Animating the Narrative: A Review of Animation Styles in Narrative Visualization

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Abstract

Narrative visualization has become a crucial tool in data presentation, merging storytelling with data visualization to convey complex information in an engaging and accessible manner. In this study, we review the design space for narrative visualizations, focusing on animation style, through a comprehensive analysis of 80 papers from key visualization venues. We categorize these papers into six broad themes: Animation Style, Interactivity, Technology Usage, Methodology Development, Evaluation Type, and Application Domain. Our findings reveal a significant evolution in the field, marked by a growing preference for animated and non-interactive techniques. This trend reflects a shift towards minimizing user interaction while enhancing the clarity and impact of data presentation. We also identified key trends and technologies shaping the field, highlighting the role of technologies, such as machine learning in driving these changes. We offer insights into the dynamic interrelations within the narrative visualization domains, and suggest future research directions, including exploring non-interactive techniques, examining the interplay between different visualization elements, and developing domain-specific visualizations.

Index Terms: Narrative visualizations, static and animated visualization, categorization, design space

1 Introduction

In the increasingly complex domain of data presentation, narrative visualization has emerged as a vital tool by enhancing communication through rich and engaging data interpretation [15], increasing user engagement with intuitive information representation [25, 20], and improving accessibility with user-friendly designs [25]. It merges storytelling with data visualization, aiming to transform intricate data sets into engaging, informative, and comprehensible stories for a broad audience [14, 35]. Furthermore, narrative visualizations can elicit and establish emotional connections through dynamic and interactive storytelling methods [13, 22, 32]. Recent advancements in technology and visualization techniques have propelled the growth of narrative visualization, particularly through animations [26, 28]. Prior research explored various methods to animate static charts [35, 13] and integrate interactivity [22], significantly enriching the user experience and understanding [19]. These approaches made data representations more dynamic and accessible while introducing new ways to engage and educate viewers.

Despite the broad usage of animation in narrative visualization, prior works highlighting the importance of animation styles are scattered across various publications and research projects. While some works categorized narrative visualization, many of these studies predominantly focused on narrative intents, organizing data facts, and selecting visual design techniques [34]. Others focused on how different narrative structures can be utilized in data storytelling to affect audience understanding and memory [4]. However, how the animation style interacts with these elements to create a cohesive and effective narrative remains underexplored.

In this work, we address this gap by categorizing narrative visualization design space, focusing on animation style. We reviewed 80 papers from prominent visualization venues including IEEE Visualization (VIS), Transaction on Visualization and Computer Graphics (TVCG), ACM CHI Conference on Human Factors in Computing Systems, and EuroVIS. We performed multiple reading passes through each collected paper. First, we identified three initial categories based on prior works and our initial reading passes including animation style, workflow, and application domain. Then, we thoroughly reviewed the papers to assign them to initial categories and added new categories following inductive and deductive coding approaches [7]. We refined the emergent categories across several iterations and finalized them into six broad categories: Animation Style, Interactivity, Technology Usage, Methodology Development, Evaluation Type, and Application Domain.

We further analyzed the papers to identify key trends, technologies, and methodologies using linear regression and Person's correlation, which led to a deeper understanding of how dynamic and static elements influence narrative effectiveness. Our findings reveal a significant growth in the use of animations in narrative visualizations, with a notable increase in animated and non-interactive techniques. This evolution reflects a trend towards enhancing storytelling and audience engagement while minimizing user interaction. Furthermore, a trend toward survey-centric evaluation for visualizations suggests the importance of user feedback in refining visualization techniques. Our Pearson's correlation revealed the complementary use of animated and non-interactive elements to enhance user understanding and engagement. Furthermore, we found a strong correlation between animated elements and case studies, which underscores the importance of combining dynamic elements with practical examples to validate theoretical models. Based on these insights, we suggest future research directions, including further exploration of non-interactive techniques, examining the interplay between different visualization elements, and developing domain-specific visualizations tailored to unique user needs.

