refer to *narrative projects* as those using visualisations exclusively within narratives, *non-narrative projects* as those using visualisation exclusively as a means for open-ended exploration without any narrative framing and *hybrid projects* as those employing visualisations both within narratives and for open-ended exploration.

3 Related Work

3.1 Interaction Taxonomies

The so-called “Visual Information Seeking Mantra: *Overview first, zoom and filter, then details-on-demand*” [78] was formulated as a principle to guide users through complex information spaces and became influential in

exploratory data analysis [4, 149], visual text analysis [40] and the development of new browsing models and taxonomies [41, 87]. Building on this foundation, numerous studies have attempted to characterise how users interact with visualisation systems. Scholars classified interaction based on user intent (i.e., what users aim to achieve) [97], provided frameworks for interaction costs in visualisation (i.e., the effort in performing and evaluating an action) [50] drawing on Norman’s action cycle [65], analysed online visualisations to build new typologies based on observed practices [28], and proposed new categories of interaction addressing aspects like participation and gamification [29]. Despite the effort, emerging taxonomies differ in both scope and abstraction, spanning different granularities from low-level interaction techniques to high-level tasks and user goals [60]. In this context, the concept of user intent was exploited to group low-level interaction techniques into higher-level categories [97], while researchers conceptualised tasks in terms of domain problems and abstract operations [62], or using key questions—why, how and what—to clarify a task’s purpose, method and subject [15, 63]. Dimara and Perin introduced the concept of “allowable actions” as intermediate-level units of analysis that are intent-agnostic, operationalisable, and have a data-related meaning. They distinguished: (1) data actions, involving operations on intangible data; (2) perceptualisation actions, affecting data presentation and (3) non-data actions, unrelated to data or its presentation [22]. For the purposes of this work, we adopt the perspective of “allowable actions” [22] as our analytical lens to evaluate the interactive capabilities of visualisation systems, drawing on terminology from the “allowable actions” taxonomy itself [22], the manipulative subset of Brehmer and Munzner’s typology [15] and user intent categories [92] to construct our classification scheme.

3.2 Narrative Design Spaces

Storytelling has been described as the “next logical step in visualization research” [44, 49], enabling the communication of complex information to non-expert audiences [16, 34]. Systematic reviews across different fields exist [20, 68, 73, 84], with a prevalent focus on data journalism [16, 90]. The relation between data stories, audiences and forms of meaning construction is of great interest [3, 33] and contributes to the redefinition of design spaces for narratives using information visualisation techniques.

In the CH domain, practitioners have proposed workflows and platforms for visualisation-driven stories [54], as well as authoring tools [69] that serve as interpretative frameworks when exploring a data collection, showing benefits in the presentation, exploration and interpretation of the CH itself [69, 76, 92]. Evaluations show positive evidence on visit duration, casual exploration and aesthetic pleasure, despite little effect on user engagement [53, 80].

Corpora of visualisation tools and visual projects have been analysed to define taxonomies of narrative genres, visual narrative tactics and narrative structures. Segel and Heer identify seven genres of narrative visualisations and distinguish between author-driven and reader-driven approaches to narratives, with potential hybrid configurations [75]. Stolper et al. restrict the focus on author-driven stories and introduce new genres, where separating visualisations from textual narrative is less important [81]. Other studies focused on rhetorical strategies related to different editorial layers—data, visual representation, textual annotation and interactivity [38], introduce taxonomies for map-based visual storytelling [71] and propose classifications grounded in communication mechanisms and media [98]. Supplementary approaches identify narrative patterns as devices dependent on narrative intents [6] and provide classification schemas for data story types, based on visual language and level of user control [73]. Notably, some narrative flow factors are demonstrated to affect the reading experience and engagement [59], such as navigation input, control over story components, navigation progress, story layout, visualisation role, story progression and navigation feedback.

Such works highlight the positive effect of interactivity on the reader experience [66, 75], despite its interference with the narrative [49]. Latest attempts to categorise interactivity produced a classification schema for “breaking the fourth wall interactions” [77], which includes readers’ input into the narrative and as a part of the story

itself, demonstrating that this leads to enhanced reader engagement, self-connection to the story and improved information recall.

Overall, we acknowledge the pivotal role of Segel and Heer’s work [75] while sharing concerns about the lack of completeness in genre-based schemas due to constant technological improvements [28, 71]. Thus, we differentiate narratives by reusing and adapting the modularity of narrative flow factors [59]. While we overlook both the rhetorical and the media-related aspects, we report possible uses of “breaking the fourth wall interactions” [77].

3.3 Uncertainty, Interpretation and Critical Adaptation

The interpretative nature of humanistic knowledge challenges conventional information visualisation methods, which were born in disciplines with different epistemological groundings [24, 25]. It has been argued that DH should reframe the approach to data as being situated, uncertain and interpreted, advocating for visual solutions able to highlight ambiguity and qualitative judgement typical of the humanistic enquiry, rather than oversimplifying complexity [24, 25]. This would imply (1) representing ambiguity and uncertainty using common visual variables, or (2) using the latter as building blocks for representation, e.g., mapping dimensions on qualitative metrics.

Methodologically securing trust in questionable research data is an epistemic need for DH visualisations [10], and several scholars have proposed solutions for modelling and unveiling vagueness, incompleteness, subjectivity and uncertainty [11, 57], which seem to positively affect users’ perception of trust and transparency [30]. However, it has also been argued that uncertainty is not equally relevant for all user groups [96], and encoding uncertainty as an additional data dimension in visualisations could negatively affect cognitive load, especially on casual users [17, 58, 94–96]. Still, faithfully representing humanities data without obscuring its complexity remains a challenge [24, 37, 86]. Scholars advocate for slower, reflective visualisation approaches as suitable and beneficial to DH enquiry [13, 27, 36]. These recognise data visualisation as a fully-fledged research method [64] with its own epistemic potential and heuristic value [74], serving as a tool for thought and as a cognition amplifier [85] that fosters critical interpretation and works as a mediator between disciplines [27, 37]. In this context, interdisciplinary collaboration between humanities experts and designers becomes paramount to better address the specificities of each discipline [12, 40, 43, 85].

Research on current practices in uncertainty visualisation identified dichotomies in representation techniques, including coincident (integrated)/adjacent (separated) views; intrinsic (altering existing symbols)/extrinsic (adding new elements) and static/dynamic (using animation or interactivity) methods [44]. Taxonomies for describing uncertainty origin and representation techniques distinguish between quantitative (or probabilistic) and qualitative uncertainty, used to classify visualisation used in DH research [67]. Other studies adapt existing codifications to the DH [83], implement multiple coordinated uncertainty visualisations and approaches to coordinate such encodings [94, 95], propose critical frameworks grounded in interaction [17] and show how uncertainty in the same collection can be addressed either by reducing it through data refinement [46], or by embracing it through the creation of *ad hoc* representations [55].

Despite the abundant debate, abstraction techniques and visual solutions to make uncertainty and interpretation explicit are still argued to be lacking [10, 43], and existing surveys hardly found visual representations of uncertainty and interpretation [43, 67, 93]. Numerous studies advocate for more efforts in the creation of critical, humanities-oriented visualisations and tools to address peculiar characteristics that common-use visual solutions are not able to accommodate [19, 39, 79, 85], and underline the need to “take on the challenge of visually representing interpretation and ambiguity on a more general level” [93, 2325].

In this study, we partially rely on existing taxonomies [44, 67] and interpretative metrics [24] to classify DH projects visualising uncertainty and interpretation. We also introduce a novel classificatory aspect to report tailored visual solutions that critically adapt general-purpose representations to accommodate the specificities of humanistic research.

3.4 Domain Surveys

Overall, a few surveys describe aspects of information visualisation, each addressing a specific and relatively narrow scope. Jänicke et al. focus on close and distant reading visualisation techniques in text analysis [40]. Khulusi et al. classified visualisations in musicology works [43]. Panagiotidou et al. analysed uncertainty representation methods in DH contributions using visualisations as part of the research process [67]. Their analysis shows that networks are among the most frequently used solutions, a preference they attribute to the widespread adoption of network analysis methods. Windhager et al. provide a more general-scope review of CH collection interfaces, covering data types associated with cultural objects, target user groups, tasks, visualisation techniques, visual granularity and interactions [93]. The work highlights that design choices in visualisation tend to reflect target audience and task requirements, while these factors do not affect the number of visualisation techniques employed. They also show that maps and networks are the most frequently employed techniques, and multiple non-temporal visualisations are very often combined (in about 80% of interfaces), arguing that such combinations mitigate the analytical limitations of single methods. Notably, and in agreement with the surveys by Khulusi et al. [43] and Panagiotidou et al. [67], Windhager et al. observe that uncertainty and interpretation—concepts that are vastly discussed in the theoretical literature—have hardly been addressed in actual CH interfaces and visualisations [93]. Additionally, their study is also the only survey in the domain to consider narrativity in visualisation interfaces, finding that only 20% of the analysed interfaces used “curated paths”—an umbrella term encompassing both author-driven and reader-driven narrative approaches [75]. Nonetheless, the work does not consider deeper narrative design choices affecting the reading experience, such as those related to structure, flow or user agency.

To the best of our knowledge, no more recent survey provides an updated overview of information visualisation practices in DH. While existing studies provide valuable insights, each focuses on specific contexts or limited dimensions, leaving important aspects unexplored. Our work aims to fill this gap by: (1) broadening the scope from the analysis of interfaces for the CH—which focuses on the preservation and study of cultural artefacts—to include also online dissemination of research results, and therefore addressing the wider DH landscape, encompassing a broader set of disciplines, source types, RQs and dissemination needs; and (2) investigating the interplay between visualisation techniques, narrative structures, interactive approaches and solutions to represent humanities epistemological problems. Notably, we introduce novel classificatory aspects that go beyond the classification of uncertainty representation to identify unique and tailored visual solutions capable of addressing peculiar data characteristics that generic visual representations are not able to accommodate.

4 Methodology and RQs

In this study, we surveyed 186 DH web-based projects leveraging information visualisation techniques. All instances were reviewed, reusing and adapting existing taxonomies. The classificatory framework was iteratively developed and progressively refined throughout the classification process, which relied on an empirical approach. The RQs that drive our analysis can be summarised as follows.

RQ1. Can we characterise the landscape of DH projects according to their usage of information visualisation, interaction and narrative strategies?

- Which are the most popular visualisations and interactions?
- How many projects are narrative projects (entirely or partially)? How does the frequency of visualisation and interaction vary according to narrativity?
- How many projects use more than one visualisation type? Are there differences across narrative, non-narrative and hybrid projects? Are there recurring multi-visualisation patterns?
- How many projects enable more than one type of interaction? Are there differences across narrative, non-narrative and hybrid projects? Are there recurring multi-interaction patterns?
- Is there a relation between the number of different visualisation and interaction types?

- How are narrative projects characterised in terms of narrative flow [59]? Are there examples of “breaking the fourth wall interactions” [77] within narrative projects?
- How are these results related to the humanities domains to which the projects belong?

RQ2. How do DH projects address the interpretive nature of humanities enquiry?

