An Interactive Visualization Platform for Exploring Co-Authorship and Co-Teaching Networks

Master's Thesis in Game and Media Technology

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Abstract

University information systems (e.g., Pure, DiVA) and bibliometric platforms (e.g., Scopus, Web of Science) primarily focus on research outputs while overlooking teaching relationships, making it difficult for administrators, coordinators, and other stakeholders to obtain a comprehensive view of collaboration. We introduce an interactive, researcher-centric visualization platform for the Department of Information and Computing Sciences at Utrecht University that unifies research and teaching ties through two coordinated views. The first view provides an overview that preserves organizational structure while highlighting patterns of collaboration. The second view constructs a concentric profile that displays a researcher's collaborators alongside the courses they teach and their publications. Filters and an adjustable edge-bundling control enable users to balance between reduced visual clutter and per-edge traceability. We conducted task-based assessments and semi-structured interviews with eight experts (lecturers, program coordinators, and research support staff). We find that the unified view supports locating staff, verifying relationships, and comparing research and teaching relationships. For future work, we highlight the need for faster hierarchy navigation and direct summaries in dense regions. We hope that these findings demonstrate the potential of department-level exploration and inform design considerations for scaling to institution-wide data.

Keywords

Research collaboration; Teaching networks; Interactive network visualisation; Co-authorship; Co-teaching; Coordinated views; Edge bundling; React; Cytoscape.js; Neo4j; FastAPI; PURE dataset

Preface

This thesis grew from a practical need inside our department: people routinely navigate co-authorship networks, but teaching ties are scattered across spreadsheets and are rarely seen together with research links. The aim of this project is not to produce yet another global co-authorship map, but to build a **department-scale** tool that helps staff explore integrated research–teaching relations with clarity, auditability, and responsive interaction.

The platform I developed combines a React/Cytoscape client (with Ant Design components) and a Python FastAPI service on top of a Neo4j graph store. It offers a constraint-aware main overview for organisational navigation and a concentric side view for detailed, person-centred inspection; layered edge bundling and a relaxation control help balance clutter reduction with traceability. A small *backend-only* runtime benchmark under out-of-the-box defaults guided the choice of bundling algorithm for interactive use. Finally, a *formative* expert study with seven in-house participants—using ICE–T per task, SUS post-session, and short interviews—provided early evidence about usability, interpretability, and workflow fit.

I am grateful to my supervisors and colleagues for guidance and feedback, and to our department for access to data and infrastructure. Any remaining limitations are mine; institution-wide generalisation remains a direction for future work.

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Chapter 1

Introduction

1.1 Background and Motivation

In recent years, academic institutions have increasingly relied on digital platforms to manage, track, and assess research activities. These platforms aggregate information from a variety of sources such as journal databases, institutional repositories, and citation indexes, enabling universities to assess productivity, foster interdisciplinary research, and facilitate informed strategic planning [80]. Despite the growing volume of research outputs, understanding the complex web of collaborations between faculty members, departments, and disciplines remains a significant challenge.

Network visualization has emerged as a powerful tool for interpreting large, interconnected datasets. In academia, such techniques can highlight collaboration patterns, identify influential researchers, and uncover hidden links across disciplines [56, 9]. Tools like VOSviewer, CitNet-Explorer, and Gephi offer general-purpose visualizations of co-authorship and citation networks. However, these tools often lack institutional customization, integration with teaching data, or real-time interactivity.

Existing academic research management systems—such as Scopus, Web of Science, and institutional Current Research Information Systems (CRIS)—focus largely on data storage and reporting, offering limited interactive visualization features. Furthermore, most systems treat teaching and research data as distinct entities, which makes it difficult to form holistic views of academic contributions or to surface interdisciplinary potential.

This thesis is motivated by the need for a unified, institution-focused visualization platform that combines research and teaching collaboration data. By enabling stakeholders to explore internal academic networks, such a platform can enhance collaboration opportunities, optimize resource allocation, and support data-informed decision-making in higher education.

1.2 Problem Statement

Although research data platforms such as Scopus, Web of Science, and Microsoft Academic Graph provide rich datasets about global academic activity, they are typically optimized for large-scale analysis and bibliometric evaluations rather than institutional insight [22]. These platforms offer limited capabilities for tailoring visualizations to the internal organizational structures of universities, such as faculties, departments, and individual researchers.

Moreover, most existing tools are designed to handle research metrics in isolation, offering little to no integration with teaching-related data. This lack of integration creates barriers for administrators and researchers who aim to align teaching roles with research output or develop interdisciplinary academic programs. Without a unified view, decision-making processes become fragmented, and opportunities for synergy are often overlooked [29].

Another challenge is the hierarchical complexity of academic institutions. Universities comprise multiple layers—colleges, schools, departments, research units, and individual staff members.

Most current systems are ill-equipped to visualize and navigate these layered relationships in a dynamic and user-friendly manner. As a result, stakeholders are forced to rely on static charts or manually compiled reports, which lack the interactivity and scalability required for modern academic analysis.

Performance is an additional concern. With growing volumes of academic output and collaboration data, visualization systems must scale effectively to support thousands of interconnected nodes and relationships without compromising responsiveness or user experience [2]. Yet, many visualization tools encounter browser performance issues or fail to support dynamic querying and filtering.

This research also addresses the following key technical challenges:

1. **Lack of integrated views:** Teaching and research data are often visualized in isolation, limiting comprehensive insight.

2. **Inadequate institutional customization:** Existing platforms do not offer tailored views aligned to the internal structure of specific universities.

3. **Limited scalability:** Current systems struggle with performance and interactivity at institutional data scales.

4. **Absence of dynamic filtering:** Users lack the ability to explore networks based on departments, collaboration types, or timeframes.

To bridge these gaps, this thesis proposes an interactive visualization system tailored to institutional needs. The platform will support multi-level exploration of academic collaborations while integrating both teaching and research networks into a cohesive, real-time visual interface.

1.3 Research Questions and Sub-questions

Based on the problem statement outlined in Section 1.2, the study poses the following core Research Question (RQ):

- **RQ:** How can we design and implement a department-scale visual analytics platform that *unifies co-authorship and co-teaching* with appropriate visual representations and interaction mechanisms to support domain experts in researcher-network exploration?

To address the above RQ, the study is further decomposed into the following Sub-questions (SQs):

1. **SQ1:** Which requirements define the analytic goals and tasks the platform must support at department scale?

2. **SQ2:** What are the properties of the available research and teaching datasets, and how do they shape a unified representation?

3. **SQ3:** How should these datasets be modelled and integrated into a single hierarchical multi-layer graph to support cross-layer queries and provenance?