2 Animation Style in Narrative Visualization

The introduction of animation into narrative visualization has been instrumental in enhancing comprehension, engagement, and emotional connection [24, 21], as it brings data to life in a way that static images can not [8, 33]. Previous research has explored ways to make static visualizations more dynamic and engaging [35, 26]. For instance, "Marching Ants", "Geometry Deformation", and "Gradual Appearance" have been introduced to animate static charts, significantly improving the speed and accuracy of visual understanding [16]. Additionally, ScrollyVis [20], Data Animator [28], and the Animated Visual Narrative Design Space [24] have facilitated the creation of dynamic narratives, combining animation techniques and visual narrative strategies to enhance viewer engagement and educational impact. Recently, graph neural networks and large natural language models have been used to transform static charts into dynamic and interactive visualizations, enhancing their interpretability and interactivity [35]. Others incorporated animation styles into narrative visualization to explore new avenues for emo-

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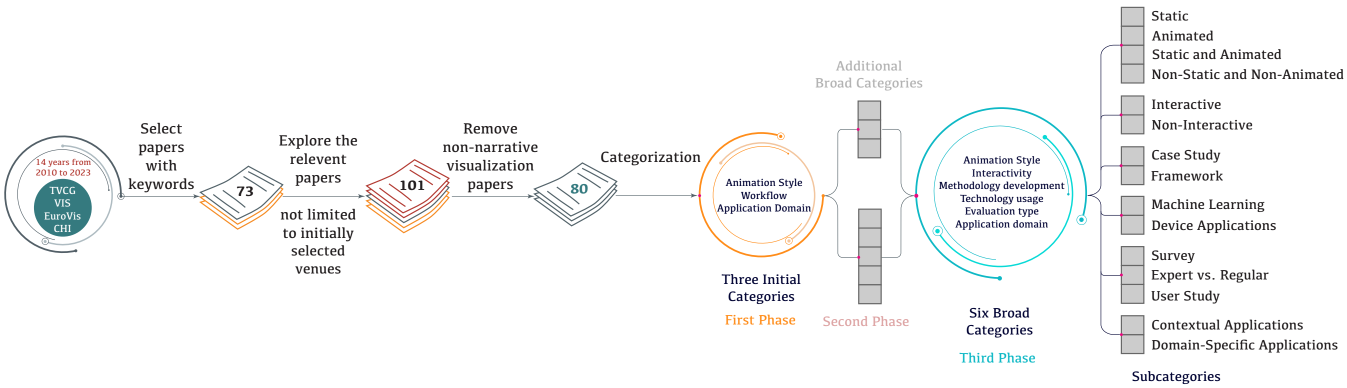

Figure 1: This figure presents our approach to categorize 80 narrative visualization papers over 14 years, focusing on animation style. First, we collected 73 papers from top-tier visualization venues (TVCG, IEEE VIS, CHI, EuroVIS). From the related works sections of these papers, we identified more papers totaling 101. Then, we filtered and removed papers that are not relevant to narrative visualization and animation to get the final set of 80 papers. We used a multi-phase approach to categorize these papers using inductive and deductive coding. In the first pass, we identified three initial categories — Animation Style, Workflow, and Application Domain. In subsequent passes, we added new categories. Following an iterative refinement method, we divided the papers into six categories — **Animation Style**, **Interactivity**, **Methodology Development**, **Technology Usage**, **Evaluation Type**, and **Application Domain**, and their corresponding subcategories.

tional expression and narrative enhancements [15, 17, 13]. For instance, Lan et al. proposed Kineticharts and visual foreshadowing techniques to underscore the importance of animation design in enhancing the emotional expressiveness of charts in data stories [13]. Data videos, Data-GIFs, and WonderFlow are prominent examples of how animated narratives can effectively combine narration and animation, emphasizing the synergy between narrative and visual elements [22, 26, 32]. These tools make dynamic data visualizations more accessible and enrich the storytelling process, making complex information engaging and easier to comprehend.

3 Methodology

In this work, we investigate and categorize current narrative visualization focusing on the animation style. This section presents our paper selection, multi-phase coding, and categorization process.

