LSN-VA: A Visual Analysis System for Ancient Chinese Literati Social Network

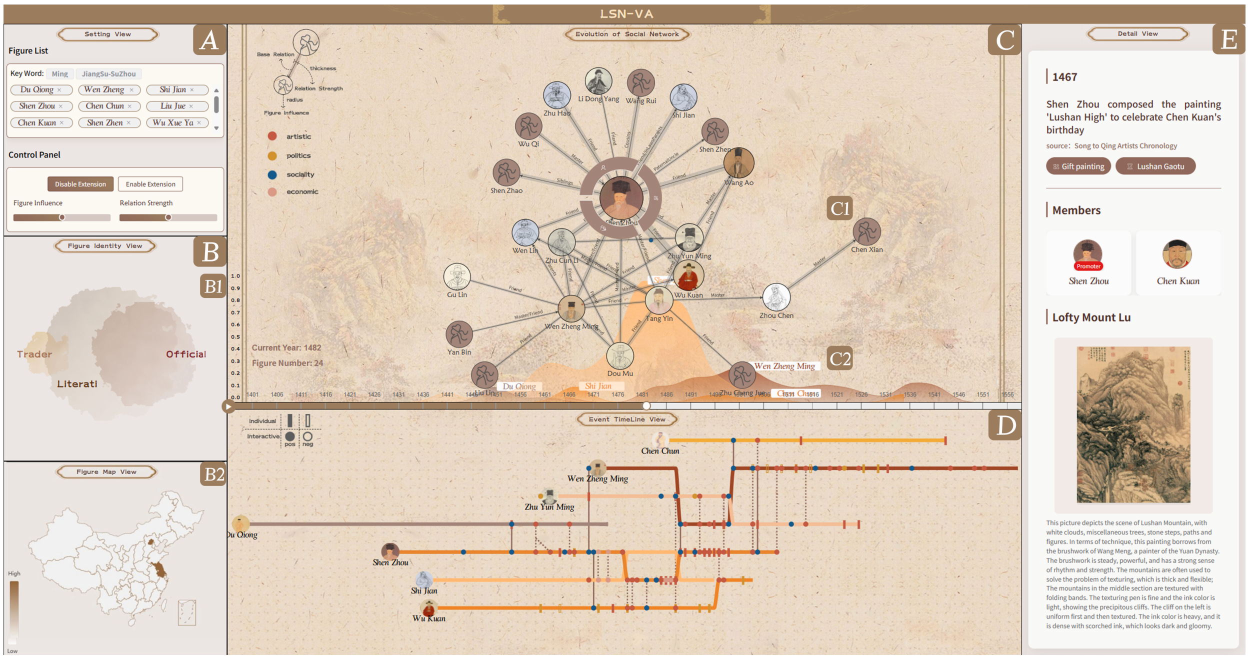

Fig. 1. The interface of *LSN-VA* consists of five components: (A) Setting View allows users to set figures of interest and visualization parameters; (B) Network Distribution Statistics provides an overview of the figure distribution according to their identities and residences; (C) Evolution of Social Network reveals the social attributes and relations of literati from different perspectives; (D) Event Timeline View constructs event-driven storylines that contextualize interpersonal exchanges within biographical timelines; (E) Detail View provides structured metadata access through detail-on-demand interactions.

Abstract—The ancient Chinese literati society is a dynamic and complex social network based on ties of consanguinity, master-apprentice relationships, and cultural relationships through artwork-centered social events, such as exchanges of calligraphy and painting, letters, etc. In this paper, we present a visual analysis system for literati social network LSN-VA, which provides a set of intuitive visual designs to support interactive exploratory analysis of the dynamic ancient Chinese literati social network and its spatial-temporal evolution. An ancient Chinese literati dataset is first built by merging 4 historical sources and augmented using a large language model. And then a new dynamic social network modeling method is proposed to automatically infer the relationship, influence, and missing attributes of ancient Chinese literati. Finally, we conducted two case studies and one user study to demonstrate the effectiveness of our system.

Index Terms—social network, visual analysis, dynamic network, historical data, digital humanities

1 Introduction

The social circle of ancient Chinese literati was a highly complex and diverse social network system, whose structure was like an intricately woven brocade. At the family level, the family network formed by blood ties through marriage and clan relations served as an important basis for resource sharing and mutual support. At the cultural level, spiritual connections established through exchanges/givings of calligraphies, paintings, etc. become crucial channels for cultural dissemination and ideological exchanges. At the political level, the power networks built by officials through relations such as classmates, teachers and students, and colleagues had a profound impact on the political development of the country. These humanistic social networks intertwined with each other, jointly shaping the development trajectory of ancient society and playing a pivotal role in cultural inheritance and social evolution.

However, the social networks of the ancient literati were not static. For instance, Dong Qichang [49] forged strong ties with Hui merchants through artwork transactions during the prosperous period of the commodity economy in the late Ming Dynasty. When facing political crises, he strategically established patronage relationships with central officials. Meanwhile, he united the Jiangnan literati group by actively spreading his painting theories. The Wumen literati [41] in the Ming Dynasty also leveraged their social networks through various calligraphy and painting practices: they consolidated community identity through the collective creation of *Collected Poems of Jiangnan Spring*, expanded their official careers by presenting artworks to officials, and strengthened alliances among scholarly families in the Wu region through interfamily marriages.

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Based on long-term communication with historians, they are deeply interested in questions such as "How did the literati social network evolve?", "What role does the individual play in the literati social network?", and "What role do the social events with artworks play in the socialization of literati?". However, traditional research methods rely on extensive collection of historical materials and inductive reasoning, which are time-consuming and labor-intensive. Moreover, the lack of data often makes it difficult to conduct sound arguments. Even with all the available data, existing data mining methods struggle to meet research needs efficiently.

Historical data are often sparse and non-reproducible, while historical questions are highly open-ended and lack definitive answers. Existing studies mainly focus on static relations between individuals, paying insufficient attention to the visual analysis of dynamic social networks. As a result, they fail to fully capture the complexity of historical figures' social networks. Existing work based on the relation between cultural carriers and individuals also ignores the social attributes of cultural carriers, thus failing to fully demonstrate their roles as a valid link in the ancient Chinese literati social network.

To overcome the aforementioned challenges, we present a Visual Analysis system for Literati Social Networks *LSN-VA*. To dynamically visualizing the evolution of ancient Chinese literati social networks, we first constructd a literati social network database based on 4 data sources and data augmentation using large language models; and then we proposed two algorithms are proposed to automatically estimate the relation strength and figure influence; finally, we design a visual analysis system that not only shows the spatio-temporal evolution of the ancient Chinese literati social networks but also provides historians interaction tools to efficiently explore characteristics of figures and their social events.