- How many projects visualise uncertainty and interpretation? How do they do it?
- Is there a relation between forms of uncertainty representation and humanities domains?
- Are there original attempts to produce tailored visual solutions to address the peculiarities of the research object? Is there a relation with the humanities domains?
- How many projects representing uncertainty and interpretation rely on such original attempts? What is the relation between these approaches and narrativity?

RQ3. How do DH projects differ from visual projects in other humanities-related contexts?

- Are visualisation techniques similarly represented within different surveys?
- How do multiple techniques, narrative approaches and co-occurring visualisations differ from CH collection interfaces?
- Is uncertainty more or less represented?

Our classification system relies on and extends prior peer-reviewed schemas to ensure the representativeness and consistency of surveyed features, which allows us to answer questions on the peculiarities of the DH domains (RQ1 and RQ2) using validated frameworks. Our corpus is partially based on prior corpora, provided that the latter respects our inclusion criteria. Results of the analysis themselves are compared to prior survey results to characterise DH practices compared to other domains (RQ3).

5 Materials and Methods

5.1 Corpus Building

To build our corpus, we relied on collection methods, sources and representativeness statements of previously discussed surveys in both the Humanities and other fields (Table 1). Most studies manually survey websites and online repositories, with a few exceptions relying on either publication only or both web sources and publications. Sources include awards websites, existing corpora and independent designers’ websites. However, we noticed that works often provide imprecise and incomplete definitions of the sources collected. Moreover, most surveys do not include a representativeness statement. Only one work claims representative results within its field [38], and a few contributions explicitly state that they are neither representative nor exhaustive [75, 77, 81].

Only half of the studies provide online access to their corpus and research materials; nonetheless, not all resources are still correctly accessible, and slight discrepancies between paper and online information sometimes exist.

We reused and adapted these approaches to build our corpus of DH projects. According to our set of selection criteria, we included only instances that were: (1) web-based dissemination projects; (2) outcomes potentially produced through visualisation tools or storytelling software, but not tools or software themselves; (3) free from access barriers like registration forms; (4) significantly reliant on visualisation techniques and (5) accessible at the time of assessment. We relied on a snowball sampling approach starting from selected sources. Entries were thus retained only if they satisfied our selection criteria and had not already been included in the corpus. From the corpus of Windhager et al. [93], we selected 14 projects out of 70 screened entries, then surveyed related practitioners’ websites (designers, developers and researchers) to find 19 additional projects. To strengthen representativeness, we reviewed the “projects” section on the websites of the Italian (AIUCD)¹ and European

¹Associazione per l’Informatica Umanistica e la Cultura Digitale (AIUCD), <https://www.aiucd.it/progetti/>.

Table 1. Methods and Materials of Prior Surveys

Reference	Sources	Collection Method	Online Materials	Declared Corpus Size	Representativeness
[28] ^a	Online journalism, blogs, advertising, research, etc.	Survey of selected sources	—	200	—
[29]	Online journalism, blogs, advertising, research, etc.	Survey of selected sources	https://rethinkingvis.com	232	—
[75]	Online journalism, blogs, videos, books, research and software packages	Survey of selected sources	—	58	Not exhaustive
[77]	Online journalism, blogs and awards	Corpora reuse and survey of selected sources	https://idvxlabs.com/btfwinteraction/	58	Not exhaustive/representative
[38]	News outlets, online news magazines, political outlets and independent designers	Survey of selected sources	—	51	Representative for journalistic narrative visualisations
[81]	Online journalism, blogs, storytelling tools' websites	Survey of selected sources	http://www.cc.gatech.edu/gvu/iidds/charts/corpus.html	45	Not comprehensive/representative
[59]	Online media outlets, websites, blogs and links posted by researchers and practitioners	Survey of selected sources	https://narrative-flow.github.io	80	—
[66]	Awards website	List of winning stories	—	44	—
[40]	Research publications	Manual scan through related journals and conference proceedings	—	— (118) ^b	—
[93]	Research publications and online interfaces	Iterative multifocal research through journals and conferences, and citations analysis	https://github.com/danubevislab/collectionvis	70	—
[43]	Research publications, websites and commercial software	Survey of selected sources	—	129	—
[67]	Research publications	Keywords scan of publications from seven venues	—	126	—

^a[28] and [29] use the same corpus but report different dimensions. The website does not show the size of the corpus. The link to the material is only present in the second study, but only the first publication is mentioned on the website. Both contributions report “etc.” in the sources.

^bManually counted by the authors.

(EADH)² DH associations (selecting 12 of 51 and 54 of 272 screened entries, respectively), and extended the enquiry to their research centres and institutions, adding 38 further projects. Lastly, we examined the “Best DH data visualisation” category of the DH Awards website,³ identifying 49 suitable projects out of 116 screened instances (mostly due to deduplication), leading to a final corpus size of 186 projects. Not all visualisations were considered for the analysis, but only those (1) falling within our definition for visualisation (see Section 2); (2) findable, either communicated in the navigation or playing a significant role for the project or its sections; (3) potentially integrated within the project but not visible only via links to external platforms; (4) not requiring specific knowledge to generate views (e.g., SPARQL queries) and (5) functioning and visible during assessment. The corpus—released at [7]—consists of 71.5% European projects, 17.2% North American projects and 11.3% projects from other continents or international cross-continental collaborations. While this distribution partly reflects the broader concentration of DH activity in Europe and North America [26, 32, 45, 89, 91], the predominance of European projects is also the result of a specific methodological choice. The selection of sources was mainly driven by institutional and cultural proximity to the European DH community, allowing for a more contextually aware evaluation of the projects and discussion of the results. Differently from surveys recording project-based on related article publications—which can be delayed by years compared to the project’s actual web release—our corpus is less biased towards older projects with a long publication history. Firstly, we recorded project web-based publication relying on the websites themselves whenever explicitly stated, or inferred from related publications, university or agency portfolios, web pages and news. In the absence of such information, we used the earliest available snapshot on the Internet Archive Wayback Machine.⁴ For each project, we then tracked website changes over time via Wayback Machine, recording the year of the earliest snapshot matching the version we evaluated at the time of assessment. Projects range from 2012 to 2024, peaking between 2018 and 2022, with 67.7% of projects from 2018 to 2024. Compared with recent surveys of web interfaces in the field [93], our corpus extends one year less into the past and peaks immediately after the last recorded date.

5.2 Classification: Methods and Schema

To develop and finalise our classification schema, we adopted an approach inspired by Segel and Heer [75], according to which the framework is progressively improved during the classification process. Every time the schema evolved, the evaluation was repeated over the sample of projects. The classification process followed an empirical method based on direct observation and interaction with the visualisation systems themselves rather than on their descriptions, to minimise the potential bias carried by documentation and scholarly articles, which do not always reflect features available at the time of the assessment. After reaching a relatively stable version of the schema, two annotators classified a random sample of 30 projects. Discrepancies were discussed in order to identify ambiguous aspects of the classification scheme, which were subsequently refined. This process was iterated until the annotators reached a shared interpretation of the categories and no major ambiguities emerged. Nonetheless, we acknowledge the presence of subjectivity, inevitable when imposing a custom taxonomy over a series of diverse design dimensions [75, 1145]. The final schema and dataset encompass:

Visualisation Techniques. Adapted from Windhager et al. [93], a set of columns (with Boolean values) identify the presence of the following visualisation types, including their variants (e.g., stacked versions): (1) *plot*; (2) *cluster or set*; (3) *map*, also reporting the additional visualisation used in statistical symbol maps (i.e., maps where data points are statistical charts); (4) *network*; (5) *hierarchical diagram*; (6) *treemap*; (7) *word cloud*; (8) *bars*, for any bar-based chart including histograms; (9) *line chart*; (10) *area chart*; (11) *pie chart*; (12) *3D plot*; (13) *proportional area*; (14) *timeline*; (15) *other*, miscellaneous. In addition, the group of techniques to encode temporality is included

²European Association for Digital Humanities (EADH), <https://eadh.org/projects>.

³<http://dhawards.org/>.

⁴<https://web.archive.org/>.

and adapted: (1) *temporal dimension*, time is mapped to any dimension of a visualisation except for timelines; (2) *animation*; (3) *visual variable*, other visual encoding strategies (e.g., colour).

Interaction Categories. Due to the empirical approach, we do not rely on abstract tasks since it is argued that although important to the design of visualisation instruments, users typically rely on intuition, ignoring predefined sequences and operations [4]. Therefore, a set of columns (with Boolean values) distinguishes the presence of different categories of allowable interactions, with a terminology that drew inspiration from the allowable actions framework [22], user-intent categories [97] and the manipulative subset of methods proposed by Brehmer and Munzner [15]: (1) *basic selection*, the demarcation of an element either for the duration of the interaction or more permanently until the occurrence of another selection; (2) *advanced selection*, the demarcation involves both the selected element and related instances within the visualisation, or leads to a brush and link effect across views. Basic selection is tacitly implied; (3) *navigation*, move interactions such as zooming, panning, rotating and scrolling but only when applied to the visualisation and not to the Web page; drill interactions to navigate through different levels or portions of data detail, often generating a new view that replaces or accompany the original; and expand interactions generating new perspectives on data by expanding and collapsing nodes; (4) *arrangement*, methods to organise visualisation elements (symbols, glyphs, etc.) or multi-visualisation layouts spatially, either manually (one by one) or automatically via criteria-based triggers; (5) *change*, alteration of visual encoding involving the visualisation as a whole, such as visualisation type, stacked or alternative visualisation variants, glyphs aspect (colour, size, shape, etc.), axes inversion, scale modifications and other possible changes⁵; (6) *visualisation filter*, to seamlessly exclude or include existing visualisation elements with respect to defined criteria without reloading or generating a new visualisation; (7) *collection filter*, visualisation elements act as a filter for a related collection or list of items (e.g., lists of items filtered by clicking on a map region) and (8) *aggregation*, changes to the granularity of visual elements according to a variable producing either visual data summarisation or segregations in smaller instances.

Narrativity. Two columns—(1) *narrative* and (2) *non-narrative*—identify whether visualisations are used within narratives. Hybrid projects combine both narrative and non-narrative approaches (e.g., using visualisations within a guided narrative in some sections and as a means for open-ended exploration in others).

Narrative Flow Factors. A set of columns adapted from McKenna et al. [59] identifies relevant patterns in the design of narratives that involve: (1) *story progression*, whether the narrative is linear and author-driven (allowing or not skipping parts) or user-directed [75]; (2) *story layout*, which may be document, slideshow, hybrid forms mixing document and slideshow or other potentially more complex options; (3) *visualisation role*, equal, figure (supporting), or annotated (driving) with respect to the textual parts; (4) *navigation input*, scroll, button (or click, or keyboard press) and slider options to progress through a narrative; (5) *navigation progress*, dots, numbers or text, progress widget or the visualisation itself to show to the reader its placement within the narrative; (6) *level of control*, describes how much control a user has over the text, visualisations and animated transitions, which could be discrete (motion is triggered), continuous (acting throughout all the keyframes) or hybrid. While visualisation control is related to the visualisation in its entirety (e.g., a plot moving up or down the page), an animated transition is related to more specific, data-relevant motion. The term “story” in factors was adopted to respect the original schema. However, according to our definitions, it should be replaced without changes in the meaning with “narrative”.