3.1 Paper Selection

We focused on papers from key visualization research venues over 14 years (2010 to 2023) including IEEE VIS, IEEE TVCG, ACM CHI, and EuroVIS. We chose them for their significance in publishing prominent works on visualization research and practices [2].

We used keyword searches to identify papers from these venues by using their publicly available digital libraries such as ACM Digital and IEEE Xplore. We employed keywords such as, "narrative", "visualization,", "data story", "static", and "animated", and their combinations to search papers that have these terms in their titles or abstracts, resulting in 73 papers. Then we skimmed the references from these papers to identify 28 more papers from various external sources and publication venues, not limited to our initially selected venues. In total, our paper collection included 101 papers. We excluded 21 papers irrelevant to narrative visualizations or data stores, leaving us with a curated set of 80 papers for analysis.

3.2 Paper Categorization

To categorize our collected papers, we followed a multi-phase approach where we initially conducted a cursory reading pass to establish three broad categories. This was followed by a detailed analysis aimed at identifying more specific subcategories. We continuously adjusted and improved these categories through an iterative refinement process, ultimately defining six comprehensive categories, each containing several subcategories (Tab. 1).

First Phase: Preliminary Categorization. In the first phase, we performed a cursory reading of the titles, abstracts, and introductions to obtain a broad understanding of the diverse approaches to narrative visualization, including design, development, application domains, workflows, and evaluation methods. From this understanding, three main components emerged: (1) Animation Style, which focuses on the impact of motion in narrative delivery; (2) Workflow, which emphasizes the procedural aspects of creating narrative visualizations; and (3) Application Domain, which considers the unique challenges and requirements of different fields. This preliminary categorization helps to identify key areas of focus and lays the foundation for more detailed analysis in subsequent phases.

Second Phase: Detailed Analysis and Subcategorization. This phase involved a deeper analysis of the papers to further investigate the nuanced interaction between design elements in narrative visualizations. Through this process, additional categories emerged, including (1) Interactivity, highlighting interactive elements that enhance user engagement; (2) Evaluation Type, detailing methodologies for assessing narrative visualizations; (3) Technology Usage, exploring tools and techniques used in narrative visualizations; (4) Emotional Support, focusing on design strategies that offer emotional engagement; and (5) Performance Improvements, identifying methods that enhance user understanding and interaction. We examined dimensions such as functional prototypes [17], innovative technology applications [1, 35], and dynamic interactions [27], which provided concrete examples for these categories.

Third Phase: Iterative Refinement. In the third phase, we conducted a thorough re-reading of the complete manuscripts. This comprehensive review allowed us to refine our understanding of the research methods, technologies, workflows, case designs, specialized devices, and user interactions described in the papers. For instance, through the reading, we found instances where machine learning was employed to analyze and identify chart elements and was paired with large language models to generate dynamic visual effects and narrations [35]. We also identified that technologies such as eye-tracking were utilized to analyze how participants handle the interaction between text and visual data [1]. Through this iterative refinement process, we reorganized the papers into six final categories: (1) Animation Style, (2) Interactivity, (3) Technology Usage, (4) Methodology Development, (5) Evaluation Type, and (6) Application Domain, each with specific subcategories.

3.3 Categories and Subcategories

Animation Style: Explores the role of motion and change in visual elements within narrative visualizations. It includes four subcat-