- An ancient Chinese literati social network dataset that is not only merged 4 historical sources but also complemented and augmented using a large language model.
- A new dynamic social network modeling method that can automatically infer the relation, influence, and missing attributes of ancient Chinese literati.
- A visual analysis system that provides a variety of intuitive visual designs and supports interactive exploratory analysis of the dynamic ancient Chinese social networks and their spatial-temporal evolution.
- Two case studies and a user study demonstrate the validity and effectiveness of the proposed method on the ancient Chinese literati social network for both expert and ordinary users.

2 Related Work

In this section, we review the relevant research work in visual analysis for digital humanities, visual analysis for social networks, and computation for social networks.

2.1 Visual Analysis for Digital Humanitities

Visual analysis techniques have been widely applied in digital humanities research, triggering scholarly discourse among researchers in both historical humanities and visualization fields. Numerous digital humanities projects and data visualization tools have been developed to facilitate humanistic inquiry [27]. Existing research focuses mainly on historical figures [11, 12, 37, 47], cultural carriers [10, 16, 24, 36, 38, 45, 48], and historical events [17, 46], etc.

Visual analysis of historical figures: The CohortVA proposed by Zhang et al. [47] aids historians in the identification and validation of historical cohorts. The CareerLens system developed by Wang et al. [37] supports historians to explore, understand and reason from occupational data of the Qing Dynasty, enabling the comprehension of historical occupational mobility and personal social networks.

Visual analysis of cultural carriers: Guo et al. [16] developed LiberRoad to probe the transmission trajectory of Chinese classics through interactive switching among three views: location graph, map, and timeline. The ScrollTime proposed by Zhang et al. [45] enables art historians to analyze handscrolls by combining multiple databases and constructing biographies of paintings. The TCPVis proposed by Wang et al. [38] is a visual analysis system for multidimensional features of painting schools in traditional Chinese painting based on the Six Principles of Chinese Painting.

Visual analysis of historical events: Zhang et al. [46] proposed a visual system for reasoning uncertainties in spatio-temporal events of historical figures. It is based on data from the China Biographical Database Project (CBDB) [18]. Han et al. [17] proposed the HisVA, which allows efficient exploration of historical events from Wikipedia using three views: event, map, and resource.

However, the aforementioned works have limitations. Most visual analyses of historical figures focus on static relation characteristics, lacking dynamic visual analysis of social networks and failing to capture the complexity of historical figures' social interactions. Visual analyses of cultural carriers often treat them as independent objects, overlooking their embedded social attributes and connective roles in social networks. In this work, we dynamically integrates figures, events, and cultural carriers in literati social networks, offering a novel visualization perspective for ancient social research.

2.2 Visual Analysis for Social Networks

Visual analysis is widely used in social network analysis. Node-link diagrams, adjacency matrices [14], and hybrid visualization formats combining both approaches [20] constitute conventional methodologies for representing social network connectivity structures. In practice, a diverse array of network visualization tools are available: programming languages (e.g. R and Python) offer dedicated graph visualization libraries; while specialized software platforms (e.g. Gephi [2], Pajek [3], and Cytoscape [35]) have been widely used in academic research.

To investigate complex expert questions, scholars have developed various interactive social network visualization systems [1,30,43]. Perer et al. [30] proposed SaNDVis, an enterprise social analytics system that extracts, aggregates, and infers social graphs from internal corporate communication. Yu et al. [43] proposed NcoVis, a visual analysis method for exploring novel academic collaboration networks.

When handling network visualization tasks with temporal attributes, dynamic visualization forms such as animations and timelines are commonly used. R-Map developed by Chen et al. [9] is a visualization analysis method using a map metaphor, which spatializes the structural forwarding tree of social media information and uses a timeline to present the information dissemination process in the network. CombiNet developed by Pister et al. [31] explores historical documents modeled by bipartite multivariate dynamic networks, which helps social scientists study and uncover the connections and changing patterns between people and events in different periods.

Existing social network visualization methods primarily target static networks or information-spread dynamics networks with limited dimensions, they often fail to capture multidimensional co-evolution (social ties, influence, identity, geography) in historical literati networks. To address this, we propose a dynamic visualization method integrating an animated timeline with three coordinated views: (1) Figure Distribution Statistics,(2) Evolution of Social Network,and (3) Event Timeline View.

2.3 Computation for Social Networks

The social network architecture is formally defined as a topological structure comprising nodes and edges, where nodes represent individual entities and edges are mathematically operationalized as dyadic connections encapsulating interpersonal relations.

At the nodal analysis level, core research trajectories encompass influence quantification [4, 6, 8, 25, 28], community detection [19, 21], and similarity analytics [7, 40]. Node influence assessment holds pivotal significance for characterizing hierarchical positions within network ecosystems. Recent advancements in this domain have yielded multi-perspective methodological frameworks: Chen et al. [7] conducted systematic assessments of Ming Dynasty literati quartet's social capital through multi-centrality fusion (degree, betweenness, and eigenvector metrics); Liu et al. [25] achieved precise artist influence measurement via entropy-constrained PageRank optimization with iterative parameter refinement; Bhattacharya et al. [4] employed Graph convolutional Net-