Breaking the Fourth Wall Interactions. A Boolean column identifies narrative projects using “breaking the fourth wall interactions” [77].

Domain. A categorical column to describe the Humanities field of the project based on DH contributions [72, 82, 138]. It includes the following fields: (1) *History and archaeology*; (2) *Art and art history*; (3) *Language and literature*, including linguistics, philology, narrativity and literary studies; (4) *Music and musicology*; (5) *Multimedia and performing arts*; (6) *Philosophy and religion* and (7) *Other*, with no unique focus. We acknowledge that these

⁵All the visualisation techniques involved in a change of visualisation type are reported.

groupings introduce some generalisation. Nonetheless, they reflect similarity in the types of data typically handled rather than strict disciplinary boundaries. Instead of focusing on visualisations used as analytical tools within disciplinary conventions, our “DH dissemination” perspective implies a computational and data-driven approach that mitigates disciplinary differences, since practitioners must make broader communicative choices to address web audiences. Lastly, the analysis of each domain in isolation would produce samples too small to enable meaningful conclusions.

Visualisation of Uncertainty and Interpretation. A categorical column distinguishes between *precise* and *impressional* communication of epistemic uncertainty—emerging from limited knowledge or subjective interpretation [83]—such as missing, unknown, uncertain or disputed data. Precise methods aim to identify uncertain datapoints, often enabling their isolation and potential quantification. We distinguish: (1) *interactive distinction*, dynamic methods that isolate uncertain data through filters without initially making it visually distinct; and (2) *visual distinction*, extrinsic and intrinsic approaches [44] that visually differentiate uncertain data (e.g., using colour or dedicated glyphs to represent incomplete or missing values). Impressional methods instead use experiential techniques to “give an impression of uncertainty” [67, 641]. Rather than emphasising distinction or quantification, they foreground the constructed and situated nature of data by exposing interpretation. We distinguish: (1) *ambiguation*, using graphical expedients like opacity, permeable glyph boundaries or broken lines to convey an impression of uncertainty; and (2) *interpretative metrics* [24], when visualisations use expressive, non-scientific or non-punctual metrics.

Critical Adaptation. A Boolean value identifies projects where at least one visualisation (1) is tailored to reflect data peculiarities instead of an uncritical repurposed, generic solution; and (2) accommodates complexity instead of simplifying it, promoting time-consuming visualisation-based enquiry. This definition is intentionally narrow and contrasts with what we refer to as *naïve reuse*, i.e., the uncritical adoption of generic, out-of-the-box, customisation-lacking solutions that are unable to account for data peculiarities. Importantly, these two categories do not exhaust the full spectrum of design choices. A project may feature custom-built or contextually appropriate visualisations falling outside both our strict definitions (e.g., sophisticated solutions whose primary intent is not to foreground uncertainty or interpretive complexity as defined here).

5.3 Analysis Methods

The final dataset [7] was analysed in a Jupyter Notebook [8] for reproducibility purposes. Aside from common statistical analyses, the Apriori algorithm⁶ [1] was used to extract association rules related to narrativity, visualisation and interaction approaches, applying market basket analysis principles in the search for frequent co-occurring elements [35]. These patterns were further assessed using statistical measures for predictive association rules described by Azevedo and Jorge [5] and reported in the notebook [8].

To compute the correlation between the number of different visualisation techniques and interaction categories, we chose Spearman’s nonparametric coefficient⁷ due to the moderate presence of outliers, the monotonic but not quite linear relation and the lack of normality in the distributions inferred from graphical methods.

6 Results

6.1 RQ1. Characterising the Landscape of DH Projects according to the Usage of Information Visualisation, Interaction and Narrative Strategies

Most Popular Visualisations. Overall, maps are the most frequent visualisations (65.6%; 122/186 projects), followed by bar-based charts (37.6%; 70/186), networks (24.2%; 45/186), other non-classified solutions (21.5%; 40/186),

⁶The documentation of the algorithm used during the analysis can be accessed at https://rasbt.github.io/mlxtend/api_subpackages/mlxtend.frequent_patterns/.

⁷Computed using the stats module of the SciPy Python library: <https://docs.scipy.org/doc/scipy/reference/stats.html>.

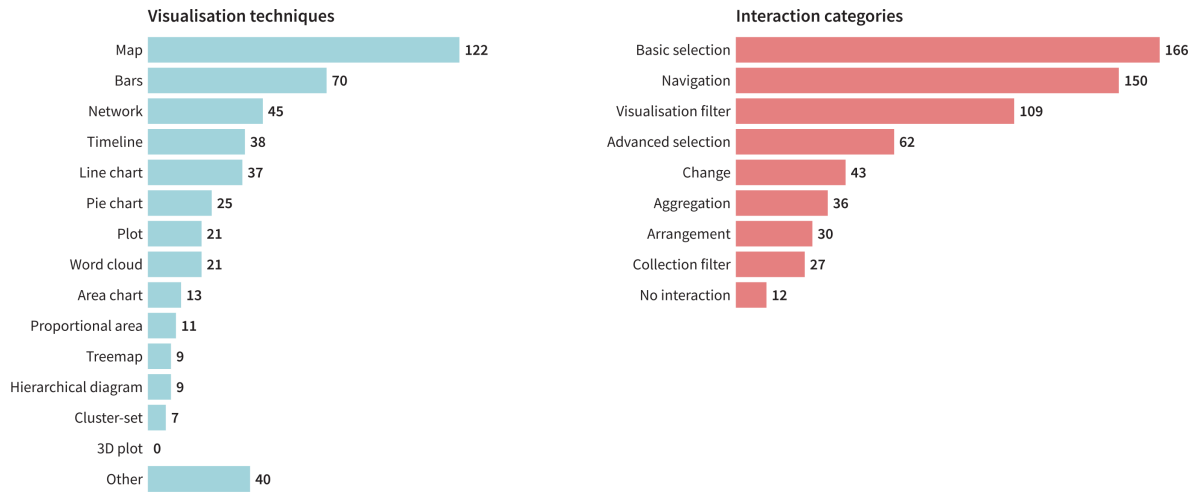


Fig. 1. Distribution of visualisation techniques (left) and interaction categories (right) used across the analysed projects.



Fig. 2. Proportion of projects using narrative solutions and not. Narrative projects are further divided into fully narrative and hybrid.

timelines (20.4%; 38/186) and line charts (19.9%; 37/186). Other solutions were less used, and no 3D plot was found (Figure 1).

Most Popular Interactions. Basic selection and navigation are the most popular interaction categories, used by 89% (166/186) and 81% (150/186) projects, respectively. Visualisation filters (59%; 109/186), advanced selection (33%; 62/186) and change (23%; 43/186), and others are less represented (Figure 1).

Narrativity and Frequency of Visualisations and Interactions. While 76.9% of the projects are non-narrative (143/186), 23.1% include at least one narrative and can be divided into fully narrative (10.2%; 19/186)—with visualisations used only in narrative contexts—and hybrid (12.9%; 24/186) projects (Figure 2).

Popular visualisations are similarly represented in narrative and non-narrative projects (Figure 3). Overall, maps appear in the vast majority of projects, appearing in 83.7% of narrative projects (36/43) and 60.1% of non-narrative ones (86/143). Bar-based charts have a similar behaviour. Instead, networks are more commonly used in non-narrative projects (25.9%; 37/143) and far less in narrative projects (18.6%; 8/43). In fully narrative cases, maps are the most used solutions (73.7%; 14/19) while networks are even less represented (15.8%; 3/19).

In non-narrative projects, the availability of interactions reflects the distribution presented in Figure 1 (Figure 4). However, in fully narrative strategies, the visualisation filter is used by 44.3% fewer projects than in non-narrative instances (15.8%; 3/19 fully narrative and 60.1%; 86/143 non-narrative), while arrangement, aggregation, change and collection filters are almost or completely not used.

Multi-Visualisation Projects, Narrativity and Patterns. 57.5% (107/186) of projects include multiple visualisation types (Figure 5) (mean = 2.5, median = 2, mode = 1, SD = 1.87, min–max range = 1–12). Most non-narrative projects (54.6%; 78/143) and hybrid projects (87.5%; 21/24) use multiple visualisations. Non-narrative projects have a median of 2, using on average between 1 and 3 visualisations, up to 6 different techniques and outliers at 12

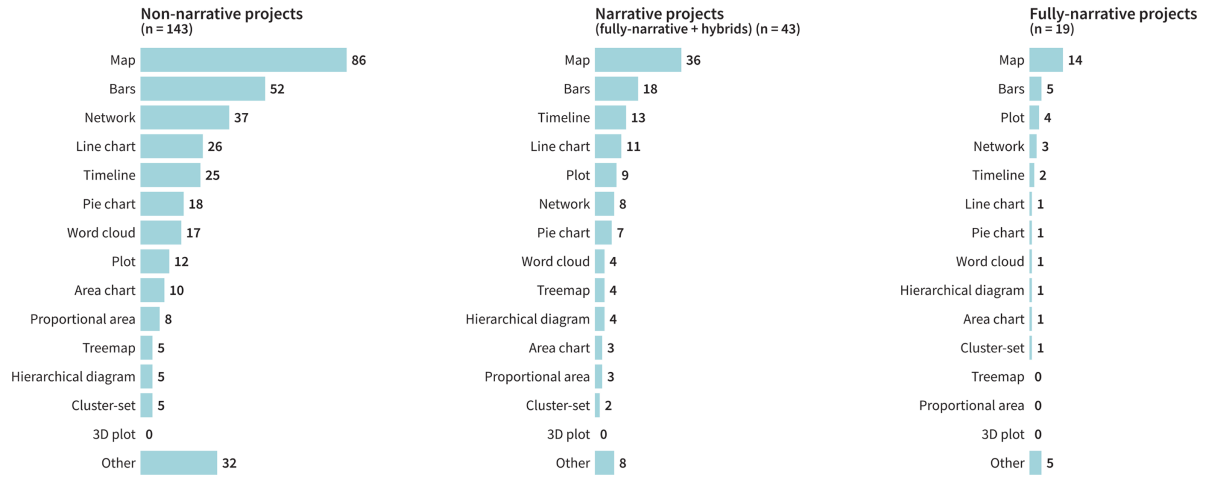


Fig. 3. Distribution of visualisation techniques across non-narrative (left), narrative (fully narrative + hybrid) (centre) and fully narrative projects (right).