4. **SQ4:** How should technologies and system architectures be implemented to achieve dynamic interaction?

5. **SQ5:** To what extent is the resulting prototype usable and interpretable for domain experts?

These RQ and SQs establish a clear framework for the research design and chapter organization of this thesis, with subsequent chapters structured around their resolution.

1.4 Scope and Limitations

This research is situated within the field of **Visual Analytics**, which aims to combine interactive visual representations with computational and analytical methods to support complex data interpretation and decision-making. The specific focus of this work is the visual analysis of academic collaboration networks within a university context. More precisely, this thesis investigates how to model, visualize, and interact with multivariate and multi-layer networks that represent different types of academic collaborations—namely, research and teaching.

The core data source is the institutional CRIS, specifically the PURE database used by Utrecht university. PURE aggregates structured metadata on research outputs, teaching involvement, affiliations, and organizational hierarchies. However, the information is scattered across multiple disjoint systems and interfaces, making it difficult for stakeholders to construct a comprehensive view of academic activity. By designing a system that integrates and visualizes this information, this work addresses a local but representative problem faced by many higher education institutions globally.

The system developed in this thesis supports two primary layers of collaboration: (1) research collaborations, represented through co-authored publications and project involvement, and (2) teaching collaborations, captured through shared instructional responsibilities on specific modules or courses. These layers are visualized in an interactive web interface that allows users to explore connections at different levels of granularity—from university-wide patterns down to individual staff members—while incorporating node-level and edge-level attributes such as department, discipline, and collaboration strength.

While this thesis aims to lay a foundation for institutional academic network analysis, several aspects remain outside the current scope. The system does not yet incorporate funding data, industrial partnerships, patent networks, or supervision relationships (e.g., PhD advising), primarily due to the lack of structured or accessible data. Similarly, while techniques from natural language processing and large language models (LLMs) could offer powerful ways to semantically cluster research topics or extract latent collaboration themes from publication texts, such functionality is not included due to data access and processing constraints. These possibilities are discussed as promising directions for future work.

It is important to note that the primary stakeholders for the system are institutional users—academic administrators, research coordinators, and department heads—rather than the general public. As such, the design prioritizes interpretability, organizational hierarchy awareness, and policy-oriented use cases over general-purpose exploration. While the techniques and design choices are generalizable, the implementation has been fine-tuned for one specific university: Utrecht University. Extensions to other contexts may require new access policies and adaptation of data structures.

This work builds on existing literature in network visualization, like the work by Kucher et al. [42], which outlines design challenges and solution patterns for visualizing multilayer networks in scholarly domains. The system presented here aligns with these principles and applies novel visual analytics techniques to a real-world, institution-specific use case.

1.5 Thesis Structure

This thesis is organised as follows. Chapter 2 surveys prior work on academic-collaboration visualisation and web-based graph techniques to motivate the research problem; Chapter 3 scopes the domain, profiles stakeholders, and derives analytic goals and task requirements; Chapter 4 details departmental data sources, schemas, and preprocessing, motivating a unified multi-layer representation; Chapter 5 presents the system and interaction design—coordinated overview and side panel, type-aware encodings, and controllable bundling—and the implementation stack; Chapter 6 outlines the evaluation design, including participants, protocol, measures (ICE–T, SUS), and the analysis plan; Chapter 7 reports the quantitative and qualitative results and then Chapter 8 provides a dedicated discussion that synthesises the findings, separates high-level features from low-level components, and integrates limitations with future work; finally, Chapter 9 restates the research question and summarises the main contributions and takeaways.

This research contributes to the growing field of academic data visualization, providing institutions with a tool to better understand and optimize research and teaching collaborations.

Chapter 2

Related Study

Visualization of academic collaboration networks is critical to understanding how knowledge moves within and among institutions. Traditional approaches (analysis of publication lists or static reports) are unable to discover complex relational patterns between the researchers and educators. Network visualization is an intuitive and effective tool in the exploration of co-authorships, teaching collaborations, and interdisciplinary relationships. Advances in interactive visualization, especially in academic research settings, allow for an exploration of hidden structures, encouraging collaboration, and steering institutional decision-making. This chapter overviews development of academic collaboration networks, current visualization methodologies, existing platforms, and highlights key research gaps explored in this study.

2.1 Academic Collaboration Networks

Academic collaboration can be studied based on co-authorship networks, co-teaching networks, and research project networks [21]. Co-authorship networks view researchers as nodes and cooperations as edges. Similarly, co-teaching networks show faculty who are responsible for a shared course. Such networks are characterized by a network small-world property and high clustering coefficients, where researchers cluster close and interact often [75]. Leahey [43], explored the evolution of interdisciplinary research stating that research units tend to have hubs of very active scholars. Similarly, [82] demonstrated that senior research practitioners act as a link that connects different disciplines in a way that it is easy to move knowledge from one discipline to another through the traditional boundaries of academics.

2.1.1 Co-Authorship Networks

Co-authorship networks have been heavily studied using graph theory and social network analysis (SNA) [50]. Various important metrics are utilized in these analyses to uncover the composition and behavior of academic collaboration. Degree centrality is how many direct collaborations the researcher has and how closely one has ties to the network. Betweenness centrality represents the extent of the roles that the researcher plays, as the bridge between the clusters, or radiation to interdisciplinary research. The clustering coefficient also measures the localization of connections around a specific researcher and offers an index that measures research group cohesion.

In this regard, [19] found that interdisciplinary co-authorship networks exhibit greater betweenness centrality which is a direct reflection of the pivotal role of the cross-field researchers in linking dissimilar fields of knowledge. Based on a sample of 150 universities, [51] also noticed co-authorship trends, reporting that most productive collaborative networks consist of a combination of local clustering and international strategic partnerships.

Ebrahimi [17] built mathematical models to simulate the development of co-authorship networks, finding that preferential attachment, established researchers attracting more collaborations, is a key driver of network growth. This phenomenon accounts for the appearance of "star researchers", who serve as key nodes in the university's intellectual terrain.

2.1.2 Co-Teaching Networks

Compared to co-authorship, co-teaching networks have received relatively less attention in academic research. The structure of co-teaching relationships is very different from co-authorship networks as they are institution-driven [67]. Although co-authorship is usually the result of voluntary scholarly collaboration, co-teaching arrangements are more often administratively assigned. This difference means that networks of co-teaching may be more policy- and logistics-driven than united by common academic interests and therefore have different dynamics and patterns of interaction.