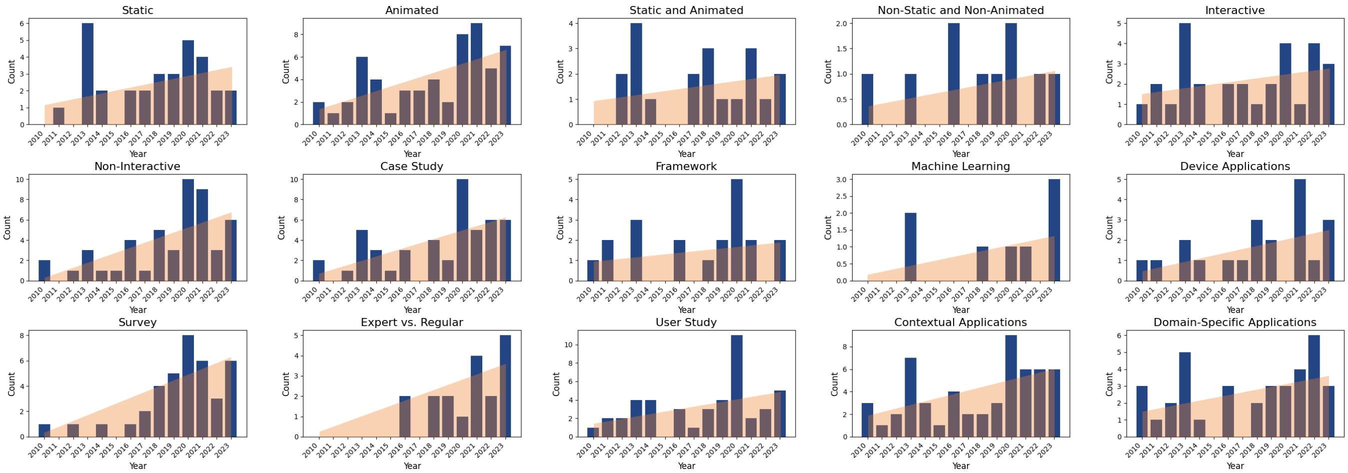

Figure 2: The yearly distribution and linear regression analysis of categories from 2010 to 2023. Each subplot represents a distinct category of publications, such as *Static*, *Animated*, *Static and Animated*. The vertical bars in blue denote yearly publication counts for each category. Overlaid on each bar chart is a linear regression slope in orange-red, indicating the linear regression line fit across the years.

egories: (a) *Static* visualizations that remain unchanged over time, providing a single, non-moving image [18]. (b) *Animated* visualizations that include elements changing or moving over time to convey information dynamically [22]. (c) *Static and Animated* visualizations that combine both static and animated elements within a single narrative visualization [16]. (d) *Non-Static and Non-Animated* visualizations that do not include animation or static images [10].

Interactivity: Examines how narrative visualizations incorporate user input to explore or alter data, enhancing engagement and personalization. It includes two subcategories: (a) *Interactive* visualizations allow user input to alter or explore different aspects of the data [20]. (b) *Non-Interactive* visualizations does not allow any user interaction and present fixed-format data [16].

Methodology Development: Focuses on the approaches taken to create and implement narrative visualizations, which is divided into two subcategories: (a) *Case Study*, where narrative visualizations demonstrate a particular use case [13]. (b) *Framework*, where a structured and repeatable set of methods is designed for developing narrative visualizations [26].

Technology Usage: Pertains to technologies used for enhancing narrative visualization effectiveness. It includes: (a) *Machine Learning*, used to analyze visual attention by tracking viewer focus to improve design [35]. (b) *Device Applications*, involving specialized devices (e.g., VR headsets, eye trackers) that support or enhance the narrative visualization experience [29, 12].

Evaluation Type: Concerns with the methods used to assess the effectiveness and impact of narrative visualizations. It includes: (a) *Survey*, gathering data through questionnaires to assess viewer perceptions or effectiveness of the visualizations [17]. (b) *Expert vs. Regular*, comparing feedback or performance between expert users and regular viewers [35, 23, 11]. (c) *User Study*, conducting structured experiments with users to observe interactions and gather qualitative or quantitative insights [32].

Application Domain: Examines how narrative visualizations are tailored for specific domains to meet unique challenges and requirements. It includes: (a) *Contextual Applications*, where visualizations are tailored to situational contexts or environments [3]. (b) *Domain-Specific Applications*, where visualizations are used for particular fields or industries (e.g., education [18], economics [31]).

4 Data Analysis and Results

We used linear regression and Pearson's correlation to identify patterns and trends from papers, which suggests increased use of animations and machine learning and reduced user interactions.