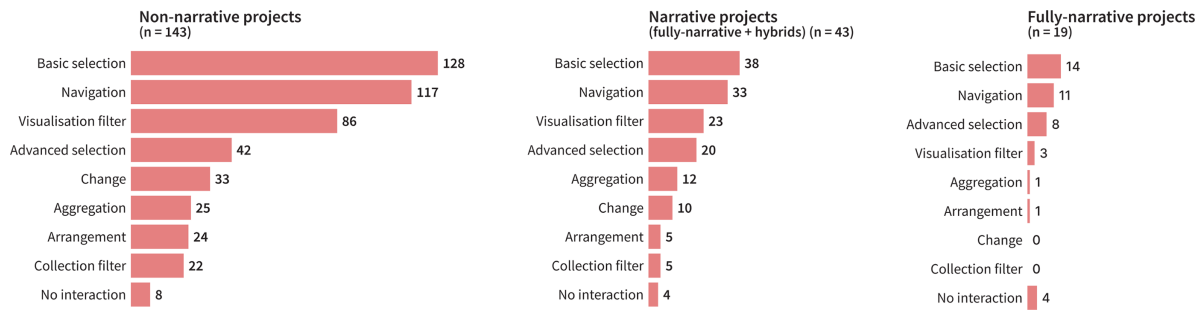


Fig. 4. Distribution of interaction categories across non-narrative (left), narrative (fully narrative + hybrid) (centre) and fully narrative projects (right).

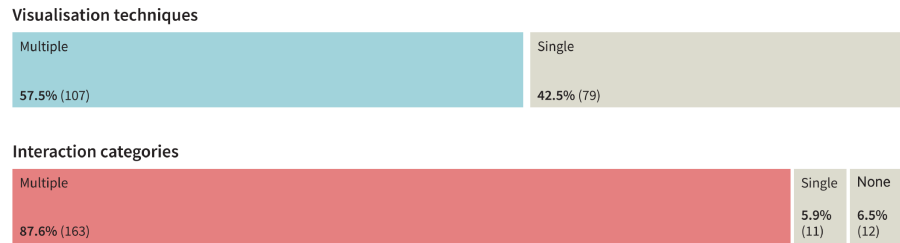


Fig. 5. Proportion of projects with multiple or single visualisation techniques (top) and multiple, single, or no interaction categories (bottom).

(Figure 6). Hybrid projects have a median of 3, with most projects using between 3 and 5 techniques, a greater variability from 1 to about 8 and outliers up to 11. Instead, more than half of fully narrative projects (57.9%; 11/19) rely on a single visualisation.

All visualisation types are more represented in multi-visualisation projects (Figure 7). Notably, treemaps, proportional area charts, line charts and area charts only appear in multi-visualisation projects, as do over 95% of

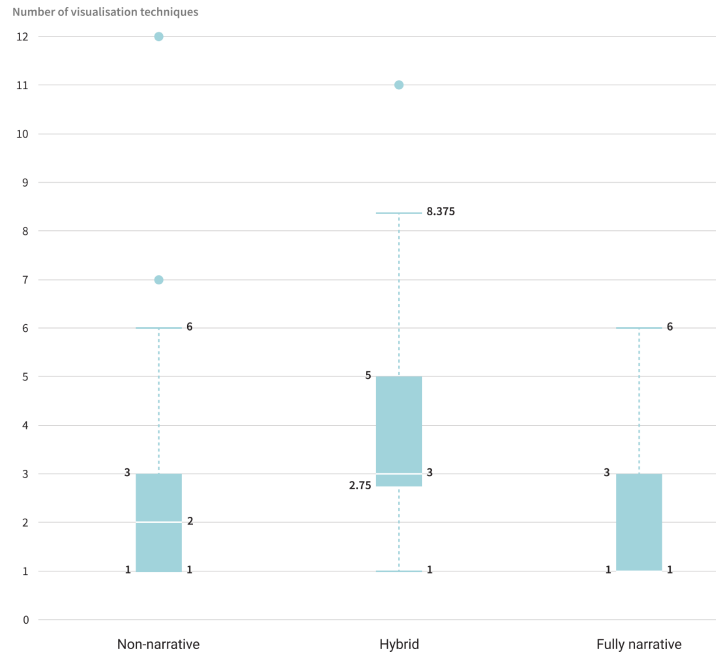


Fig. 6. Number of visualisation techniques used by projects, grouped by narrative type (non-narrative, hybrid, fully narrative).

bar-based charts, pie charts, plots and 92% of timelines. Other niche visualisation types appear along with other charts in 85% of cases, as well as networks in 77.8% of cases. Maps seem to be more balanced since only 58.2% of them appear with other charts.

The most frequent patterns (Figure 8) involve (1) the use of maps only (27.4%; 51/186); (2) maps and timelines (5.4%; 10/186) and (3) networks only (5.4%; 10/186). To understand correlations between visualisations, we applied the Apriori algorithm (support = 0.01 to account for less represented visualisation techniques; confidence = 80%). Results show the following strong associations (Table 2): (1) pie charts to bars; (2) word clouds to bars; (3) area charts to bars and (4) proportional area charts to maps.

Multi-Interaction Projects, Narrativity and Patterns. Most projects (87.6%; 163/186), regardless of narrativity, support multiple interaction categories (Figure 5) (mean = 3.35, median = 3, mode = 3, SD = 1.79, min–max range = 0–8). Only 5.9% of projects (11/186) implement a single type of interaction—the majority using basic selection (6/11)—and 6.5% (12/186) provide no interactivity.

While hybrid projects offer more choices than non-narrative and fully narrative projects, non-narrative projects account for the highest variability, ranging from 0 to 7 types and outliers up to 8 (Figure 9). Fully narrative projects support interactions across far fewer categories.

The most frequent interaction patterns (Figure 10) observed across the projects involve (1) basic selection, navigation and visualisation filters (14%; 26/186); (2) basic selection and navigation (12.9%; 24/186) and—notably—(3) projects with no interactions (6.5%; 12/186). The analysis performed through the Apriori algorithm (using a higher support threshold of 0.4, given the higher frequency rate of interaction categories) identified strong associations between (1) basic selection; (2) visualisation filter and (3) navigation, with diverse directions of implication in the association rules (Table 3).

Visualisation-Interaction Correlation. We found a moderate positive correlation between the number of visualisations and interactions (Spearman coefficient = 0.394), characterised by a strong statistical significance (p-value = 2.54e-08) (Figure 11).

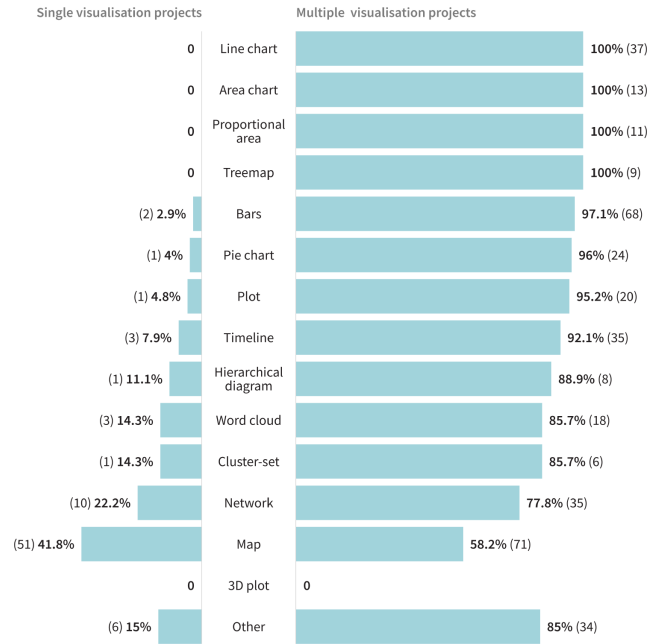


Fig. 7. Use of visualisation techniques in single-technique (left bar) and multi-technique (right bar) projects. Each pair of bars represents the relative frequency of a specific technique across the two project types.

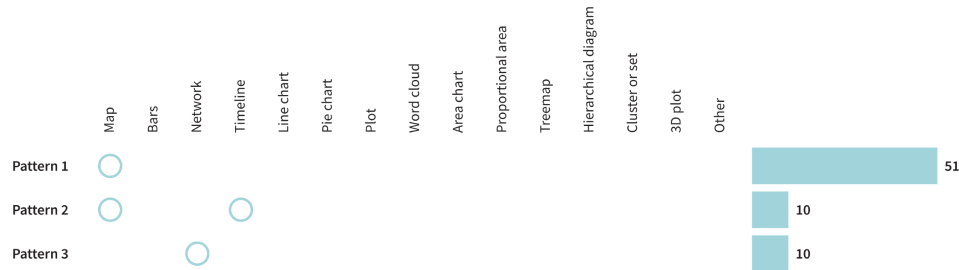


Fig. 8. The three most frequent visualisation patterns in use by the analysed projects.

Table 2. Association Rules for Visualisation Techniques and Evaluation Metrics

Antecedent	Consequent	Support	Confidence	Lift	Leverage	Conviction	Zhang's metric
Pie chart	Bars	0.224299	1.000000	1.573529	0.081754	inf	0.469880
Word cloud	Bars	0.140187	0.833333	1.311275	0.033278	2.186916	0.285393
Area chart	Bars	0.112150	0.923077	1.452489	0.034938	4.738318	0.354610
Proportional area	Map	0.084112	0.818182	1.233035	0.015897	1.850467	0.210648

Narrative Flow Factors (Figure 12). Narrative projects mainly use a linear narrative progression (95.4%; 41/43). 58.5% (24/41) allow skipping sections. Only one project is based on a user-driven narrative (2.3%), and another uses both linear author-driven and user-driven approaches (2.3%).

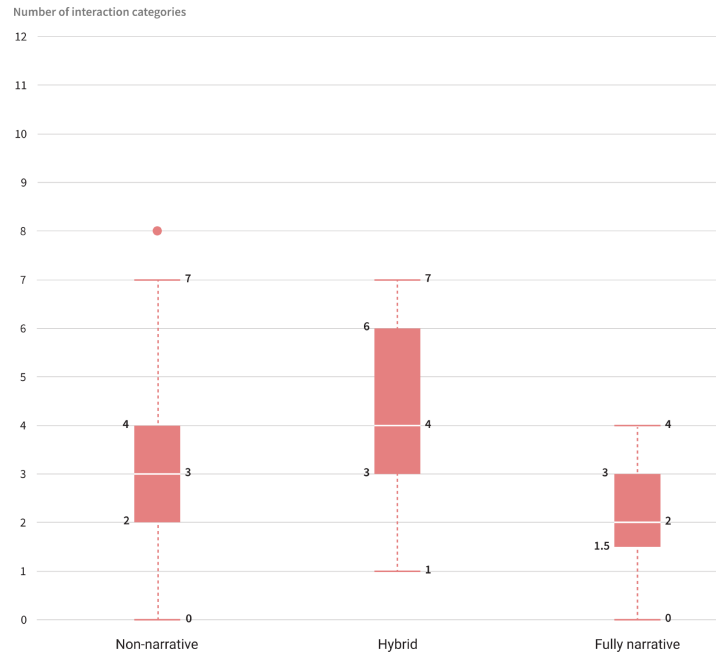


Fig. 9. Number of interaction categories supported by projects, grouped by narrative type (non-narrative, hybrid, fully narrative).



Fig. 10. The three most frequent interaction patterns in use by the analysed projects.

Layout preferences include slideshows (44.2%; 19/43), document layouts (37.2%; 16/43) and document-slideshow hybrids (4/43). Only a few projects choose more complex formats (2/43) and different layout solutions (2/43). Most visualisation types appear more in document layouts rather than in slideshows. Maps exceptionally appear in 18 slideshows (out of 19) and in 10 documents (out of 16), and are the most used visualisation also in slideshow-document hybrids (4 out of 4).