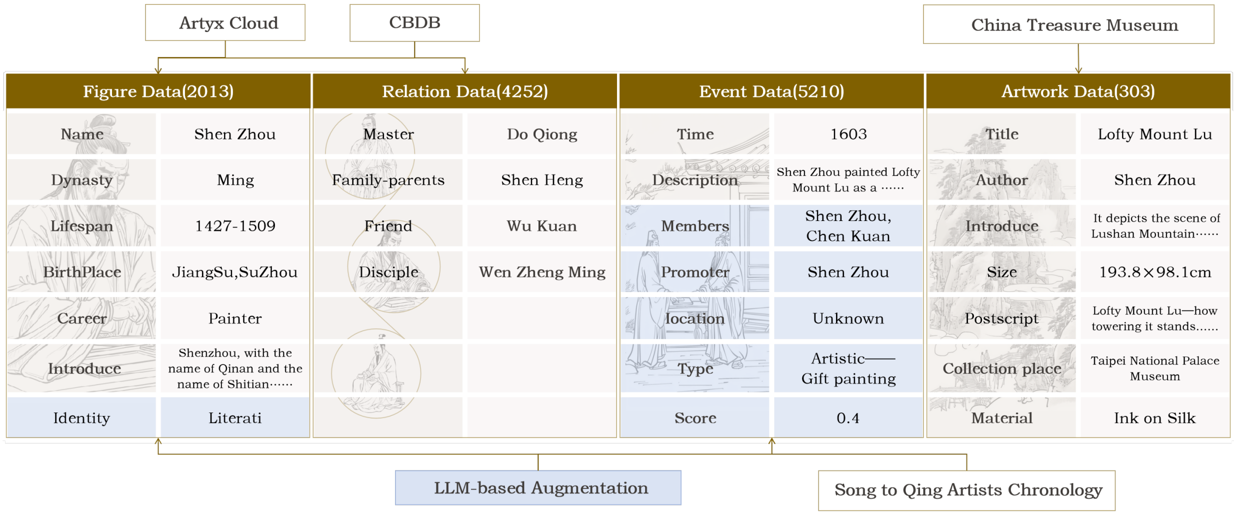

Fig. 2. Dataset of Chinese Ancient Literati. It integrates multi-source historical records and is enhanced by large language models (LLM). Four types of data are included, with each type displaying two columns: data attributes (left) and data examples (right). These attributes comprise both the attributes collected from source data and the attributes extended by LLM.

works (GCNs) that predict nodal attributes with topological propagation for dynamic influence modeling.

At the edge analysis level, principal research directions include relation strength computation [22, 32, 39], relational inference [33, 34], and edge prediction [42, 44]. The relation strength quantifies the intensity of inter-nodal associations, which plays an important role in deciphering social network interaction paradigms. To this end, Khadangi et al. [22] established a quadripartite strength classification framework, implementing decision tree architectures and multilayer perceptron frameworks for predictive strength modeling. Xiong et al. [39] pioneered Bayesian probabilistic graphical models that holistically measure relational intensity through homophily metrics and cross-domain behavioral vectors.

In our work, we mix intrinsic relation and interaction events together to quantify the relation strength of figures, while integrating indivisual influence with social influence for nodal influence assessment. Compared to conventional methodologies, the proposed framework demonstrates enhanced applicability in small-scale social network analysis, achieving the best balance between computational stability and algorithmic efficiency.

3 Background

In this section, we summarize the requirements obtained through interviews with domain experts. To characterize the domain problem and develop system requirements, we have worked closely with three experienced domain scholars over the past year. One of them is a professor (E1), whose research focuses on the study of Chinese historical figures, and two are Ph.D. students (E2, E3), all of whom have experience in researching the Chinese figures social network.

3.1 Data collection

We have collected and organized four categories of historical data: figure data, relation data, event data, and calligraphy-painting data, with their attributes shown in Figure 2.

Figure data and relation data: The data primarily derive from the China Artists Database(Artyx Cloud) [1]. This database contains basic information of Chinese painters, calligraphers, and art collectors across historical periods (e.g., name, gender, dynasty, birthplace, and career), and social relations(e.g., family, master, disciples, and friends). While Artyx Cloud covers most literati data, it lacks information on some affiliated figures like officials and traders and their social ties. Therefore, we additionally integrated the China Biographical Database (CBDB) [18] to supplement the data.

Event data: Existing event datasets have limitations in missing event timestamps and insufficient records of literati-related events. Therefore, we compiled event data from the book *Song to Qing Artists Chronology* [15], which contains a substantial amount of time-specific event data related to figures. These include events such as independent creation, collaborative painting and painting presentations.

Artwork data: We scraped artwork data from the Chinese Treasures Museum[2], covering image resources and basic artwork information.

3.2 Requirement and Task Analysis

We discussed the core issues that our collaborators focused on in the study of literati social network through interviews and summarized the requirements as follows:

- **R1 How did the literati social network evolve?** The experts hope that the overall characteristics of the literati social network can be visualized, not only to clearly present the relation between the figures but also to statistic information such as identity and geographical distribution, so as to help researchers quickly grasp the overall picture of the literati society in a specific period of time. At the same time, the experts suggest adopting a dynamic visualization method to intuitively visualize the changes in the social network.When there are significant changes in the network, they can correlate with related historical events and explore the reasons for the changes in the network.
- **R2 What role does the individual play in the literati social network?** Experts pointed out that on the basis of exploring the evolution of the macro network, it is necessary to further focus on the individual.By assessing their influence and analyzing connections with other network nodes, researchers can determine whether an individual occupies a core or peripheral position, thereby enhancing micro-level studies of literati social networks.
- **R3 What role do the social events with artworks play in the socialization of literati?** Experts mentioned that the social events with artworks are of great significance in the literati social network. They seek to analyze the unique influences of such events across political, economic, and cultural domains, and explore how calligraphic and painting works, as cultural carriers, serve as connective bonds in the construction and maintenance of literati social relations.

According to the requirements, we define the following design tasks (corresponding user requirements are assigned in the end):

- **T1 Statistical analysis of network characteristics.** Provide statistical analysis on the number of nodes, identity distribution,