Varga [72] performed one of the few integrated studies on co-teaching networks, examining five years of teaching data from three universities. Their findings showed that co-teaching networks were more fragmented than co-authorship networks, with fewer cross-department linkages. They also determined that interdisciplinary teaching programs formed strong bridges among otherwise separate academic silos, which were intervention points for administrators looking to improve interdisciplinary work.

2.1.3 Combination of research and teaching networks

Combining research and teaching networks offers richer, multi-dimensional insights into institutional collaboration than analyzing them separately. Research networks, typically based on co-authorship, reveal intellectual partnerships and scholarly productivity patterns across fields [51]. Teaching networks, on the other hand, model the administrative and pedagogical ties between instructors [27]. While both types of collaboration reflect important aspects of academic life, they offer complementary, yet traditionally isolated, perspectives.

Integrating these networks captures a fuller academic ecosystem, highlighting both scholarly influence and educational contribution. It reveals hidden interdisciplinary hubs where individuals connect research and teaching efforts, facilitating holistic analysis of faculty activities. As [41] demonstrated through their work on visual exploration of bibliographic data, enabling multi-faceted views helps universities understand collaboration patterns, data quality issues, and research impact more effectively. However, even their system, and most others, focus mainly on research collaborations without extending into teaching relationships.

By bridging the research-teaching divide, institutions can better identify underrecognized contributors, strengthen cross-departmental collaboration, optimize resource allocation, and design integrated strategies for academic growth. This combined approach is particularly crucial for strategic planning and fostering innovation, yet remains absent in most existing academic visualization tools, a key gap this project addresses.

2.2 Data Visualization Techniques

Node-link diagrams remain one of the most intuitive ways to depict academic networks, with researchers as nodes and collaborations as edges. They excel at showing relationships and communities, as articulated by [12], however, for very dense networks, adjacency matrices are often preferred. These visualize relationships in a grid format and prevent the clutter that overwhelms node-link views. Geospatial visualizations add a geographic dimension, allowing the mapping of institutional or international collaboration patterns.

2.2.1 Graph Layout Techniques for Network Visualization

Network Graphs have become among the most effective and intuitive visualizations for tracing academic cooperation and the structure of scholarly community [14]. These graphs depict the researchers as nodes, and their collaborative relation; say co-authorship or concurrent involvement in projects as the edges.

One of the initial big data analysis tools of a network was Pajek developed by [6] which can deal with a network of thousands of nodes and edges in the best way possible. Pajek added a vast range of analytical capacities such as component detection, path analysis, and clustering to the software. Cytoscape.js is a JavaScript library enabling network visualizations to be incorporated into the application of dynamic web applications therefore making it the tool of choice in contemporary browser-based platforms applied in academic and scientific literature.

Huang [30], evaluated 45 scientific visualization tools and categorized them by usability, analytical capabilities, and visual clarity. Their analysis uncovered a significant gap between competent desktop applications like Gephi, and web-based visualization libraries, and this gap needs to be bridged if analytical depth is to be combined with online ease of use. This section outlines major layout families, discussing their principles, advantages, and limitations.

Force-Directed Layouts

Force-directed layouts are one of the major algorithmic approaches for the layout of network graphs to visualize the underlying structure and relationships between entities. These arrangements are used in visualization libraries such as D3.js and Cytoscape.js and schematize physical forces to organize the nodes logically for the visual display [16]. Specifically, connected nodes pull each other and unconnected drive away. This physics-informed model allows the layout to smoothly partition the clusters and keep them in adjacent nodes close, resulting in an extremely readable and nice to look at visualization.

They support real-time interaction, enabling users to zoom, drag, and highlight areas of interest dynamically. While widely used due to their intuitive structure, force-directed layouts may become computationally expensive for large-scale networks and can lead to overlapping nodes in dense areas. The adaptation by [46] in recent times has been centered on tuning these algorithms with regard to how extensively large-scale networks can be visualized, therefore facilitating seamless interaction even if the graphs have hundreds or thousands of nodes, quite common when dealing with the visualization of the institutional collaboration networks.

Winkelmolen [79], developed adaptive force-directed layouts, which self-tuned parameters based on density and clustering in a network, which were useful in solving a key problem in academic network visualization, where subnetworks may be very different in density.

Spectral and Multidimensional Scaling (MDS) Layouts

Spectral layouts leverage linear algebra, using eigenvectors of a graph Laplacian matrix to embed nodes in a low-dimensional space that preserves graph structure. Similarly, Multidimensional Scaling (MDS) translates node similarities or distances into coordinates in two or three dimensions [63]. According the authors, these excel at highlighting clusters and the global structure of the network, making them useful for identifying community boundaries or academic subfields. However, the resulting layouts can be abstract and hard to interpret without familiarity, and the computational requirements grow significantly with the size of the graph.

Hierarchical / Sugiyama Layouts

Hierarchical or Sugiyama layouts are particularly suited for directed acyclic graphs (DAGs), where nodes are organized in layers from top to bottom [18]. This layout is useful for representing workflows, institutional structures, or course prerequisites, allowing users to follow logical flows from source to sink nodes. As pointed out by [48], one of its strengths lies in its clear depiction of dependencies and causality. However, it is less effective for undirected or highly cyclic networks, where forced layering can distort relationships and create excessive edge routing.

Tree and Radial Layouts

Tree layouts such as the Reingold–Tilford algorithm are designed to visualize hierarchical structures where each node has a clear parent, creating tidy and space-efficient visualizations. Radial tree layouts extend this approach by arranging nodes in concentric circles around a root, often used to visualize lineage, organizational charts, or faculty supervision networks [66]. According to the authors these layouts are visually appealing and emphasize branching structures, making them ideal for exploring inheritance, mentoring, or curricular structures. However, they assume tree-like data and do not accommodate cross-links or cycles, limiting their use in general academic collaboration networks.

Circular and Chord Diagrams

Circular layouts arrange nodes around a circle and use curved lines or chords to represent edges. Chord diagrams are particularly useful for visualizing inter-group relationships and symmetrical interactions, such as co-teaching between departments or interdisciplinary publication links [59]. Their visual symmetry aids pattern recognition and group comparison, making them popular for highlighting flows and mutual collaborations as highlighted by [4]. However, as network density increases, these diagrams become cluttered, and overlapping chords reduce clarity.

Adjacency Matrix Views

Adjacency matrix views use a tabular format where rows and columns represent nodes, and cell values indicate the presence of connections. These views are highly effective for visualizing very dense networks, where node-link diagrams become unreadable [11]. They allow precise inspection of link patterns, symmetrical relationships, and structural regularities such as cliques or community overlaps [11]. Despite their scalability, matrix views can be less intuitive, especially for tasks involving path tracing or understanding overall network flow. They also require row/column reordering for cluster detection, which can be computationally nontrivial.