Navigation is ensured by buttons or click approaches (44.2%; 19/43), scroll (32.6%; 14/43) and sliders (2.3%; 1/43). 20.9% of projects use multiple solutions (9/43). Instead, the navigation progress is mostly communicated to users through visualisation methods, e.g., embedded in the visualisation or via progress bars (25.6%; 11/43), text elements, e.g., section titles (11.6%; 5/43), dots in reading bars (2.3%; 1/43) and multiple solutions 7% (3/43). However, most projects do not use any method to indicate the user's position within the narrative (53.5%; 23/43). Among these, 65.2% are document layout narratives (15/23), which corresponds to 93.8% of all document layouts not conveying the user's position (15/16).

Table 3. Association Rules for Interaction Categories and Evaluation Metrics

Antecedent	Consequent	Support	Confidence	Lift	Leverage	Conviction	Zhang's metric
Navigation	Basic selection	0.883436	0.979592	0.997959	-0.001807	0.901840	-0.020408
Basic selection	Navigation	0.883436	0.900000	0.997959	-0.001807	0.981595	-0.100000
Visualisation filter	Basic selection	0.650307	0.981481	0.999884	-0.000075	0.993865	-0.000343
Visualisation filter	Navigation	0.595092	0.898148	0.995906	-0.002446	0.963748	-0.012037
Navigation, visualisation filter	Basic selection	0.582822	0.979381	0.997745	-0.001317	0.892638	-0.005551
Visualisation filter, basic selection	Navigation	0.582822	0.896226	0.993775	-0.003651	0.945901	-0.017598
Visualisation filter	Navigation, basic selection	0.582822	0.879630	0.995692	-0.002522	0.968381	-0.012661

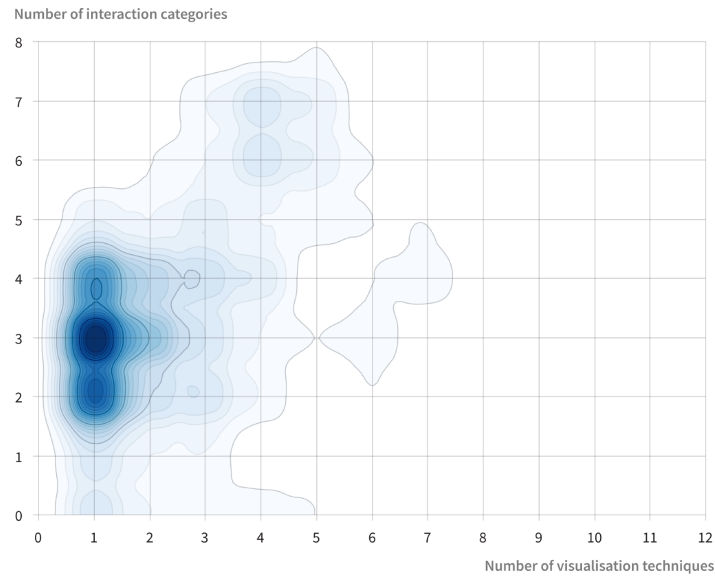


Fig. 11. Relationship between the number of interaction and visualisation techniques used per project. The density plot highlights the frequency of specific combinations of visualisation and interaction counts across the dataset.

Forms of discrete and continuous control are equally employed to control textual elements in narratives (21/43; 48.8%), with only one project using them both (2.3%). Differently, control over visualisations is mainly continuous (72.1%; 31/43), and less hybrid (14%; 6/43) or discrete (11.6%; 5/43). Only one project has different narratives with continuous and discrete forms of control. Most animation control is discrete (65.1%; 28/43), followed by hybrid (7%; 3/43). Only one project uses more options (2.3%), while 23.3% of projects (10/43) use no animation control. The most common control pattern consists of discrete text, continuous visualisation, and discrete animation control (37.2%; 16/43), which is always used by slideshows. The second most common pattern includes continuous text, continuous visualisation, and no animation control (20.9%; 9/43), which is in turn always used by document layouts.

Visualisations and text elements have an equal role in narratives in half of narrative projects (53.5%; 23/43), while 18.6% of projects use visualisations to support text (8/43), and 11.6% privilege visualisations over text components (5/43). The remaining 16.3% use multiple solutions (7/43).

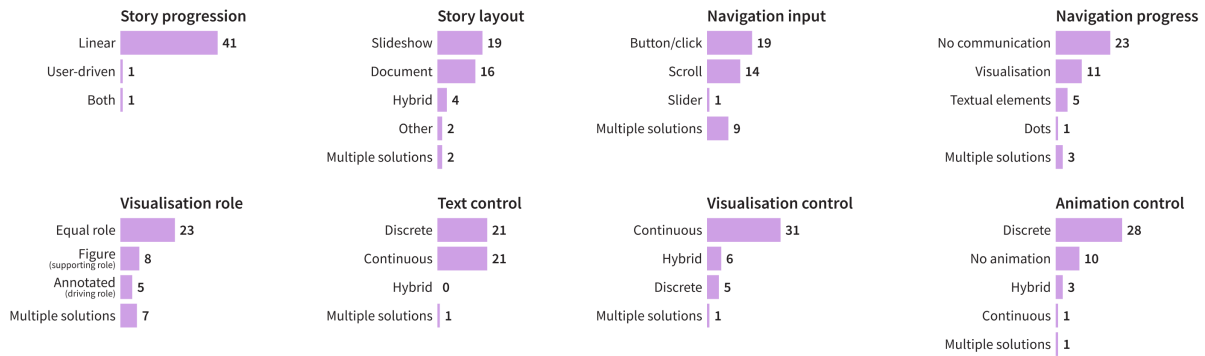


Fig. 12. Frequency of different narrative-flow factors used by projects that adopt narrative strategies (fully narrative + hybrid) (n=43).



Fig. 13. Frequency of roles assigned to visualisation techniques in narrative projects (fully narrative + hybrid). The figure excludes projects that use both multiple roles and multiple visualisations to isolate one-to-one role–technique associations (n=37).

After having excluded six projects containing both multiple roles and visualisations that impeded correct tracking between the two variables, among the most frequent visualisation techniques, we found maps (71%; 22/31), networks (62.5%; 5/8), bars (58.3%; 7/12) and timelines (54.6%; 6/11) to be mostly used with an equal role alongside text components. Line charts, in contrast, show a relative balance, with 50% (4/8) used with an equal role (Figure 13). Notably, among these techniques, timelines are the only type used more often in a driving role (4/11) than in a supporting one (1/11).

Similarly, after having excluded one project with multiple visualisation roles and narrative layouts, we found that the majority of narrative projects giving equal weight to text and visualisations use slideshows (69.6%; 16/23) (Figure 14), corresponding to 84.2% of all slideshows (16/19). Similarly, all projects using visualisation as support for text use document narratives (8/8), corresponding to 50% of all document layouts (8/16). Two narratives (40%; 2/5) that privileged visualisations over text used “other layout” narratives, accounting for all projects in this category (2/2).

After having excluded two projects with multiple navigation inputs and narrative layouts, we found that almost all projects using button/click input are slideshows (94.7%; 18/19), corresponding to 94.7% of all slideshows (18/19);



Fig. 14. Frequency of narrative layout types used in conjunction with the roles assigned to visualisations in narrative projects (fully narrative + hybrid). Projects featuring both multiple roles and multiple layouts are excluded to focus on one-to-one role–layout associations (n = 42).

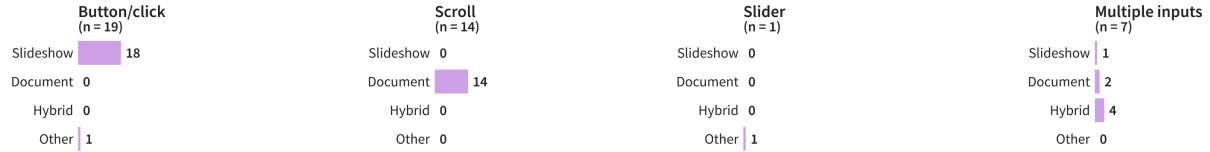


Fig. 15. Frequency of narrative layout types used in conjunction with the navigation input types in narrative projects (fully narrative + hybrid). Projects featuring both multiple layouts and multiple inputs are excluded to focus on one-to-one layout–input associations (n = 41).

all narratives using scroll input are documents (14/14), accounting for 87.5% of all documents (14/16) and all document-slideshow hybrids use hybrid scroll-click navigation (4/4) (Figure 15).

In summary, accounting for all combinations of factors, the most likely frequency-based patterns used by projects involve (1) slideshows with equal-role visualisations, linear skip progression, button input only, visualisation-based progression feedback, discrete text control, continuous visualisation control, and discrete animation control (6/43)⁸; (2) document layouts with subordinate-role visualisations, linear no-skip progression with scroll input only, no position feedback and continuous control over both text and visualisations, but no animation control⁹; (3) a third configuration, similar to the first slideshow pattern, but without progress position feedback (5/43).¹⁰ Association rules generated through the Apriori algorithm (with support threshold of 0.4, confidence threshold of 0.9 to filter results with high conditional probability, and lift threshold of 1.5 to maintain only more significant positive influences) underline connections within two groups of factors (Table 4): (1) document layout, scroll input and continuous text control; and (2) slideshows, button input and discrete text control. Lastly, it is worth noticing that no narrative project employed a “breaking the fourth wall” interaction [77].

Humanities Domains. Most projects fall under “language and literature” (39.8%; 74/186) and “history and archaeology” (34.9%; 65/186), followed by “art and art history” (10.8%; 20/186), “multimedia and performing arts” (3.2%; 6/186), “music and musicology” (1.1%; 2/186) and 10.2% others (19/186) (Figure 16).

All domains are mostly characterised by non-narrative projects (Figure 16). “Language and literature” is the most frequent domain in non-narrative cases (43.3%; 62/143), followed by “history and archaeology” (30.8%; 44/143) (Figure 17). However, “history and archaeology” is the most frequent domain in projects with at least a narrative (48.8%; 21/43), while “language and literature” is less represented (27.9%; 12/43). In particular, fully narrative cases mostly belong to “history and archaeology” projects (58%, 11/19), while 21% to “language and literature” (4/19).

All domains account for more multi-visualisation projects, except “history and archaeology” (33 single- and 32 multi-visualisation projects) and “music and musicology” (1 single- and 1 multi-visualisation) (Figure 18).

⁸They are all instances using StoryMapJS or TimelineJS, such as <https://gams.uni-graz.at/o:ges.story> and <https://gams.uni-graz.at/archive/objects/context:kofler/methods/sdef:Context/get?mode=ereignisse>.

⁹For example <https://plaintalkhistory.com/monroeandflorencework/>.

¹⁰For example <https://tgu.urbanization.org/>, and other StoryMapJS instances like in <https://www.freedomofthestreets.org/visualisation/amsterdam1790> and <https://projects.dharc.unibo.it/uhdw/>.