[1]https://www.artyx.cn/

[2]https://ltfc.net

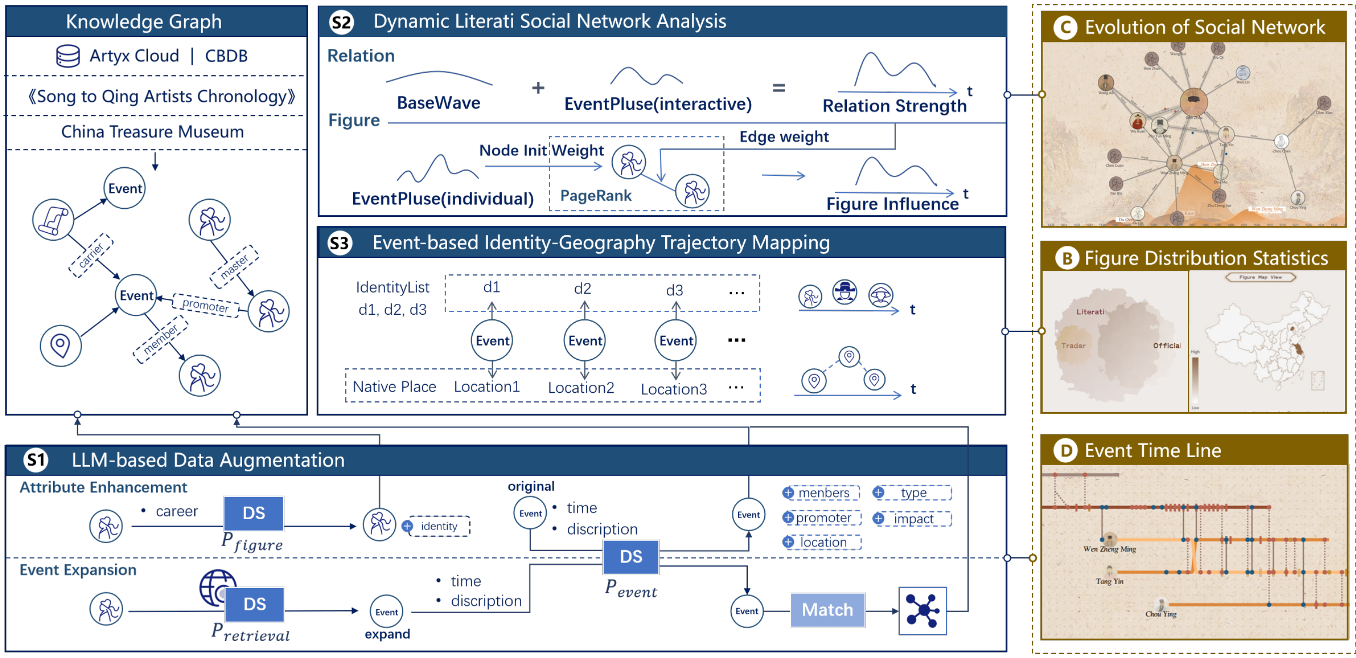

Fig. 3. LNS-VA comprises three core methods (S1-S3) and three primary visual interfaces (B-D). We first built a knowledge graph with four data sources. For figure and event data, we employ LLM to augmentation them (S1), foundational for analysis and visualization (C-D). We then compute the dynamic relation strength and figure influence to model the evolution of literati social networks (S2), and visualize the results in C. Additionally, we map the identities and geographical trajectories of the figures based on events (S3), and visualize their distributions in B.

geographic distribution, etc. of the social network. (**R1**)

T2 **Dynamic social network visualization.** Real-time display of the nodes and characteristics of the current social network, through the animation transition to visualize the evolution of the network structure, such as: the process of the marginal figure to become the central figure, the process of dynamic connection of the network members, and so on. (**R1**, **R2**)

T3 **Visualization of individual characteristics.** Visualize each node's influence size, identity type, relation between nodes, and relation strength. (**R2**)

T4 **Event Visualization.** Visually present figure chronology events, visualize interactive events involving figures, visualize event types (e.g., politics, artistic, sociality, economic), visualize event impacts as well as event positivity and negativity,visualize social events with artworks. (**R1**, **R3**)

T5 **Detailed information display.** Provide detailed information on figure attributes, event details, painting and calligraphy data. (**R1**, **R2**, **R3**)

4 System Method

In this section, we introduce three core methods(Fig.3 S1-S3).

4.1 LLM-based Augmentation of Data

The raw data we collected and organized exhibits certain deficiencies. First, there is a lack of attribute dimensions: In figure data, the recorded occupation types are excessively diverse, including various official positions and professional categories, which hinders our statistical analysis of figures in the network. Event data only contains time and description, making it difficult to conduct further analysis and visualization around events. Second, the event distribution shows skewness - the original event data is predominantly concentrated in the art domain, failing to reflect the multidimensional social activities of figures. We adopt the following methods to address these two deficiencies.

4.1.1 *Attribute Enhancement*

For figure data, we define identity attributes $F_{identity} = \{literati, official, trader, else\}$ based on expert annotations. Using a structured prompt template P_{figure}, we input the figure's career information and employ the DeepSeek [13] large language model for automatic classification:

$$d = \text{DeepSeek}(P_{figure}(career)), \quad d \in F_{identity} \tag{1}$$

For example, when *Career*="painter and Hubu Shilang" (Minister of Revenue), the prompt guides the model to map it to the "literati, official" categories.

For event data, we define the prompt template P_{event}, Given unaugmented event data $E = \{e_1, e_2, \ldots e_n\}$, where each e contains only time and description attributes, we perform: 1) **Entity Extraction**: Extract event participants, initiator, artwork, and location. 2) **Hierarchical Classification**: Classify event types into two levels, first level classification represents the nature of the event $Type_{macro} = \{artistic, politics, sociality, economic\}$, second level classification represents the content of the event $Type_{micro} = \{creation, joint\ travel, apprenticeship, government\ service, \ldots\}$ (total of 8 types). 3) **Impact Assessment**: Evaluate event influence within $[-1, 1]$, where negative values indicate negative events. The final augmented structured event becomes $S_{event} = \{s_1, s_2, \ldots s_n\}$:

$$s_i = \text{DeepSeek}(P_{event}(e_i)) \tag{2}$$

with added attributes:$\{members, prompter, artwork, location, type\{macro, micro\}, impact\}$

4.1.2 *Event Expansion*

For the expansion of event data, we define three stages:

Knowledge retrieval: We constructed a retrieval prompt template $P_{retrieval}$ for character event data. For each figure in the database, we used the character information as a template input to retrieve related events from public literature using large-language model. The model outputs information confidence scores, and events with low confidence are filtered out to obtain an expanded event set $E' = \{e'_1, e'_2, \ldots e'_m\}$, where each event records time and event description attributes.

Event attribute expansion: Reuse the P_{event} template (Formula x) to generate structured event data $S'_{event} = \{s'_1, s'_2, \ldots s'_m\}$ from E'.

Fusion verification: To avoid duplicate recording of identical events, we calculate the similarity between the obtained structured events

S'_{event} and existing data in the database using Levenshtein distance [23], discarding events with similarity higher than the set threshold.

Finally, we conduct sampling checks on the expanded data, retaining high-quality data and correcting erroneous data.

4.2 Dynamic Literati Social Network Analysis

In our method, the network dynamics emerge from the evolution of both relation strength and figure influence.As shown in Fig. 2S2, we quantify relation strength changes through base relations and interaction events (4.2.1), and measure figure influence changes using PageRank [29] that combines individual traits and network context (4.2.2).

4.2.1 *Relation Strength Modeling*

Historical figure relations are typically recorded as static categorical labels (e.g., "friends," "teachers," "family"), which are expert-verified but lack temporal dynamics. While interaction frequency may reflect temporal variations in relation strength,data sparsity makes this unreliable. We therefore propose a dynamic strength calculation method combining base relation with interaction events.

We model the base relation as a BaseWave, a parametric temporal function that roughly corresponds to the change of the relation.When base relation exist, the corresponding BaseWave serves as a quantitative strength benchmark, providinga priori constraints for modeling relation strength evolution over time.