Edge Bundling Techniques

As highlighted by [78], edge bundling techniques aggregate similar or parallel edges to reduce visual clutter in dense node-link diagrams. By routing multiple edges along shared paths, bundling reveals structural flows and common patterns, such as interdepartmental teaching pathways or collaborative publication hubs. Variants include force-directed bundling and geometry-based approaches. While bundling enhances visual clarity, it can obscure individual connections and may introduce ambiguity in interpreting specific relationships. Effective edge bundling depends on careful control of curvature, distance, and tension parameters.

Dynamic and Multilayer Layouts

As highlighted by [7, 72], dynamic layouts visualize temporal changes in networks through animated transitions or time-sliced views. They allow users to observe how academic collaborations or teaching relationships evolve over semesters or years. Multilayer (or multiplex) layouts go further by displaying different relationship types, such as co-authorship, teaching, and committee involvement, as separate but interconnected layers. These layouts are powerful for analyzing institutional dynamics, revealing overlaps between research and teaching domains. However, their complexity can be cognitively demanding and may require interactive filtering to remain usable.

2.3 Web Technologies for Visualization

This shift to web-based academic visualization platforms has been a direct result of robust libraries and frameworks of JavaScript giving rise to responsive and interactive user experience. These are technologies that offer real time data rendering, easy database integration and wide accessibility on devices and platforms.

2.3.1 D3.js and Cytoscape.js

D3.js (Data-Driven Documents) is a very useful JavaScript library designed by [8] that makes it possible to recreate data using web standards like SVG, HTML, and CSS interactively. D3 enables developers to connect any datasets to a Document Object Model (DOM) and then perform data-driven transformations on the document. It provides fine control of the visual representation of data to facilitate the drawing of customized charts, plots, and graphs.

For specialized network visualization requirements, Cytoscape.js has a full toolkit for intricate structures of graphs. Initially designed for use in the biological sciences, Cytoscape.js has been adopted in academic network visualization on a large scale because of its high-level APIs, extensibility and support for force directed layouts, event handling and graph traversal algorithms [23].

Surveys of JavaScript-based network visualisation report a trade-off between low-level toolkits such as D3 (flexibility) and domain-specific graph libraries such as Cytoscape.js (graph layouts/operations and performance) [16, 23]. In practice, systems often *combine* these roles—using D3/React for UI scaffolding and scales, and a graph library for rendering and interaction.

2.3.2 React for User Interfaces

React is a popular front-end JavaScript framework that is widely used for developing user interfaces, especially dynamic and real-time interaction-oriented ones. React, introduced by Meta (previously Facebook) as a component-based architecture, allows developers to devise modular, reusable UI components that make it easier to manage the state and behavior of large applications [69]. In academic network visualization platforms, React is frequently used to build dashboards, filtering menus, and interactive panels where users can navigate through the data from various positions. Its virtual DOM and efficient update strategies make it ideal for sending frequent changes as a result of the user input such as node highlighting, subgraph selection, and timeline filtering.

2.3.3 Graph Databases

Graph databases such as Neo4j and ArangoDB are designed for highly interconnected data, which makes them a natural fit for academic collaboration networks where ties among researchers, departments, and projects are many-to-many [62]. Unlike relational DBMSs that store information in tables, property-graph stores model information as labeled nodes and edges with key–value properties. This enables concise expression of neighbourhood- and path-centric queries in languages such as Cypher (Neo4j) and AQL (ArangoDB)—for example, "find all collaborators for a given researcher in a specified department" or "identify the shortest collaboration path between two authors".

These systems support transactional updates and interactive querying, and are commonly used as backends for visualization tools that ingest and explore evolving collaboration data. In practice, performance depends on the workload, graph size, and configuration.

2.4 Case Studies and Existing Platforms

Several platforms have been designed to map academic networks and to support the analysis of such patterns of collaboration between the institutions and the disciplines. Table 2.1 provides an overview of existing platforms, their core features underlying technologies, and current limitations.

Table 2.1: Summary of Existing Academic Network Visualization Platforms

Platform	Key Features	Technologies Used	Limitations	Integration
DIVA [41]	Interactive visual exploration of bibliographic data for university research administration; supports multi-level filtering	Information visualization techniques, interactive dashboards	Limited to bibliographic data; does not incorporate teaching activities	No teaching network integration; focuses exclusively on research outputs
CiteVis [83]	Temporal analysis of citation patterns; cluster detection for research communities	Network visualization, temporal analytics	Focuses only on citation relationships; no institutional-level customization	No teaching network integration
NetLens [38]	Iterative exploration of content–actor network data; multi-level exploration	Coordinated multiple views, faceted navigation	Limited to publication data; no teaching or administrative data	No integration with teaching activities
CollaboVis [84]	Collaborative knowledge visualization; dynamic filtering of research topics	Interactive visualization techniques, topic modeling	Primarily designed for research collaborations; limited institutional contextualization	No teaching data integration
VIVO [28]	Maps academic researchers and their collaborations using semantic web technology	RDF/OWL ontologies, SPARQL, D3.js	Limited customization at the institutional level; complex interface for new users	Minimal teaching data integration; primarily research-focused
ResearchFlow [65]	Knowledge flow visualization in academic networks; temporal patterns analysis	Flow-based visualizations, interactive filtering	Research-centric approach; no teaching activity representation	No teaching network integration
RICGraph [35]	Connects research, innovation, and commercialization data across institutions	Neo4j, Django, D3.js	Complex deployment requirements; primarily focused on innovation metrics	No teaching network integration

While a number of platforms exist for visualizing academic collaboration and bibliographic data, they primarily focus on research outputs and scholarly publications. Tools such as DIVA, CiteVis, and NetLens provide powerful exploration of co-authorship, citation, and knowledge networks. However, none of these systems integrate teaching collaboration data into their models. Most solutions are designed either for research trend analysis or administrative reporting, without recognizing the pedagogical collaborations that are equally critical within academic institutions. As shown in Table 2.2, the absence of teaching network integration remains a consistent limitation across existing platforms. Addressing this gap by unifying research and teaching networks is a central contribution of the proposed system.

2.5 Research Gaps and Contributions

The importance of academic collaboration visualization in improving research productivity, interdisciplinary partnerships, and institutional resource optimization is highlighted in existing literature [65]. However, many gaps remain to be filled in current visualization platforms. The limitations include the lack of institution-specific customization, real-time interactivity, and scalability limitations when working with large academic networks. This part critically examines these gaps and explains how the proposed research fills these gaps.