Table 4. Association Rules for Narrative Flow Factors

Antecedent	Consequent	Support	Confidence	Lift	Leverage	Conviction	Zhang's metric
Slideshow	Discrete text control	0.441860	1.000000	1.954545	0.215792	inf	0.875000
Document	Continuous text control	0.418605	1.000000	1.954545	0.204435	inf	0.840000
Document	Scroll input	0.418605	1.000000	1.869565	0.194700	inf	0.800000
Continuous text control	Scroll input	0.488372	0.954545	1.784585	0.214711	10.232558	0.900227
Discrete text control	Button input	0.511628	1.000000	1.535714	0.178475	inf	0.714286
Slideshow	Button input	0.441860	1.000000	1.535714	0.154137	inf	0.625000

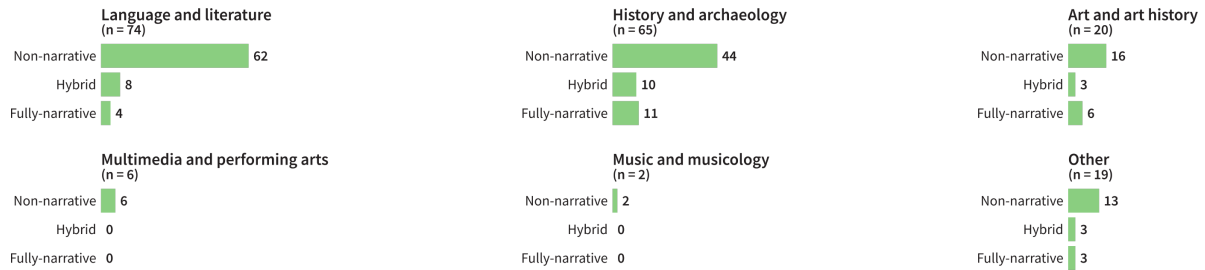


Fig. 16. Frequency of non-narrative, hybrid and fully narrative projects across different disciplinary domains.

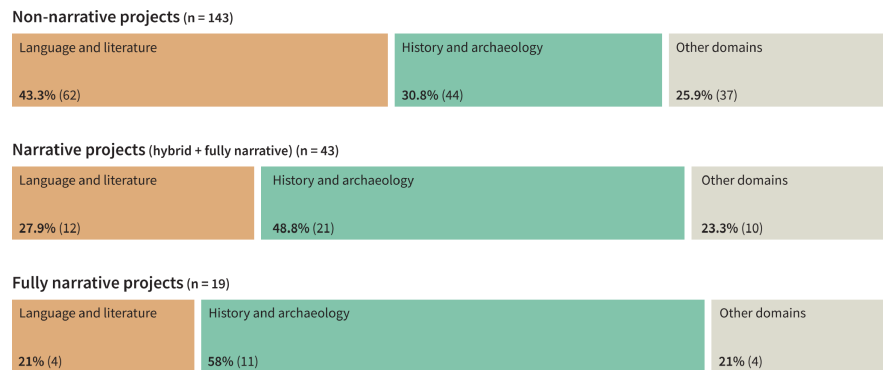


Fig. 17. Disciplinary domain composition of non-narrative, narrative (fully narrative + hybrid) and fully narrative projects, with particular emphasis on the two most represented: “Language and literature” and “History and archaeology.”

Maps are the most frequent visualisations in all domains except “multimedia and performing arts” (Figure 19). “History and archaeology” use them the most (nearly half of the overall map occurrences: 57/122), while bar-based charts (20), line charts (10) and other techniques are less employed. “Language and literature” accounts for more diversity: maps are the most popular (39), followed by bars (32), networks and line charts (20),

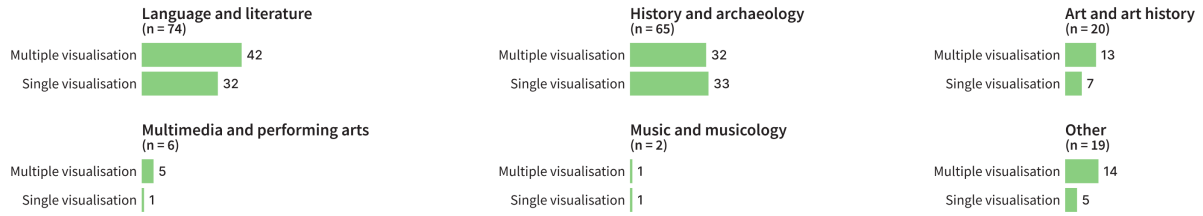


Fig. 18. Frequency of multiple and single visualisation projects across different disciplinary domains.

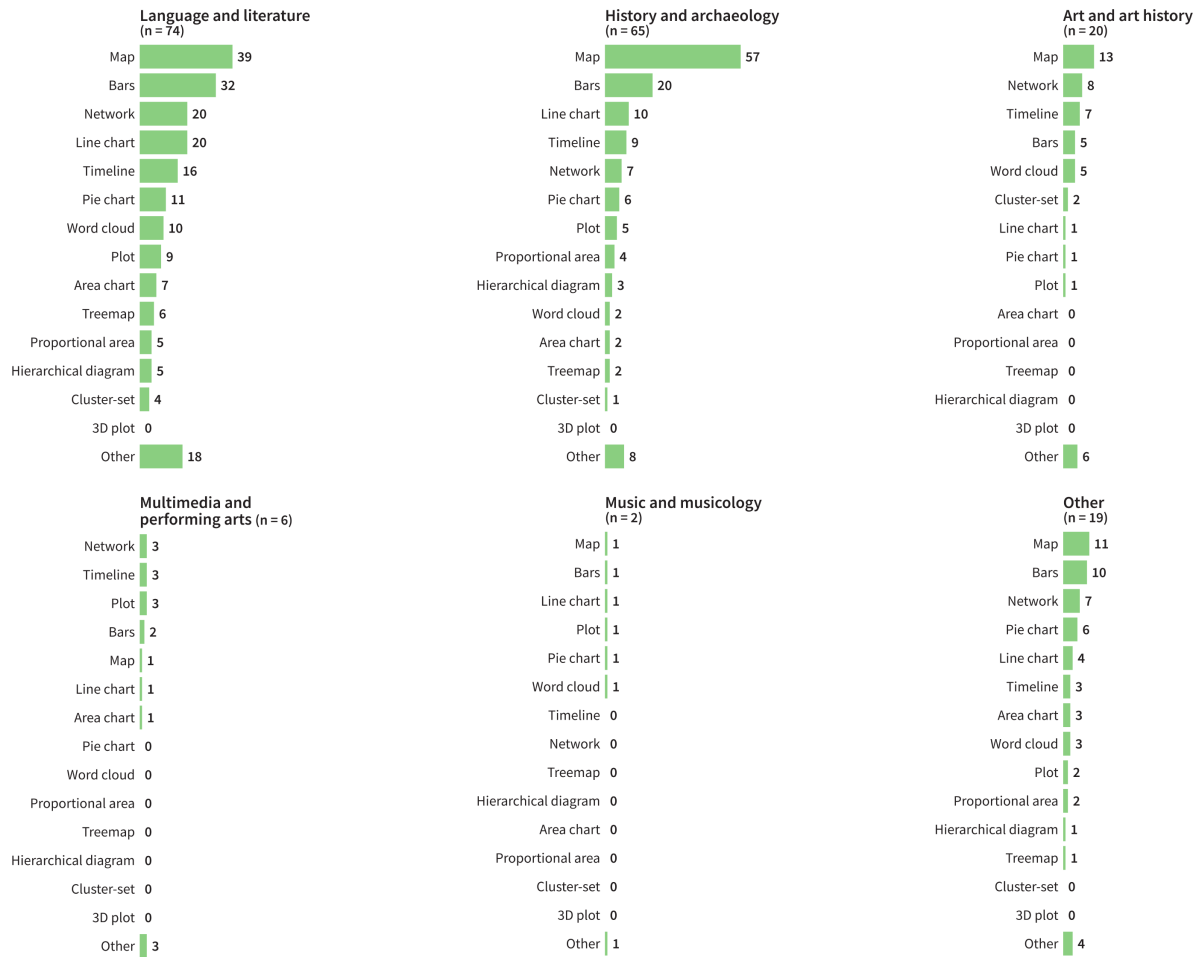


Fig. 19. Frequency of visualisation techniques across different disciplinary domains.

unspecified visualisations (18), timelines (16) and pie charts (11). In “art and art history,” maps (13) are followed by networks (8) and timelines (7). In other non-classified domains, maps (11) are followed by bar-based charts (10) and networks (7). Due to its low frequency, “music and musicology” does not show significant patterns.

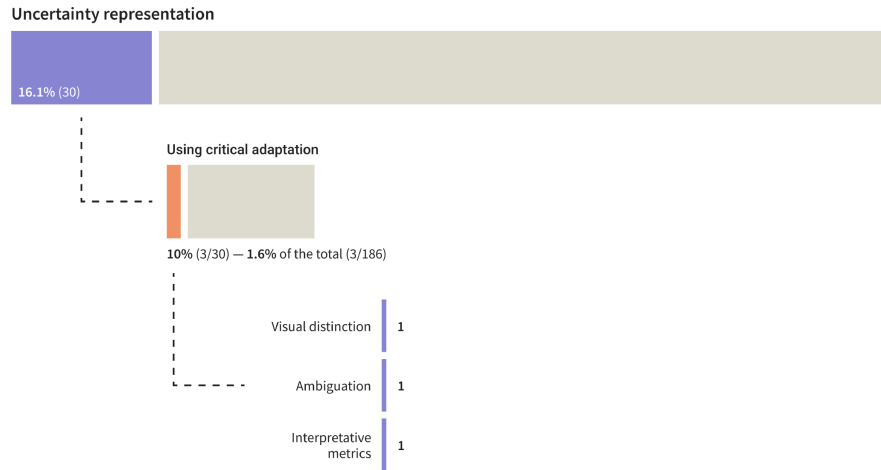


Fig. 20. Proportion of projects that represent uncertainty ($n = 186$), with a breakdown showing how many also incorporate critical adaptation strategies ($n = 30$). Among these, a further subdivision displays the distribution of specific uncertainty visualisation methods used ($n = 3$).

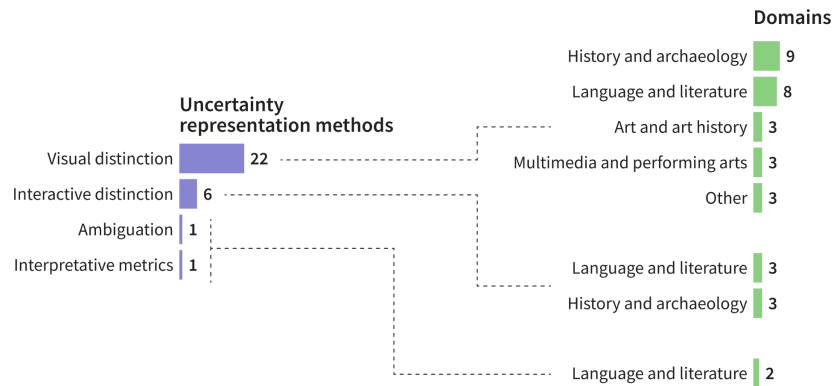


Fig. 21. Frequency of use of different representation methods across projects that visualise uncertainty ($n = 30$). For each method, an additional bar chart shows the distribution of disciplinary domains in which it is applied.