Suppose that there exists an annotated relation k (e.g., friend, political opponent) between a pair of figure, with a time range defined as the intersection interval of their birth and death years $t \in [t_{start}, t_{end}]$. Define the duration of the relation as $T = t_{end} - t_{start}$, and denote the list of interactive events between the two individuals as $E = \{e_1, e_2, \dots\}$ (where $\mathrm{len}(E)$ represents the number of events). The BaseWave of the relation is defined as follows:

$$\mathrm{BaseWave}_k(t;\alpha,\beta,E) = \underbrace{\mathrm{Beta}\left(\frac{t - t_{start}}{T}, \alpha, \beta\right)}_{\text{shape term}} \cdot \underbrace{\sqrt{\mathrm{len}(E)+1}}_{\text{amplitude term}} \quad (3)$$

The BaseWave uses the beta distribution's probability density function as the shape term, with inputs of normalized time and shape parameters (α, β) controlling peak position and skewness. The amplitude term employs a sublinear function to enhance the influence of the number of interactive events on the intensity magnitude.

For different annotated relations k, we preset distinct shape parameters (α, β) for the beta distribution. If no interactive events occur between figures, we directly use the predefined parameters for their relation category.If interactive events exist, we optimize parameters by minimizing the weighted negative log-likelihood over event sequence E, where each event $e = (t_e, w_e)$ contains timestamp t_e and signed impact $w_e \in [-1, 1]$:

$$(\hat{\alpha}, \hat{\beta}) = \mathrm{argmin} \sum_{e \in E} |w_e| \cdot \left[-\log \mathrm{Beta}\left(\frac{t_e - t_{\mathrm{start}}}{T}; \alpha, \beta\right)\right] \quad (4)$$

The L-BFGS-B algorithm [5] executes this constrained optimization (200 iterations max).

The relation event pulse is defined using a Gaussian pulse function, where the total event pulse intensity is the linear superposition of individual events:

$$\mathrm{EventPulse}(t;E) = \sum_{e \in E} \frac{w_e}{\sigma\sqrt{2\pi}} \cdot \exp\left(-\frac{(t - t_e)^2}{2\sigma^2}\right) \quad (5)$$

whereσ controls the time decay rate of the pulse (we set $\sigma = 3$), and the event impact $|w_e|$ regulates the amplitude.

The final relation strength combines the BaseWave and EventPulse(Fig. 4). It should be noted that figure relations are sometimes complex: there are two types of base relation (positive and negative, e.g., friend and opponent), and two types of interactive events (positive and negative, e.g., joint travel and impeachment). While both positive and negative influences affect the relation strength, simple additive or offsetting approaches are inadequate. Thus, we decompose relation strength into $S^+(t)$ and $S^-(t)$ for separate calculation.

The positive relation strength $S^+(t)$ only considers the positive relation type k^+ and the list of positive relation events E^+ (where $w_e > 0$); the negative relation strength $S^-(t)$ only considers the negative relation type k^- and the list of negative relation events E^- (where $w_e < 0$):

$$S^+(t) = \mathrm{BaseWave}_{k^+}\left(t; \hat{\alpha}, \hat{\beta}, E^+\right) + \lambda \cdot \left|\mathrm{EventPulse}\left(t; E^+\right)\right| \quad (6)$$

$$S^-(t) = \mathrm{BaseWave}_{k^-}\left(t; \hat{\alpha}, \hat{\beta}, E^-\right) + \lambda \cdot \left|\mathrm{EventPulse}\left(t; E^-\right)\right| \quad (7)$$

where $\lambda = 0.6$ is the pulse contribution weight.

We treat relation strength as a 2D vector with positive strength $S^+(t)$ on the horizontal axis and negative strength $S^-(t)$ on the vertical axis.The final total relation strength is defined as the magnitude of the resultant vector:

$$S(t) = \sqrt{[S^+(t)]^2 + [S^-(t)]^2} \quad (8)$$

And the vector angle can determine the relation tendency:

$$\theta = \arctan\left(S^+(t)/S^-(t)\right), \ \theta \in [0°, 90°) \quad (9)$$

Relations are positive for $\theta \in (0°, 45°)$ and negative for $\theta \in (45°, 90°)$.

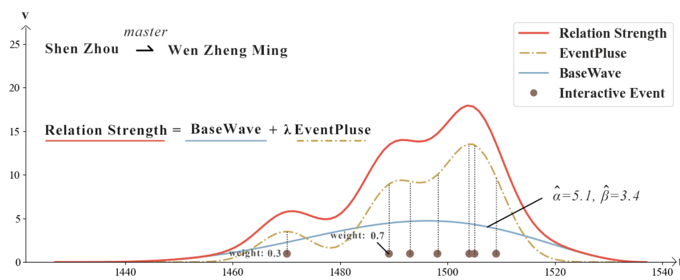

Fig. 4. The relation events between Shen Zhou and Wen Zheng Ming are primarily distributed between 1490 and 1510, with a relatively even spread. The BaseWave is relatively gentle, with a peak around 1495. The final relation strength (red line) is formed by the superposition of the BaseWave (blue line) and the EventPulse (red line).

4.2.2 *Figure Influence Modeling*

We define influence as deriving from two sources: social networks and individual events (e.g., creative works, official appointments). The influence of the social relation network is quantified by the dynamic relation strength defined in Section 3.2 (Formula 9), while the impact of individual events is calculated using the event pulse model (Formula 5). Unlike relation strength, individual events' influence allows positive-negative cancellation, which better aligns with the actual fluctuations of a character's influence.

Based on this, we extend the classic PageRank algorithm to a time-series dynamic algorithm. Let the set of figures be V. At time t, the list of individual events is E_i, and the initial influence weight of each node $v_i \in V$ is determined by its individual event pulse:

$$\mathrm{I}_{\mathrm{self}}(v_i, t) = \mathrm{EventPulse}(t; E_i) \quad (10)$$

The dynamic propagation strength of social relations is described by the adjacency matrix $A(t)$, where its element $A_{ij}(t)$ represents the relation strength from v_i to v_j at time t. It is calculated using Formula 9 (i.e., $A_{ij}(t) = S(t)$) and used to define the edge weight. The dynamic character influence is solved through iterative computation:

$$\mathrm{I}(v_i, t) = \sum_{v_j \in V} \left[\frac{A_{ji}(t) \cdot \mathrm{I}_{\mathrm{self}}(v_j, t)}{\sum_k A_{jk}(t)}\right] \quad (11)$$

$\mathrm{I}_{\mathrm{self}}$ quantifies the character's own independent influence at time t. In the social relation network, the influence of other nodes v_j is proportionally transmitted to v_i through the relation strength $A_{ji}(t)$.

4.3 Event-based Identity-Geography Trajectory Mapping

In data processing, to achieve dynamic presentation of character identities and geographical locations, we adopt an event-based calculation approach, detailed as follows:

Dynamic Identity Calculation Initially, identity data is static. To endow it with dynamic attributes in the temporal dimension, we define it based on an event-driven approach:

- Scholar identity: Activated when the figure first encounters a creative event (e.g., literary or artistic creation).
- Official identity: Activated when the first official event occurs.
- Trader identity: Activated when the figure participates in the first economic transaction event.