Most of the already existing academic collaboration visualization tools are oriented toward the analysis of large-scale research networks at the national or global level, instead of working at the institutional level [74]. Despite significant advancements in academic network visualization, major gaps remain. Existing systems predominantly focus on research collaborations, offering detailed exploration of co-authorships, citations, and institutional affiliations. However, they overlook teaching collaborations, which represent equally critical dimensions of academic relationships. Platforms like DIVA [41], VIVO, and RICGraph emphasize research output but do not integrate teaching activities into their models. This lack of integration limits universities' ability to fully understand interdisciplinary dynamics, identify hidden academic communities, or foster comprehensive institutional planning.

Table 2.2: Comparison of Limitations and Proposed Solutions for Institution-Level Collaboration Platforms

Limitations of Existing Systems	Proposed Solutions
Broad Scope: Tools analyze global or national collaborations, offering limited value for internal university planning.	**Institution-Specific Focus:** A platform that enables internal mapping of faculty and departmental collaborations within a single institution.
Limited Customization: Lack of filtering options for departments, faculties, or specific research themes.	**Advanced Filtering:** Ability to filter collaborations by department, faculty, or research area for deeper insights.
Restricted Data Access: Proprietary systems such as Scopus and Web of Science limit data availability and customization.	**Open Data Integration:** Use of Neo4j and integration with internal repositories for real-time updates and full control over datasets.
Static Visualization: Many tools present static, pre-generated graphs.	**Interactive Dashboards:** Dynamic web-based interfaces using React to explore data interactively.

The proposed research addresses this gap by developing an institution-specific visualization platform that enables fine-grained study of institutional collaboration networks. It allows the academic stakeholders to use customizable queries, interactive dashboards and integration with institutional data sources in real time for making data driven decisions.

Visualization of academic collaboration networks and their interpretation is a multidisciplinary problem, which needs data science, network theory, visualization techniques as well as integration of institutional data. This chapter discusses the literature and technologies that form the basis of this research with a focus on academic collaboration modeling, graph visualization, and the use of teaching networks and existing platforms. The objective is to position the proposed system in the academic discourse, identify research gaps, and demonstrate how this project advances or diverges from previous work.

2.6 Network Visualization: Foundations and Applications

Network visualization has become a critical paradigm for investigating complex relational data from a wide range of domains. Network visualization has long been at the center of the visualization research community, with dedicated venues, like the International Symposium on Graph Drawing and Network Visualization reporting methodological developments and applications.

2.6.1 Evolution of Network Visualization Research

The field of network visualization has been transformed a lot over the past two decades. Early studies mainly targeted layout algorithms for node-link diagrams, with Force-Atlas [34] algorithms serving as the foundations. Recent research has focused on the inherent problems in visualizing large and complex networks.

Filipov [20], offer a detailed review of the development of network visualization methods reporting a change from the static graph drawing to interactive and multi-level exploration systems. They point out that now modern methodologies combine topological analysis and interactive exploration in order to deal with visual complexity without losing significant insights.

Network visualization innovation has led the IEEE VIS conference series (InfoVis, SciVis, and VAST). Analysis of VIS publication dataset (VISPubData) by [32], found that network visualization papers have always made up roughly 18% of all publications in the last decade, highlighting their importance within the visualization community. These papers have presented new interaction techniques, visual encodings and evaluation methodologies that are tailored for use with relational data.

2.6.2 Task Taxonomy for Network Visualization

Understanding user tasks is essential for designing effective visualization systems. Task taxonomy for graph visualization by Lee et al. [44], which organizes user tasks into four categories:

Topology-based Identify adjacency and reachability; find shortest paths; assess connectivity (components, clusters, bridges, articulation points).

Attribute-based Filter or query nodes/edges by attributes; find extremes; characterize ranges and distributions.

Browsing Follow paths step-by-step and revisit previously seen nodes during exploratory navigation.

Overview Obtain a quick global sense of size, structure, and prominent groupings.

For academic collaboration networks, existing systems typically support *topology-based* and *overview* tasks well, with *attribute-based* filtering/search offered to a lesser extent. However, *temporal* and *comparative* analyses (e.g., across semesters, units, or cohorts) require capabilities beyond Lee's base taxonomy—namely dynamic graph analysis and, for layered data, multilayer modeling—where current tools often remain limited [7, 73].

2.7 Network Visualization in Academia and Research

Network visualization has found particular relevance in academia, where complex relationships between researchers, publications, and institutions naturally lend themselves to network representations. The visualization of scholarly data has emerged as a distinct subfield with specialized techniques and systems.

2.7.1 Bibliometric Network Visualization

Bibliometric networks depict relations between scholarly entities such as authors, publications, journals, and institutions. There are four major types of bibliometric networks that have been the subject of visualization research:

1. Co-authorship networks: Connecting authors who have published together
2. Citation networks: Linking papers through their citation relationships
3. Co-citation networks: Connecting papers cited together by the same sources
4. Bibliographic coupling networks: Linking papers that cite the same sources

Visualization systems of these networks have evolved from basic static to complex interactive systems. VOSviewer [3], has been among the most sought-after instruments for a bibliometric network visualization based on density-based clustering that reveals the research communities and citation trends.

The author, Skute [68] conducted a thorough review of visualization methods for scholarly data, which identified that although many systems for denoting global citation trends abound, most of them are not accurate for institutional analysis. Their research highlighted the difference between big picture bibliometric visualization tools and the needs of university administrators and researchers that require an understanding of local collaboration trends.

2.7.2 Co-authorship Network Visualization

Co-authorship networks have been of great interest to the visualization research community. Isfandyari and his team, [33], researched on the structural nature of co-authorship networks among disciplines and noted that the networks exhibit small-world characteristics and scale-free degree distribution. Their visualizations identified different patterns of collaboration across fields, whereas mathematics revealed fairly isolated clusters, in comparison to the highly interrelated network of biomedical research.

The visualization of co-authorship networks presents a distinctive set of challenges on scale, time, and richness of attributes. The authors in [71], suggests a new way of representing co-authorship networks based on the timeline where users can track the changes in the patterns of collaboration over time. Their system, modifies the visual representation based on the period selected, showing how research communities evolve, merge, and dissolve throughout decades.

The geographic dimension of academic collaboration has also been researched using visualization. In previous work [64], elaborated on the GeoSocialVis system, which unites topological and geographical layouts to visualize co-authorship networks. Their strategy resonates with a fundamental dilemma in visualizing academic networks. Preserving the structure of the network as well as a geographic context. This is particularly crucial for institutional administrators to understand both internal and external partnerships.