Table 1: Categories, subcategories, and example papers

Category	Subcategory	Example Papers
Animation Style	Static Animated Static and Animated Non-Static and Non-Animated	[18] [17] [22] [26] [28] [5] [19] [10]
Interactivity	Interactive Non-Interactive	[22] [22] [16] [35]
Methodology Development	Case Study Framework	[13] [22] [17] [26]
Technology Usage	Machine Learning Device Applications	[35] [22] [29] [12]
Evaluation Type	Survey Expert vs. Regular User Study	[17] [16] [35] [23] [32] [25]
Application Domain	Contextual Applications Domain-Specific Applications	[3] [16] [18] [31]

4.1 Trend Analysis using Linear Regression

We chose linear regression (Fig. 2) to analyze how our subcategories of narrative visualization evolved from 2010 to 2023, for its capability to describe and predict how one variable changes in relation to another (e.g., categories vs. year). The analysis reveals distinct trends in various categories, reflecting the evolution and focus areas in narrative visualization over time. In the following, we present the slope of the linear regression with our observations.

We found that the *survey* displayed the most significant growth rate among all categories, as evidenced by the largest slope (0.51), growing from -0.60 in 2010 to 6.03 in 2023. This trend suggests the importance of comprehensive surveys in evaluating visualization techniques, consolidating knowledge, identifying gaps, and guiding future research directions in narrative visualization. Similarly, our analysis shows that most categories of narrative visualization have experienced growth over the years. Categories such as *animated* (0.41), *non-interactive* (0.49), *case study* (0.42), and *contextual applications* (0.32) have shown particularly strong upward trends, indicating significant growing interest in more dynamic, engaging, and research-focused narrative techniques. Notably, the use of animation in narrative visualization is gaining increased focus, growing from 1.43 in 2010 to 6.71 in 2023, due to its ability to

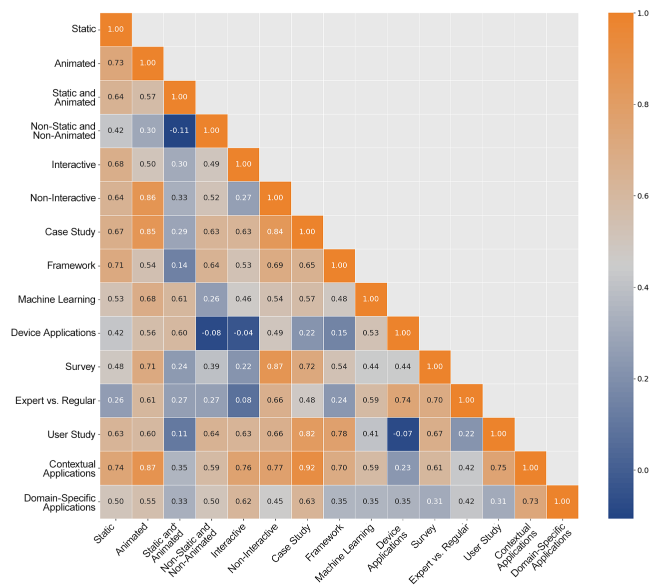

Figure 3: A correlation matrix showcasing the pair-wise relationship between each subcategory. The color gradient from blue through white to orange represents the spectrum from a strong negative correlation, through no correlation, to a strong positive correlation.

enhance storytelling and engage audiences effectively [22, 26, 32]. This increase in animation usage underscores the trend toward creating more immersive and visually compelling narratives that can capture and retain audience attention.

In contrast, categories, such as *non-static and non-animated* (0.05) and *frameworks* (0.07) show minimal growth, reflecting lesser emphasis or slower adoption in these areas. The minimal growth in *non-static and non-animated* suggests a preference for more dynamic and interactive methods over static presentations. Despite their slow growth rates, categories such as *static* (0.18), *interactive* (0.10), and *machine learning* (0.10) have shown steady increases, indicating a consistent rise in their importance over time. This growth reflects a balanced interest in traditional and emerging technologies, ensuring that foundational methods continue to evolve alongside innovative approaches.