Dynamic Geographical Data Calculation A character's initial geographical location is set as their native place. Subsequently, based on the locations where various events occur, their geographical location information is gradually updated to form a complete trajectory of geographical location transformations.

5 VISUAL DESIGN

Aligned with the designed design task, this paper presents a novel visualization system for investigating social networks among ancient Chinese literati. The system features six interactive visual views (Fig. 1) that enable multi-perspective exploration of historical figure connections, with each view supporting specific analytical tasks.

We implements a unified chronological controller, dynamically calibrated based on temporal lifespan of selected figures(according to earliest birth year and latest death year among selected literati) in Setting View (Fig. 1A). The unified chronological controller integrates two regulatory mechanisms: 1) Governing temporal filtering in Network Distribution Statistics (Fig. 1B) and Social NetWork View (Fig. 1C1); 2) Serving as temporal reference axis (x-axis) for both Influence Mountain View (Fig. 1C2) and Event Timeline View (Fig. 1D)

5.1 Setting View

Setting View (Fig. 1A) serves as the foundational setup component for *LSN-VA*, allowing users to select figures of interest. It consists of two parts: Figure List and Control Panel.

Figure List provides two distinct configuration modes. The primary interface (”Add Figure”) utilizes an intelligent modal panel supporting batch operations, enabling users to add/remove figures through filter and directly edit views based on various conditions (e.g., dynasty, region), direct in-view editing. Alternatively, the system offers a structured file upload mode through standardized CSV/Excel templates, which can bulk importation of figure list. Control Panel provides a filtering function for figures. The ”Extension” button controls whether to add the crowd around selected figures. ”Figure influence” filters figures based on their highest influence, while ”relation strength” filters relations based on highest connection strength.

In addition to the foundational setup in View **A**, the system enables dynamic control of figures through Social NetWork View (Fig. 1C1).

5.2 Network Distribution Statistics

Network Distribution Statistics (Fig. 1B) addresses Requirement R1 and Task T1 through two coordinated views: Figure Identity View (Fig. 1B1) quantitatively delineates identity stratification (e.g., Official, Literati) within targeted cohorts, while Figure Map View (Fig. 1B2) employs cartographic visualization to reveal spatial clustering patterns. These two views provide an overview of the group distribution from different directions.

5.2.1 *Figure Identity View*

Figure Identity View (Fig. 1B1) employs a Venn diagram to visualize the collective identity characteristics of literati groups. This view allows users to highlight the compositional traits of literati(e.g., literati, officials, merchants) by their identified roles. we uses stackable gradient colors to distinguish different groups and simulates irregular ink-brush edge textures (including jagged outlines and scattered ink dots) to symbolize individuals undergoing identity transitions. The greater

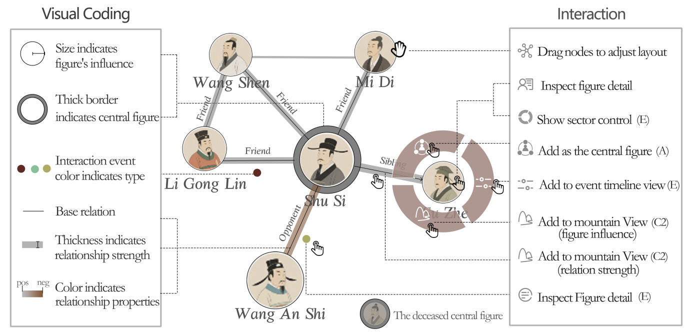

Fig. 5. The size of the figure node represents the current influence of the figure, black solid lines between literati represent baseline relations such as friend or opponent, with arrows on these lines symbolizing hierarchical order in inheritance or family relations. Wider line represents the degree of intimacy, the color of the line represents the nature of the relation between figures, gray represents positive tendencies, and brown represents negative tendencies.

number of change in figures identity, the greater the change in ink dots and edge textures.

5.2.2 *Figure Map View*

Figure Map View (Fig. 1B2) employs a geographical map to visualize figure distributions. The intensity of the color represents the number of selected figures in a province, darker shades signify higher figures. As time progresses, passing by this view, there may be a potential significant events happening when abrupt color changes occur in specific areas. Additionally, View **B2** features a dual-layer functionality: by selecting a specific province, users can access the detailed city-level distribution of literati within that region, enhancing the granularity of geographical analysis.

5.3 Evolution of Social Network

Evolution of Social Networks (Fig. 1C) serves Requirement R1-R2 and Tasks T2-T3 via dual mechanisms: Social NetWork View (Fig. 1C1) constructs literati-centric network topologies through force-directed layouts, and Influence Mountain View (Fig. 1C2) utilizes horizon-aligned mountain plots to quantify individual influence at user-selected temporal anchors through interactive timeline. These two views reveal the social attributes and relations of literati from different perspectives.

5.3.1 *Social NetWork View*

Social NetWork View (Fig. 1C1) constructs a social network expanding outward from the central literati selected in Setting View (Fig. 1A). Figure 5 is a schematic diagram of figure relations, it introduces the basic information of figure nodes and the relations between figures.

Each node represents a figure: in its initial state, a translucent gray background signifies the figure has not been born or is inactive; upon birth or the start of their active period, the background changes to a portrait or light brown, indicating the node has become active. A dynamic node influence calculation formula is set in the system to ensure that the average size and extreme values of nodes are controllable on the current page. Repulsion forces between nodes prevent overlaps, and after a selected figure's death, their node background turns black and is pushed to the view's edge by these forces.

Figure relations and nodes will change dynamically. During chronological controller dragging or playback, new relevant nodes may appear in empty spaces and form connections with existing nodes. Non-selected figures with no connections to selected figures gradually fade and are repelled to the edge. In dense interaction scenarios, node lines extend to reduce visual congestion. Additionally, a dragging function allows user to manually reposition nodes; when dragged, all nodes adjust their positions dynamically under applied forces to maintain a balanced layout.

5.3.2 *Influence Mountain View*

Influence Mountain View (Fig. 1C2) features a mountain plot where the horizontal axis represents time and the vertical axis measures the influence of selected figure at different time points. Each selected figure is assigned a distinct color, with their influence curves interleaving to form the overall mountain plot—the influence calculation method is detailed in Section 4.2. Stackable colors differentiate figure categories and resolve visual overlaps for concurrent influence values. The height and darkness of the mountains indicate influence strength: taller, darker peaks signify greater impact.