6.2 RQ2. DH Projects Addressing the Interpretative Nature of Humanities Enquiry

Representing Uncertainty and Interpretation: Magnitude and Methods. Only 16.1% of projects (30/186) visualise uncertainty or interpretation (Figure 20). Only two of these projects represent uncertainty using impressional methods: one using ambiguation techniques (dashed lines and permeable boundaries to suggest uncertainty in the length of time spans), and the other building the visualisation on interpretative metrics (Figure 21). Instead, the majority of projects (28/30) use precise methods to visualise uncertainty. Among them, 22 rely on visual distinction methods such as dedicated glyphs (e.g., bars that quantify unknown-data entities), different colours and patterns or dedicated sections of the visualisation, while 6 use only interactive distinction methods to include or exclude uncertain data elements (uncertainty-based visualisation filters).

Uncertainty Representation and Humanities Domains. Both instances using impressional methods are “language and literature” projects (Figure 21). Differently, almost all projects using visual distinction aids fall under “history and archaeology” (9/22), “language and literature” (8/22) and “art and art history” (3/22), while interactive

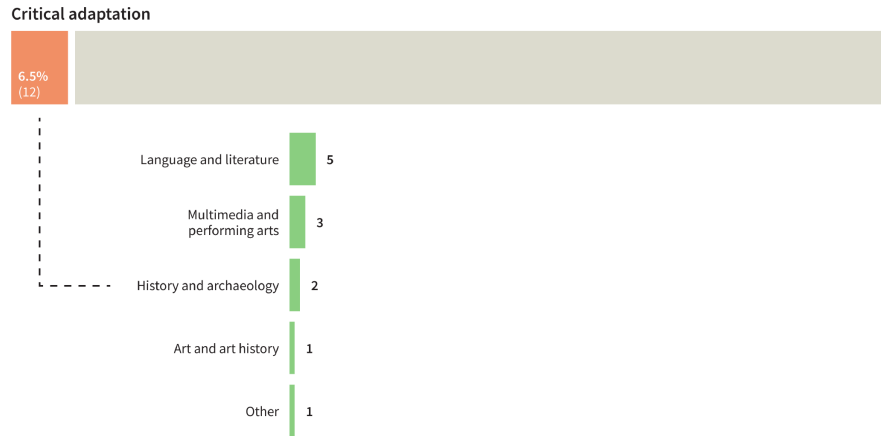


Fig. 22. Proportion of projects using critical adaptation strategies ($n = 186$), with a further subdivision displaying the frequency of these projects across different disciplinary domains ($n = 12$).

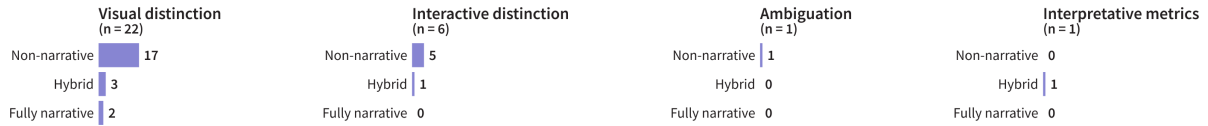


Fig. 23. Distribution of non-narrative, hybrid and fully narrative projects across different uncertainty visualisation methods, based on the subset of projects that visualise uncertainty and interpretation ($n = 30$).

distinction methods are equally used in “history and archaeology” (3/6) and “language and literature” (3/6) domains.

Critical Adaptations and Humanities Domains. Only 6.5% of the projects (12/186) critically adapt visualisations proposing tailored solutions (Figure 22). Among these, five are “language and literature,” three are “multimedia and performing arts,” and two are “history and archaeology” projects. Only one is related to “art and art history” and the other to non-classified domains.

Uncertainty, Critical Adaptation and Narrativity. Almost all projects that represent uncertainty and interpretation employ non-tailored visualisations (90%; 27/30). The remaining instances (10%; 3/30) consist of both of the aforementioned projects using impressional methods and one using visual distinction methods (Figure 20). These correspond to 1.6% of the total projects (3/186). Qualitative analysis reveals that, in the two projects using impressional methods,¹¹ uncertainty is represented within the same visualisation using tailored solutions, while in the third project,¹² such aspects are addressed by different visualisations.

Non-narrative solutions prevail in projects that visualise uncertainty, characterising the great majority of solutions using visual (17/22) and interactive (5/6) distinction methods, with three additional hybrid projects (Figure 23). Impressional methods are used by one non-narrative and one hybrid project. Thus, 76.7% of projects representing uncertainty are entirely non-narrative (23/30) (Figure 24).

From another perspective, we can say that most fully narrative (89.5%; 17/19) and hybrid (79.2%; 19/24) projects do not visualise uncertainty or interpretation (Figure 25). The percentage rises by considering narrative instances lacking tailored approaches and critical adaptation—94.7% of fully narrative (18/19) and 91.7% of hybrid projects (22/24) (Figure 26). Therefore, most projects accounting for critical adaptations are completely non-narrative (75%;

¹¹<https://uclab.fh-potsdam.de/arete> and <https://atlantecalvino.unige.ch/archipelago>.

¹²<https://dunhamsdata.org/portfolio/visualizations>.



Fig. 24. Proportion of non-narrative projects among projects that visualise uncertainty (top) and projects that critically adapt visual solutions (bottom).

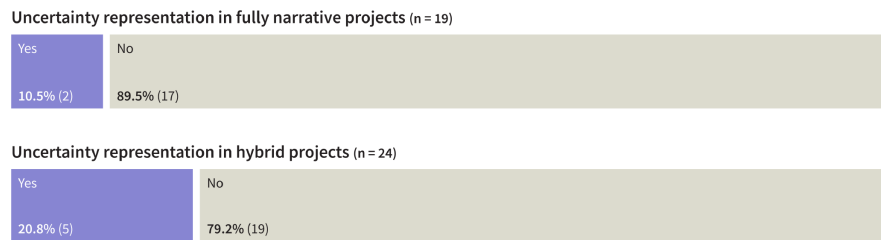


Fig. 25. Proportion of projects that use uncertainty representation methods in fully narrative (top) and in hybrid projects (bottom).

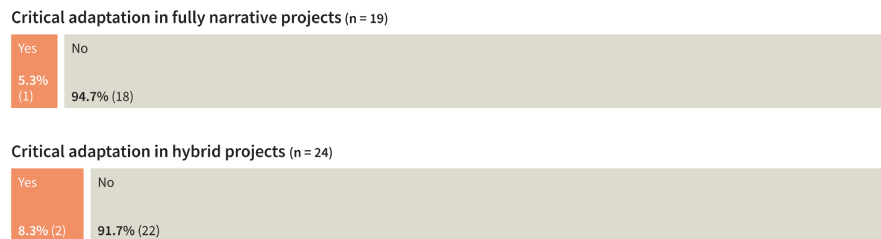


Fig. 26. Proportion of projects that critically adapt visual solutions in fully narrative (top) and in hybrid projects (bottom).

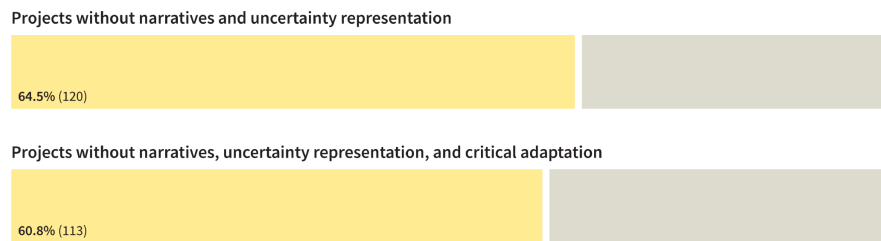


Fig. 27. Proportion of projects lacking narrative approaches, and uncertainty visualisation methods (top), and proportion of projects lacking narrative approaches, uncertainty visualisation methods and critical adaptation over the whole set of analysed projects (n = 186).

9/12), with only 3 narrative instances (1 fully narrative and 2 hybrid) (Figure 24). Finally, 64.5% of projects (120/186) neither use narrativity nor represent uncertainty, while 60.8% (113/186) also do not use critical approaches to visual solutions (Figure 27).

6.3 RQ3. A Comparison with Other Surveys on Humanities Projects

Visualisation Frequency. In CH collections [93] and the music domain [43], maps and networks are the most represented solutions. Our results confirm the role of maps. However, while in previous studies networks closely follow maps (only 3 fewer occurrences; 4.3%), in our study networks are used by 41.4% fewer projects than maps. The underrepresentation is even more evident within narrative projects and in comparison to DH research contributions [67]. Likewise, temporality is also less represented than in CH collections [93], since, in relative terms, it appears in 30.5% fewer projects (from 81% to 50.5%). In our study, DH projects use visualisation axes and dimensions (37.1%; 69/186), animations (14%; 26/186) and other visual variables (3%; 6/186) to encode temporality, with a rarer use of multiple techniques and a lower overall average.

Multiple Visualisations, Co-Occurrences and Narrativity Compared to CH Collection Interfaces [93]. In CH collection interfaces, timelines are mostly used with maps and networks. We found timelines mainly occurring with maps, bar-based charts and line charts. Moreover, we noted less use of multiple non-temporal techniques (30% less—from 80% of projects to 50%), although the mean value is very similar but with a slightly greater variability within our projects (higher standard deviation and max value). Also, multiple temporal techniques are less represented. Lastly, narrativity is found slightly more frequently (23.1% compared to 18.6%).

Uncertainty Representation. Compared to musical visualisations [43], we found a higher number of instances that represent uncertainty (16.1%; 30/186). This is in line with uncertainty representation in DH research (15.9%; 20/126) [67].

7 Discussion

7.1 Visualisations and Interactions

Web-based DH projects are dominated by maps and bar charts, while networks appear to be increasingly underrepresented compared to other contexts [43, 67, 93]. On the one hand, maps are recognised as powerful storytelling tools that facilitate the placement of abstract concepts, trigger emotional states, such as empathy, and are easy to understand [51]. Instead, networks are perceived as difficult to interpret in dense configurations, and connections are not best suited to encode data across different scales [47]. We can argue that fully narrative projects, which mostly rely on a single visualisation technique, may prefer to rely on such solutions to accommodate diverse audiences.

Multi-visualisation projects are the majority in our dataset, showing a high diversity of chart types. Notably, bar-based charts frequently occur along with other charts (Table 2), suggesting that they serve a supporting function.

The need for simplicity seems to drive the selection of interactive solutions, too. The most recurring categories are also the most intuitive and usable out-of-the-box (e.g., charting solutions for maps mostly come with embedded navigation actions). The extensive use of non-tailored visualisations allows us to assume that the relation between selected chart types and available interactions is due to the choice of adopted charting libraries or web-based solutions. Although we cannot infer the quality of the experience from the number or the types of supported interactions [22, 50], design choices are limited to basic selection, visualisation filter and navigation—which is a rather narrow set of choices that likely limits the appreciation of different perspectives on data. In this context, finding different ways to represent and interact with information is crucial to promote multiple perspectives, potentially leading to serendipitous discoveries.