4.2 Pearson's Correlation between Categories

To investigate the relationships among the subcategories, we used Pearson's correlation [9] to create a confusion matrix heatmap (Fig. 3). The correlation coefficients range from -1 to 1, where values nearing 1 signify strong positive correlations, -1 denotes strong negative correlations, and around 0 suggests negligible correlation.

Analyzing Pearson's correlation between the categories, several significant relationships emerge. Notably, a high positive correlation between *Animated* and *Non-interactive* (0.861) suggests non-interactive designs are often associated with animated elements. Similarly, *Animated* and *Case Study* correlate positively (0.847), highlighting a strong connection between case study methodologies and the use of animated designs. Other noteworthy positive correlations include *Contextual Applications* and *Case Study* (0.921), suggesting that contextual applications frequently employ case study approaches; *Contextual Applications* and *Animated* (0.870), indicating that contextual applications tend to incorporate animated elements, and *Non-interactive* and *Contextual Applications* (0.771), further underscoring the tendency for non-interactive designs to be utilized in contextual applications. These correlations signal that non-interactive narrative visualizations are often integral to surveys, case studies, and domain-specific applications, reinforcing their pertinence in research settings where user interaction may not be the focus ([26]). Further correlations are identified between the *Expert and Regular* and *Non-Interactive* (0.660), *Device Applications* (0.738), and *Survey* (0.696), implying a frequent convergence between studies distinguishing expertise levels and those employing surveys without interactivity ([35, 13]).

Conversely, we found several negative correlations. For instance, *Device Applications* and *Non-Static and Non-Animated* show a negative correlation (-0.076), suggesting that applications for devices perform less effectively when non-static and non-animated. Additionally, *Interactive* and *Device Applications* negatively correlate (-0.039), hinting at a minimal inverse relationship between interactive elements and device applications. The *Static and Animated* category shows a moderate correlation with *Machine Learning* (0.612) and *Device Applications* (0.599), indicating some level of association between these categories. However, its correlation with other categories is generally lower, suggesting that static and animated designs are less prevalent in other contexts.

5 Discussion

5.1 Implications for Practice and Future Directions

The insights from our analyses provide valuable implications for researchers and practitioners in the narrative visualization field. For instance, the focus on animated and non-interactive visualizations highlights the need for techniques that enhance storytelling without excessive interactions. Further exploration of non-interactive visualization techniques, especially for device applications, is required to understand their potential to create balanced visualizations.

Researchers should investigate the interplay between different visualization categories in greater depth to integrate these components to create cohesive and compelling narratives. While our analyses provide initial insights, a more detailed examination of how various elements interact and influence each other will enhance our understanding of effective narrative visualization design. This could involve exploring new combinations of static, animated, interactive, and non-interactive elements to discover innovative approaches that maximize user engagement and comprehension.

The link between case studies and contextual applications emphasizes the need for practical validation to advance theoretical models. However, researchers could develop domain-specific visualizations for different user groups beyond experts [2] to consider their unique requirements and challenges.

Finally, as the usage of machine learning in narrative visualizations grows, research into ethical implications and best practices becomes essential. Ensuring transparency, fairness, and accessibility in machine learning-enhanced visualizations is vital for maintaining user trust and equitable information access and communication [6].

5.2 Limitations and Future Work

In this work, we focused on academic papers from selected top-tier venues, which might have restricted the findings' pertinence across a broader range of visualization practices, potentially limiting insights from less prominent sources. Furthermore, we did not consider research publications before 2010, which reduced our focus on traditional techniques still used across various settings [30].

In the future, we plan to investigate a broader range of approaches from both academia and industry to gain a more holistic view of the effectiveness and reception of narrative visualizations. Furthermore, we plan to conduct longitudinal studies to understand the long-term effects and sustainability of engagement through animated visualizations. Such studies would provide insights into how different contexts influence the effectiveness of narrative visualizations over extended periods, helping to determine their impact on comprehension, learning, retention, and user satisfaction. Future research could also explore the adaptability and accessibility of animations in narrative visualizations across languages and cultures to be a more useful communication channel for a broader audience.

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