5.4 Event Timeline View

Event Timeline View (Fig. 1D) achieves the Requirement R3 and design Tasks T4-T5 by constructing event-driven storylines that contextualize interpersonal exchanges within biographical timelines. This view initially displays selected figures, with additional figures in Social Network View (Fig. 1C1) . Each figure has a timeline: the line color matches their representation in the mountain plot, aligned with the timeline axis at the top. The left side of the line features the figure's portrait and name—clicking the name triggers Detail View (Fig. 1E) to show detailed figure information.

Circular or square nodes on the timeline denote events at specific times: circles for interaction events, squares for individual events. Node colors correspond to event categories, with hollow nodes indicating negative events and solid nodes positive ones; clicking an event reveals its details in View **E**. During interaction events between figures in the view, their timelines move closer, with straight lines connecting the corresponding event nodes to visualize connections. If the interaction event involves calligraphy and painting, a dotted line will be drawn, otherwise it will be a solid line. The timeline uses the StoryFlow method [26] to minimize crossovers and distortions, ensuring readability. When events involve the same calligraphy or painting, dashed lines connect the nodes to highlight artistic dissemination trajectories.

5.5 Detail View

Detail View (Fig. 1E) achieves the Requirements (R1-R3) and design Task T6, providing structured metadata access through detail-on-demand interactions.This view displays detailed information for selected elements, including figure profiles, event specifics, and artwork details across three primary sections:

Figure Details. This section presents a figure's portrait, basic information, and biography. Basic details include their courtesy name, artistic name, native place, occupation, alternative names, and titles, followed by a brief biography.

Event Details. The event details section is divided into three areas: **Event description:** Lists the occurrence time, description, source, and extracted attributes (event type, location, and artwork medium involved). **Members:** Highlights the event initiator and lists all involved figures, with clickable names for quick access to their profiles. **Related artwork:** If the event involves artworks (e.g., calligraphy/paintings), this area shows a preview of the artwork (if available in the database). Clicking the "Details" button navigates to the artwork details section for deeper analysis. For artworks linked to multiple events, dashed lines visualize their dissemination routes, with descriptions below the line and involved button above—clicking button adds them to the social network or timeline view for further exploration.

Artwork Details. Sourced from the Chinese Treasure Museum, this section provides in-depth information about artworks, including dimensions, introduction, inscriptions, poetic translations, annotations, and creation background.

6 Case Study

6.1 Case 1: The Social Network Evolution of Wumen Literati Group

Expert E1 conducted research on the literati Group in Wumen (now Suzhou, Jiangsu) during the Ming Dynasty. This area exhibited concurrent economic prosperity and cultural flourishing, fostering frequent, multi-layered social interactions among literati. To reveal the evolution patterns of their social network, E1 employed *LSN-VA* for investigation.

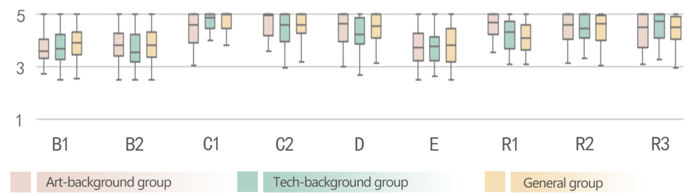

Fig. 6. The statistics of our user study evaluation with 12 volunteers, the overall average of user satisfaction scores is 4.37. Left 6 are user satisfaction scores for visual design, right 3 are user satisfaction scores for historians' requirements.

In the Setting View (Fig. 1A), E1 applied spatiotemporal filters for "Ming Dynasty" and "Jiangsu", retrieving 88 literati nodes. By increasing the influence threshold parameter to 0.5, the system filtered a core group of 32 figures. The Social Network View (Fig. 1C1) displays their connection structure, while the Influence Mountain View (Fig. 1C2) presents key figures with notable influence in the network, including Shen Zhou, Wen Zhengming, Tang Yin, and Qiu Ying.

After examining View **C2**, E1 positioned the timeline to Shen Zhou's influence peak year(1482).View **C1** revealed Shen Zhou as the core node with strong connections to literati-officials including Wu Kuan and Wang Ao, while maintaining intensive interactions with collectors Zhu Cun liand Shi Jian. In contrast, Wen Zhengming and others who later gained prominence exhibited significantly weaker influence during this period. Network exhibited a pronounced single-core structure, with other nodes demonstrating comparable influence levels in a homogeneous distribution. E1 further added figures like Wu Kuan and Shi Jian to Event Timeline View(Fig. 1D) to observe interactive events with Shen Zhou, and found most of the interactions were cultural events such as painting gifts and traveling together. E1 further examined the Figure Identity View(Fig. 1B1), which revealed Wumen literati group comprised 39.1% official and 13% trader during this period. Based on these findings, E1 concluded early social network of the Wumen literati community exhibited a radial structure centered around Shen Zhou. Through cultural interactions, a three-tiered social structure gradually emerged, connecting officials, literati, and trader. The literati can established patronage relations with official through artwork gifting, while securing economic support through collection transactions.

As E1 advanced the timeline to the period of Wen Zhengming's dominant influence(1501), View **C1** dynamically showed his node expanding and shifting to the central canvas area, replacing Shen Zhou as the core node. Concurrently, Qiu Ying and Tang Yin migrated from the network periphery towards the central zone, while emerging figures like Zhu Yunming and Chen Chun formed densely interconnected groups. View **D** revealed frequent political events during this period, with increased imperial examination participations and official visits. E1 concluded that during this period, the Wumen literati's social network underwent significant expansion, political affiliations were substantially reinforced, and artistic interactions began to exhibit utilitarian tendencies.

Further advancing the timeline, View **C1** displayed a decentralized structure: though Wen Zhengming remained a core node, Qiu Ying and Tang Yin formed independent subnetworks with significantly denser connections to trader Xiang Yuanbian. View D showed fewer political events, stable cultural interactions, and increased market-oriented activities such as Tang Yin's collaborative paintings with art restorers. View **B1** indicated rising trader proportions and an increase in professional painter identities. E1 concluded that political elements in the Wumen literati had diminished during this period, professional painter groups began to emerge, and artistic activities gradually shifted toward market-oriented practices.

After completing the exploration, E1 stated that *LSN-VA* effectively supports users in analyzing group network structural characteristics and evolutionary patterns.

6.2 Case 2: Dong Qichang's Social Network

Expert E2 analyzed Dong Qichang's multi-identity social network spanning political, literary, and commercial domains using *LSN-VA*. E2 added Dong Qichang in the Setting View(Fig. 1A) and enabled node expansion. The Influence Mountain View(Fig. 1C2) showed a double-peaked graph indicating two growth phases.