2.8 Specialized Visualization Systems for Academic Networks

Beyond generic network visualization, specialized systems have been developed specifically for academic collaboration networks. These systems combine domain specific data sources, analytic procedures and visualizations appropriate for academic settings.

2.8.1 Institutional Research Intelligence Systems

A variety of institutional research–intelligence systems help universities monitor activity and reveal collaboration patterns, but they differ in scope and in how well they support *internal* decision making.

Commercial analytics suites (e.g., Elsevier's SciVal and Clarivate's InCites, as well as Dimensions Analytics) aggregate publication–centric indicators and offer collaboration modules for benchmarking and partner discovery across institutions. These platforms are effective for high-level strategy and KPI tracking, yet they remain oriented toward research outputs and cross-institutional metrics rather than day-to-day, department-level exploration of *internal* co-authorship structures, and they typically do not integrate teaching/co-teaching data out of the box.

Bibliometric network tools such as VOSviewer are widely used to build and visualize co-authorship, co-citation, and related scholarly networks from bibliographic databases. They provide rich maps of scientific collaboration, but they operate at the level of publication metadata and do not link to institutional teaching rosters or course co-teaching relations.

Institutional knowledge-graph frameworks aim to unify heterogeneous sources. VIVO deployments expose institution-wide researcher profiles and include co-author/co-funding visualizations when data are available. Ricgraph goes further in flexibility: it harvests and links items (persons, skills, publications, datasets, software, projects, (sub-)organizational units) from multiple systems into a single Neo4j-backed graph, and offers a web “Explorer” for interactive traversal. While such frameworks are promising substrates for institutional intelligence, their *out-of-the-box* focus is on research information integration; they do not natively model or visualize co-teaching relations needed for program- and course-level decision support.

2.8.2 Teaching Network Visualization

Although research collaboration has attracted significant attention, the visualization of teaching networks is less developed. According to [81], teaching collaborations are a distinctive version of academic connection with different structural properties compared to research networks. Analysis of co-teaching-related data from three Australian universities showed teaching networks to be more hierarchical and less clustered than co-authorship networks, which indicated the need for specialized visualization.

TeachViz, one of the few visualization systems for teaching collaborations, was developed by [57]. Their platform represents co-teaching relationships between departments – patterns of disciplinary overlap and faculty functioning as connectors between disciplines. TeachViz’s assessment showed that it is possible to reveal structural insights that are concealed in traditional departmental reporting constructs by visualizing teaching networks.

2.9 Technical Approaches to Network Visualization

Academic network visualization system utilization incorporates a variety of technical approaches that have their own advantages and limitations. This segment discusses the prevailing technical paradigms of the current systems and their suitability for institutional collaboration platforms.

2.9.1 Web-Based Visualization Frameworks

Web technologies are widely used in present academic network visualization for accessibility and cross-platform compatibility. D3.js (Data-Driven Documents) has become a foremost platform for custom network visualizations and unmatched flexibility and control. Iglesias and Marcos [31] investigated the development of D3-based network visualization approaches and found out that although D3 has strong primitives, it requires a lot of work to create complex and engaging applications.

Domain-specific visualization libraries that sit on top of D3 or stand-alone have become popular. Cytoscape.js which was developed for biological network visualisations, is used widely in academic environments for its capabilities in graph analysis and improvements for large networks. Similarly, Sigma.js provides WebGL-accelerated rendering for very large graphs, fitting to institutional networks with thousands of nodes.

React-based visualization frameworks are a more recent innovation that integrates declarative component designs with strong rendering capabilities. Smelov [69] analyzed multiple React-based approaches to network visualization and discovered that they provide better maintainability and developer experience than pure D3 implementations, even though they sometimes with a performance hit for highly large networks.

2.9.2 Data Management for Network Visualization

The underlying network visualization data infrastructure has a significant effect on the system capabilities and performance. Conventional relational databases are not well positioned in the traversal queries that characterize the network analysis and this has led to the use of specific graph databases in modern systems.

Neo4j has become the network visualization of choice for academic graphs due to its developed ecosystem and the expressive Cypher query language, which is optimized for relationship-focused data models. kejriwal, [39] demonstrated that Neo4j bests relational databases by orders of magnitude for the typical academic network queries like finding all collaborators of a particular researcher within a certain distance.

For systems where real-time updates and higher concurrency are needed, hybrid approaches using graph databases in combination with document stores (MongoDB), or search engines (Elasticsearch) have proven practical. This architecture allows the system to retain graph structure in Neo4j while moving text search and aggregation out to more specialized systems.

2.10 Gap Analysis and Research Opportunities

The review of related work presents a series of significant gaps in the existing academic network visualization systems in terms of institutional collaboration analysis. These gaps provide opportunities for the current research to make considerable contributions.

2.10.1 Integration of Research and Teaching Networks

Although research and teaching are interrelated in academic institutions, most visualization systems distinguish these areas from one another. This artificial division prohibits an integral analysis of faculty activity and collaboration which cross both domains. The proposed system closes this gap by modeling research and teaching relationships in a common data model and visualization context, allowing users to uncover the relation between these activities.

2.10.2 Real-Time Interactivity for Large Networks

Most existing academic network visualization tools have performance issues when working on large institutional networks with thousands of researchers and relationships. This limitation limits their applicability for real-time exploration and analysis. Making use of modern web technologies such as WebGL rendering and efficient data structures, the proposed system seeks to preserve responsive interactivity even for institutions with comprehensive networks.

2.10.3 Institution-Specific Customization

Although institutions like Scopus and Dimensions are crucial for global academic visualization, they do not offer the level of customization required for institutional analysis. They usually fail to combine with internal data feeds or present views in a way that reflects institutional structures and priority. This limitation has been directly addressed by the proposed system that allows flexible data integration with the institutional repositories and customizable visualizations with organizational hierarchy.

2.10.4 Temporal Analysis of Collaboration Evolution

Academic networks change continuously as new collaborations emerge and research focus changes. The majority of current systems offer static snapshots or deficient temporal analysis. The suggested visualization platform includes robust timeline views and temporal filtering to help visualize the evolution of collaboration networks over time and their emerging patterns and trends.

2.11 Positioning the Current Research

This research is based on previous work on academic network visualization and is filling the identified gaps with several key aspects of innovation:

1. **Unified Data Model**: Unlike existing systems that distinguish between research and teaching data, the proposed platform utilizes a combined graph model that presents both activities under a unified model.

2. **Interactive Web-Based Visualization**: The system uses modern web technologies (D3.js, Cytoscape.js, React) to build an extremely interactive exploration environment, available via standard browsers, no special software required.