7.2 Narrativity

Despite the well-known advantages of narrativity in quantitative projects [16, 34, 69, 76, 93], only a minority of surveyed instances use it systematically. While we found a slightly higher number of narrative projects than in CH collections [93], fewer than half of the narrative projects rely exclusively on narrativity, while most instances are hybrid, meaning they also exploit non-narrative presentations.

We believe that the tendency to stick to available ready-to-use charting solutions also affects narrative strategies. Narratives appear to be too often linear and author-driven, and mostly present a single visualisation in fully narrative projects. The extensive use of slideshows with maps, timelines and related flow-factors patterns is evidence of the increased adoption of storytelling tools such as StoryMapJS and TimelineJS,¹³ which offer out-of-the-box solutions for dissemination projects requiring fewer technical skills from practitioners. The convenience derived from the usage of such solutions may be the reason for the lower number of document-layout narratives with a high number of visualisations, which would instead require extensive storytelling and charting skills. Likewise, we can assume that such out-of-the-box single-chart solutions limit the number and types of interactions, which we have shown to be slightly correlated, and foster linear author-driven approaches, preventing reader-driven explorative options.

Differently, the higher number of visualisations and interactions in hybrid projects can likely be explained by their structure, typically consisting of at least two sections (one narrative and one non-narrative), and therefore more likely to host different visual and interactive solutions.

Reading flow factors, such as the lack of indicators for user position in more than half of narrative projects, are yet another symptom of poor narrative design choices, this time mostly affecting document-layout projects. While it can be argued that the scrollbar could represent a placeholder for the reader, the length of a web-page may not reflect the actual length of the narrative space, therefore giving the user potentially misleading feedback [65].

Overall, the narrative design space is rather restricted to a small set of solutions, which limits the valorisation of the information and prevents the creation of alternative perspectives, precluding further interpretations, which are at the core of humanistic knowledge. To this extent, we argue that DH approaches, instead of promoting information visualisation methods as interpretative frameworks to unfold complexity, adopt visual narratives as a means to oversimplify information, willingly or not.

7.3 Humanities Domains

Notably, “language and literature” and “history and archaeology” are active practitioners of information visualisation, although with different preferences for narrative strategies, multi-visualisation solutions and specific visualisation types. On the one hand, non-narrative, multi-visualisation projects in “language and literature” are more frequent overall and make use of a more diverse set of visualisation techniques. Such an approach reflects typical scenarios of exploratory data analysis and text analysis, where the added value of the dataset has yet to be revealed, rather than scenarios of knowledge discovery, where a hypothesis has to be tested and validated with visual aids. On the other hand, “history and archaeology” accommodates most of the narrative solutions and the majority of maps. In line with previous observations on narrativity, it is also the only domain with more single-visualisation approaches, even if multi-visualisation projects are the majority within the overall corpus. In this case, the approach seems to be more educational, based on qualitative curated content or aimed at sharing information with a broad audience.

7.4 Approaches for Humanities-Centred Visualisations

Similar to previous studies [43, 67], only a limited number of projects represent uncertainty. It is argued that the choice to address both uncertainty and complexity is affected by researchers’ goals [56], since they make results noisy, and the lack of standard solutions to visualise them [67]. Notably, the empirical evidence contrasts with the huge size of the theoretical debate [93], being uncertainty and interpretation hardly represented in interfaces and visualisation design.

Our survey reinforces the disappointment of previous studies for such an imbalance [67], highlighting the lack of critical adaptation of existing charting solutions as a related phenomenon. Indeed, only a few projects propose

¹³ Accessible at <https://storymap.knightlab.com/> and <https://timeline.knightlab.com/>, respectively.

innovative and tailored visual solutions fulfilling the requirements for critical adaptation. The majority are part of “language and literature” and use a non-narrative approach. The lack of critical approaches to visualisation reflects a broader trend in DH that favours quantitative validation and measurable outputs over tailored, interpretative solutions [2]. The uncritical repurposing of generic and technically convenient visualisations often reduces them to proofs for output production, which, however, neglects their epistemological potential as humanistic forms of knowledge, failing to integrate them within the interpretative framework that aligns with the humanistic roots of the projects.

Impressional methods to cope with uncertainty are rare. On the contrary, more traditional approaches to represent uncertainty through visual distinction methods are the majority. A smaller but still relevant number of projects use filters for the same purpose. It can be argued that this approach prevents adding visual complexity and related issues [17, 58, 94–96]. However, the lack of visual distinction in the initial views remains potentially misleading, since ambiguity is imperceptible without deeper engagement with interactive components, interfering with the effective communication of critical information. Interestingly, projects using impressional methods are among the few representing uncertainty while also meeting our criteria for critical adaptation, testifying to the challenges of integrating qualitative aspects and the lack of ready-made solutions to this aim [10, 43]. Conversely, almost all the projects using precise methods to represent uncertainty rely on traditional non-tailored approaches, demonstrating that uncertainty can still be represented without extensive customisation. Notably, uncertainty representation and critical adaptations are mostly found within non-narrative projects, while narrative approaches tend to rely on more conventional representations.

7.5 Actionable Recommendations

The narrow set of recurring simple or ready-made visualisations, interactive categories and narrative solutions, as well as the lack of tailored solutions and projects representing uncertainty, disclose a substantial lack of criticality, defined as the “reflections and design strategies, that can help to meet specific epistemic standards” [93, 2323]. This suggests that treating visualisations as cultural artefacts needs reflection rather than a technical solution. We extend this concern to all the aforementioned elements, suggesting the adoption of a more thoughtful approach to visualisation and narrative design to better match DH epistemic needs. As argued by Ringler, computational outputs are neither neutral nor self-evident and require an interpretive framework to become meaningful [70]. Thus, moving beyond the uncritical repurposing of off-the-shelf solutions becomes an epistemological necessity to prevent interpretation from being constrained by pre-defined output formats. For example, while standard and convenient linear authorial narratives can guide users through content according to specific data dimensions, user-driven or hybrid approaches may offer a solution to let different perspectives and interpretations emerge. Since heterogeneous data and interpretations are at the core of DH research, the resulting complexity should be unfolded instead of reduced. However, this can hardly be tackled by stacking information over a set of visual solutions, nor by depending solely on pre-packaged narratives for dissemination, whose pre-established formats and perspectives tend to oversimplify data.

We argue that DH practitioners often lack specific visualisation skills. As the difficulty of being experts in both their humanities discipline and in software engineering is frequently regarded to be a problem affecting code quality, research reliability and the advancement of the field—calling for improved training and collaborative work in teams with relevant expertise—[21], we argue the same holds for visualisation. Limited visualisation expertise constitutes an obstacle to the interpretation of humanities data and to the effective dissemination of research results. We believe such a barrier can be overcome through interdisciplinary collaboration with visualisation designers, in addition to developing such expertise in a dedicated educational path. Moreover, while out-of-the-box solutions to represent uncertainty are yet to be investigated and developed, general-purpose visualisation and precise methods remain viable to achieve basic results. Given the renowned benefits of storytelling to improve the communication and interpretation of complex information [16, 34, 69], we suggest that narrativity could

compensate for the lack of uncertainty visualisation methods and mitigate the complexities that uncertainty is argued to introduce in visualisations [17, 58, 94–96]. Most projects neither represent uncertainty nor use narrative or tailored approaches, disclosing substantial room for improvement with potentially great benefits, especially for casual users.

7.6 Limitations and Future Work

Our classification schema focuses on specific, selected approaches and categories. As such, it does not capture examples like the one described by [31], whose project is present within our corpus but is not reported since constructedness and interpretation emerge from interaction rather than from visual representation. The corpus size is larger than the one analysed in other DH-related studies, which allowed us to derive some representative conclusions on the impact of narrativity, critical approaches and uncertainty representation. Nevertheless, the little support for visualisations in the small set of narrative projects prevents us from generalising conclusions.

Furthermore, the focus on projects, rather than on single, independent visualisations, as the primary object of enquiry, inevitably leads to limitations. For instance, we cannot distinguish when multiple visualisations are used within the same view or in separate sections of the website. Also, it is not possible to distinguish the exact context in which precise techniques are used within hybrid projects. This approach also limits conclusions on the relationship between specific visualisations and supported interactions, whose link is inevitably lost in the aggregation. To this extent, a study focused on visualisation-interaction units is needed to grasp more peculiar and precise insights at a lower level of abstraction.

While partially mirroring European and North American predominance in DH research activities, the geographical distribution of our corpus may cause the findings to reflect European DH practices more than global ones, and should be interpreted accordingly. Moreover, although this survey can be used as a tool to better understand the state of the art of DH visualisation practices, its nature confines us to deriving results and arguments based on the past. Even if including more recent projects than previous studies, the study remains limited by its timeframe and by the constant and rapid advancements in the field. On the one hand, this limits the temporal generalisability of our results, but on the other, it confirms the relevance of continuously monitoring the evolution of DH visualisation practices.

Finally, we also report a bias when trying to define requirements for critically adapted, innovative, tailored visual solutions through classification tests. Distinguishing truly tailored and innovative visual solutions from more conventional but customised, aesthetically pleasant, well-designed and usable visual systems proved to be challenging. Together, such features were rarely encountered during our review, and our framework is not able to measure them properly. However, qualitative aspects such as clarity, appropriateness of choices, usability and aesthetics are important factors that contribute to the success of one another and concur to more easily understandable visualisations and interfaces [47]. Therefore, we advocate for further analyses addressing qualitative aspects to understand visualisation effectiveness in the DH.

8 Conclusion

We presented an extensive analysis of information visualisation, interaction and narrative strategies in web-based DH projects, with a focus on humanities domains, interpretation and uncertainty visualisation methods and critical adaptations of visual solutions to accommodate the peculiarities of humanistic data.

We extended both the context and the scope of previous studies by analysing the state of the art of DH web interfaces, leveraging information visualisation techniques and comparing results across contributions. The increasing availability of humanities data and the manifold discussion around visualisation methods and issues posed by their peculiarities underscore the relevance of this study and reinforce the belief that such topics are poorly reflected in the design and development of DH projects. The analysis reveals a field characterised by naïve reuse of techniques without critical re-evaluation, which relies on a small set of popular visualisations, interaction

and narrative configurations, a long tail of less common solutions, seldom usage of narrative approaches and visual representation of uncertainty and interpretative phenomena, as well as critical adaptations of visualisation methods to accommodate the specificities of humanistic data.

Our findings suggest the need to advocate for more informed and critical approaches to the design and development of DH visualisation interfaces. We encourage greater interdisciplinary collaborations among digital humanists, humanists and information visualisation practitioners to design novel solutions that fill the gaps highlighted in the theoretical discussion. We also propose leveraging narrativity to unfold complexity rather than simplifying or omitting it and to overcome readability issues posed by uncertainty representation, compensating for the lack of alternative solutions. By doing so, we advocate for critical reflection to support the development of projects that aim at maximising the quality of information visualisation while staying deeply aligned with humanistic goals.

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Received 28 May 2025; revised 19 March 2026; accepted 18 April 2026