Early Period (1555). E2 adjusted the timeline to Dong's early years (1555),The Social Network View(Fig. 1C1) showed a radial network; Figure Identity View(Fig. 1B1) classified connected nodes as 20% official (mostly from Songjiang), 51% literati (e.g., Mo Shilong, Lu Shusheng), and 27% trader(early Hui merchants); The Figure Map View(Fig. 1B2) highlighted 74% of nodes concentrated in Songjiang (now Shanghai). E2 inferred that Dong's early network was anchored in his native Songjiang.

First Influence Peak (1589). Advancing to 1589, when Dong's influence reached its first peak, View **C1** displayed sudden appearances of grand councilor nodes like Xu Guo and Wang Xijue with thick connection lines, alongside dense (Hanlin Academy) colleague nodes. The Event Timeline View(Fig. 1D) revealed key events: after becoming a Hanlin Academy Compiler through the imperial examination, Dong expanded his political network via calligraphy-painting gifts, such as presenting paintings to Xu Guo. The Figure Map View revealed Beijing nodes (51%) overtaking Songjiang (30%). E1 concluded Dong had integrated into the political center, shifting his social circle northward.

Political Marginalization and Artistic Turn (1600). Further advancing the timeline to 1600, View **C1** showed weakened connections with bureaucratic nodes, replaced by thick lines linking to Southern literati nodes and Hui merchants. View **B1** indicated trader nodes rose to 39%; View **B2** showed Su-Hang nodes at 68% and Beijing nodes shrinking to 11%. View **D** revealed that in 1592, Dong missed a Hanlin Academy promotion due to escorting his mentor's coffin out of Beijing. During this period his artistic creation and interactions increased. In 1600, he toured Su-Hang with masterpieces, promoting his painting theory through frequent connoisseurship events and strengthening ties with collectors via inscriptional appraisals. E2 deduced that while politically marginalized, Dong leveraged cultural capital to shift his network from political dependence to market-oriented operations.

Late Period (1621). E2 push the timeline to Dong's later years (1621), View **C1** showed revived connections with Beijing grand councilors like Ye Xianggao. View **D** displays Dong's return to official posts and use of art gifts to secure political patronage from senior official. View **B1** showed official nodes rebounding to 35% and trader nodes reaching 43%; View **B2** displayed Beijing and Su-Hang nodes at 41% and 49%. E2 concluded that Dong maintained dual political-economic networks through artwork, constructing a cross-regional power nexus.

Through continuous spatiotemporal and network analysis, E2 emphasized that *LSN-VA* enabled rapid synthesis of Dong's network evolution, effectively supporting complex figure's social network exploration.

7 Evaluation

We designed a user study to evaluate the proposed system objectively.

7.1 User Experiment

Participants. We recruited 12 volunteers (6 males and 6 females, aged 24-45) to participate in our experiment, including 6 art-background scholars in the fields of history, literature, or art history, and 6 tech-background researchers without ancient humanistic backgrounds. Participants were screened through questionnaires to ensure that their knowledge level in the field met the experimental requirements.

Procedure. The experiment with three phases:

1) System Tutorial (10 mins): Standardized demo video and instruction manual for sytem core functionalities;

2) Task Exploration (30 mins): Participants were guided to explore the system through 4 analytical questions below:

Q1: What are the dominant identity types in the social circles centered on Shen Zhou, Wen Zhengming, Qiu Ying and Tang Yin? (**R1**)

Q2: What are the changes in Dong Qichang's social network geographic center? (**R1**)

Q3: Who exerted the greatest influence on Shen Zhou in his life? (**R2**)

Q4: What relection do the social events with artworks play in the social network of Su Shi? (**R3**)

Note that these questions are categorized by user requirements (**R1**, **R2** and **R3**), shown in the end of each question. And participants can ask any question during exploration.

3) Questionnaire (15 mins): We used a 5-point questionnaire (1 to 5 present "disagree", "weakly disagree", "borderline", "weakly agree" and "agree"), and required participants to rate their satisfaction with different views (including **B1**, **B2**, **C1**, **C2**, **D** and **E**) and evaluate whether different user requirements were well-implemented (including **R1**, **R2** and **R3**). The statistics are shown in Fig. 6.

7.2 User Feedback

After the exploration of all tasks, volunteers gave positive comments for our system:

Figure Identity View (B1): Art background volunteers say that **B1** provides an intuitive visual form for the entire social network to visualize the evolution patterns of character identities. Meanwhile, the ink edge that changes over time effectively demonstrates the changes in the official status of the character, with strong observability. However, some volunteers think the evolution of an individual's central character identity can be manifested in some way.

Figure Map View (B2): 4 art background volunteers gave high ratings, while some other expressed the hope that personal changes can be displayed in View **B2** when events change.

Social NetWork View(C1): Most volunteers gave high praise, one said that although they cannot see people really gathering from this perspective, they can imagine literati sitting together and communicating with each other. Meanwhile, art background scholars believe that social networks can effectively reveal social interactions between literati.

Influence Mountain View(C2): Most volunteers say that this view intuitively allows them to understand the ups and downs of the influence of ancient literati in their personal lives. Meanwhile, art background scholars have also pointed out that this view clearly demonstrates the contrast of influence between different characters.

Event Timeline View (D): Art background scholars generally recognize the timeline and storyline changes presented by this view, and believe that it can provide an accurate anchor for changes in other views. At the same time, some volunteers also point out that they hope the view can better distinguish between different types of events.

Detail View (E): Most volunteers say that this view accurately helps them understand more background information about characters and works, thereby gaining a clearer understanding of the presentation of other views. However, some tech background scholars point out that some of the information can be more concise.

8 Conclusion and Future Work

In this work, we present an interactive visualization system for ancient Chinese Literati Social Network, *LSN-VA*. 4 historical sources are collected and merged to an ancient literati social database, which is further completed and augmented using a prompt-based LLM. Based on this database, we proposed a dynamic social network modeling method that automatically estimates the relation, influence, and missing attributes of ancient Chinese literati. Finally, various visual encodings are designed, including social network evolution view, figure influence view, and event-centered timeline view for ancient literati, etc. Two in-depth case studies and a user study demonstrate the validity and effectiveness of *LSN-VA* in investigating the dynamic evolution of the ancient Chinese literati social network.

The feedback from user interview also inspires us many valuable suggestions regarding future work. In the future, we intend to extend our database to more types of ancient Chinese literati (such as poets, calligraphers, etc.) and more types of interaction events (such as prefacing, touring together, etc.). Moreover, we plan to support more figures of interest. For this sake, we have to solve the visual confusion of the Social Network View (Fig. 1C1) with a large number of nodes.

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