3. **Institution-Specific Design**: Instead of trying to come up with a general solution, the platform is explicitly designed for institutional deployment and customization options that would match universities' structures and priorities.

4. **Temporal Exploration**: The system uses temporal filtering to enable the analysis of collaboration networks' temporal evolution, which demonstrates emerging patterns and historical trends.

5. **Scalable Architecture**: The platform uses a graph database backend (Neo4j) and optimized rendering to be effective in large institutional networks without losing responsiveness; even when there are thousands of nodes and edges.

These innovations place the current research in a strong position as a breakthrough in academic network visualization, satisfying practical needs for institutional analysis while providing innovative contributions to the visualization research community.

2.12 Conclusion

This chapter has discussed background work for network visualization, academic collaboration modeling, teaching network analysis, and interactive web-based visualization systems. The analysis of the available literature shows active research in academic network visualization, specifically regarding research collaborations, but also denotes major gaps in the existing approaches.

The proposed visualization system extends the existing techniques in the manner that these gaps are addressed through a unified modeling of research and teaching activities, institution-specific focus, and the emphasis put on interactive exploration. By combining established visualization techniques with new methods for data integration and interaction with users, the aim of the system is to deliver significant insights both to academic stakeholders and benefit the state of the art in network visualization.

The next chapter outlines the requirements analysis and system design that translates those theoretical foundations into a practical visualization platform for academic collaboration networks.

Chapter 3

Requirements and Task

Before identifying specific user requirements and analytical tasks for our visualization tool, we conducted a stakeholder analysis to find out the primary stakeholders in different levels and their distinct needs. This analysis was based on three sources: (1) informal interviews with several faculty members in the Department of Information and Computing Sciences at Utrecht University, (2) a review of related work that identifies key user groups for similar tools [41, 64, 49]. As a result, we identified five key stakeholder groups: department leadership, academic staff, administrative personnel, students, and potential external collaborators. Understanding these stakeholder perspectives helped us formulate targeted user requirements that directly reflect real-world needs and expectations within our institution.

3.1 Stakeholder and Requirement Analysis

3.1.1 Scope Defined by Data Availability

This thesis aims to support the analysis of collaborative relationships in teaching and research. While the ideal scope would include all university staff and courses, data availability currently imposes significant limitations.

Specifically, our current data sources are limited to the Department of Information and Computing Sciences at Utrecht University: teaching data are provided as an Excel file by the department leadership, and research data are extracted from Utrecht University's Pure database. Access to other data is restricted due to privacy regulations, and Utrecht University does not maintain a database that could provide more information we might require to perform more complex analyses. As a result, the system is currently limited to:

- Visualizing research collaborations within the Department of Information and Computing Sciences.
- Visualizing teaching collaborations within the Department of Information and Computing Sciences.

Importantly, our approach aims to integrate these two perspectives by modeling them within a single collaboration network, enabling joint exploration of teaching and research interactions.

Potential future integrations with a graph-based institutional knowledge base like RicGraph could significantly expand the system's coverage to include other departments, faculties, and external stakeholders (e.g., industry partners, startups, societal impact). RicGraph is a university-wide knowledge graph developed at Utrecht University to represent and analyze relationships among people, research outputs, teaching activities, and organizational structures [60]. If RicGraph becomes available for external use and gains necessary approvals, we could extend our system to leverage its data for more comprehensive, real-time analyses. However, for the scope of this thesis, only collaborations within the Department of Information and Computing Sciences are supported due to data availability.

3.1.2 Stakeholder Analysis

This project aims to visualize multi-level relationships among staff members within the Department of Information and Computing Sciences, with a particular focus on collaborative relationships in both research and teaching. We identified several groups of stakeholders who are expected to benefit from such a visualization tool, previous work suggests that several stakeholder groups could benefit from academic collaboration visualization tools. Research support offices and funding bodies, for example, can use such systems to explore collaboration patterns and assess institutional research capacity, which in turn informs funding allocation strategies [15]. Industry partners and knowledge transfer units may leverage these visualizations to identify key researchers or groups with high collaboration potential, thereby facilitating technology transfer and applied research initiatives [25].

Academic leaders and strategic planners can also use it, as they need a clear picture of how their institution works—who collaborates, what areas are linked, and where there are gaps. They can find new interdisciplinary projects, underrepresented teams, and undersupported groups by visualizing collaboration patterns as Kucher et al. stated [41]. Department heads can use the tool to examine how their staff collaborates on different research topics, while faculty and university staff can compare departments, plan strategic hires, and align research directions with long-term goals.

If the system can be expanded to include more data and information from other departments and institutions, it will be a valuable tool for people interested in the big picture of academic impact. Policymakers, for example, might use the visualization data to determine which research groups are working on significant societal concerns like climate change or public health, as well as how different departments or academics collaborate on these topics. Rathnasabapathy et al. [58] show in their immersive climate-communication tool, giving decision-makers an interactive overview lets them quickly spot the most active teams on a given issue and identify where new collaborations could be fostered. Our system could similarly highlight teaching and co-authorship links at a glance, helping policy makers allocate funding, seed interdisciplinary projects, and plan university-wide strategies.

The specific roles and interests of the envisioned stakeholders of our system are described below:

- **Department Leadership:**
  - Obtain a comprehensive overview of internal collaborations in research and teaching.
  - Evaluate and compare individual or group contributions in terms of research output and teaching effectiveness.
  - Identify potential and existing opportunities for cross-group collaboration.
- **Research Support Offices and Funding Bodies:**
  - Monitor collaboration patterns to spot high-performing research teams.
  - Assess institutional research capacity and interdisciplinarity to guide grant strategies.
  - Track the impact of funded collaborations and adjust funding allocations accordingly.
- **Industry Partners and Knowledge Transfer Units:**
  - Identify academic groups with relevant expertise and proven collaboration records.
  - Evaluate which research teams are most active in applied or translational projects.
  - Facilitate partnerships and spin-off opportunities based on existing co-authorship links.
- **Academic Leaders and Strategic Planners:**

  - Benchmark collaboration intensity across departments or research themes.
  - Spot gaps or silos where new interdisciplinary initiatives could be launched.
  - Plan strategic hires and allocate resources in line with collaboration trends.

- **Policymakers and Societal Impact Evaluators:**
  - See which teams address major societal challenges.
  - Understand how academic work connects with external partners, NGOs, or the public.
  - Use visual insights to inform policy decisions, allocate national-level funding, and measure broader impact.

- **Students:**
  - Explore the network to find potential supervisors and mentors based on co-authorship and teaching links.
  - Discover peers and research groups working on topics they are interested in, helping them choose projects or theses.
  - Identify courses taught by active researchers to plan their curriculum around faculty expertise.

- **Researchers:**
  - Map existing co-authorship ties to spot new collaboration opportunities and interdisciplinary partners.
  - Analyze teaching collaborations to recruit skilled students or form project teams across courses.
  - Benchmark their own collaboration patterns against departmental norms to guide grant proposals and group formation.

As noted in Section 3.1.1, our available data comprise teaching assignments (Excel, provided by department leadership) and research metadata from PURE. Given these constraints, we scope this thesis to the stakeholder roles already introduced above whose needs can be addressed with the current data. Specifically, we focus on *four* primary user types: **Department Leadership**, **Academic Staff**, **Education Coordinators**, and **Students**.

By focusing on the following four stakeholder groups—Academic Staff (Professors, Lecturers, Researchers), Education Coordinators, Department Leadership, and Students—the tool can deliver meaningful, actionable insights based solely on the available Pure metadata and teaching Excel data. Other stakeholder needs (e.g., Research Support Offices, industry partners, policy makers) are acknowledged as avenues for future expansion once more comprehensive data sources (e.g., RicGraph) become accessible.

We conducted prototype-demo–assisted questionnaire (details in Appendix B) with several lecturers, researchers, and members of the department leadership in the Department of Information and Computing Sciences at Utrecht University. From these questions, we gathered and organized their specific needs and tasks. The following user requirements, derived directly from these interviews and the data available, will guide the development of our visualization system.

Table 3.1: Summary of User Requirements

ID	Requirement	Stakeholders	Rationale
R1	Integrate actual departmental data, including co-authorship records and teaching assignments.	Academic Staff, Education Coordinators, Department Leadership, Students	Ensure visualizations reflect real activity and maintain trust in the results.
R2	Distinctly represent two collaboration layers: research (co-authorship) and teaching (co-instruction).	Academic Staff, Education Coordinators	Allow users to separate and analyze each type of collaboration clearly.
R3	Enable exploration of individual collaboration profiles and identification of the *strongest* collaboration links for a given researcher.	Academic Staff, Students	Support discovery of primary collaborators, mentors, and peer clusters.
R4	Provide various filtering (by academic term).	Academic Staff, Department Leadership	Allow trend analysis and comparison of collaboration over different conditions.
R5	Support keyword search and filtering by name, topic, course, or metadata.	Academic Staff, Education Coordinators, Department Leadership, Students	Facilitate quick access to relevant individuals and relationships.
R6	Offer both hierarchical overview (University > Department > Division > Research Group) and interactive network views.	Department Leadership, Education Coordinators	Follow "overview first, details on demand" to support strategic and operational tasks.
R7	Be web-based and optimized for desktop environments.	Academic Staff, Education Coordinators, Department Leadership, Students	Ensure accessibility and good performance on common devices.
R8	Feature a user-friendly interface requiring minimal training.	Academic Staff, Education Coordinators, Department Leadership, Students	Lower the barrier to adoption and reduce learning time.
R9	Allow export of visualizations for reporting or presentations (optional).	Academic Staff, Department Leadership, Education Coordinators	Enable sharing insights in meetings, reports, and external documents.

3.1.3 Current vs. Future Capabilities

While the user requirements described above cover a broad set of desired functionalities, it is important to distinguish between capabilities that are currently supported by the available dataset and those that are considered potential extensions for future development.

Currently Supported Capabilities (MUST have): Based on the available data—which includes co-authorship records and course assignments within the Department of Information and Computing Sciences—the following requirements are fully supported in the scope of this thesis:

- **R1** – Integration of actual departmental data (research and teaching)
- **R2** – Dual-layer representation of collaboration (research and teaching)
- **R3** – Exploration of individual collaboration profiles
- **R4** – Temporal filtering of collaborations
- **R5** – Keyword-based search and filtering

- **R6** – Hierarchical and network views (within the department)
- **R7** – Web-based system optimized for desktop
- **R8** – User-friendly interface

Potential Future Extensions (NICE to have): The following requirements, while desirable, are currently only partially supported or require future integration with broader institutional data sources (e.g., RicGraph or full university-wide datasets):

- **R6** – Institutional hierarchy visualization across departments (University > Department > Division > Research Group)
- **R9** – Exporting visualizations (optional feature depending on frontend integration)

Extended Possibilities with RicGraph Integration: If integrated with more comprehensive data sources such as the RicGraph system could support a much broader range of analytical tasks, including:

- Cross-faculty and cross-department collaboration network analysis
- Visualization of university-industry or societal partnerships
- Identification of interdisciplinary research hubs and emerging collaboration trends
- Tracking technology transfer, spin-offs, or innovation impact across the university

These enhancements fall outside the current scope but demonstrate the extensibility of the system architecture and the potential value of integrating with institutional knowledge graphs in the future.

3.1.4 Analytical Tasks

Network visualization is essential for understanding collaboration in both research and teaching: it makes complex relationships among individuals and groups immediately visible, supports detection of clusters or gaps, and lets users drill down from an overview to individual details. We adopt the task taxonomy of Lee et al. [44], which defines four categories of graph-analysis tasks:

- **Topology-based tasks** (4 tasks): e.g. find adjacent nodes, identify connected components, compute shortest paths, detect common neighbors.
- **Attribute-based tasks** (3 tasks): e.g. locate nodes by attribute value, filter edges by metadata, summarize attribute distributions.
- **Browsing tasks** (3 tasks): e.g. follow a node's neighbors, explore subgraphs, trace a path step by step.
- **Overview tasks** (2 tasks): e.g. recognise overall cluster structure, compare global connectivity patterns.

We chose tasks mainly from the topology, attribute and overview categories because they map directly to our users' needs and to the data we have (see Table 3.1):

- **AT1 Overview of department-wide collaboration.** *(Overview task)* Show the full research and teaching network in one glance to spot the main clusters and gaps.
- **AT2 Explore individual collaboration profiles.** *(Topology task)* On node-select, list and highlight all co-authors or co-instructors.
- **AT3 Filter by time or topic.** *(Attribute task)* Restrict the graph to a given year, term, course, or research theme.

- **AT4 Drill down to details on demand.** *(Overview and browsing task)* Upon clicking a node or edge, display metadata (publications, courses) in a side panel.

We exclude more advanced browsing tasks (e.g. shortest-path queries) and attribute tasks (e.g. complex multi-field filtering) because they exceed our current data scope and are not directly called for by our core user requirements. Future work with richer data (e.g. via RicGraph) could support these additional tasks.

3.1.5 Supported Analytical Tasks

Topology-based Tasks

- **Adjacency (Direct Connection):** Identify the direct collaborators of a specific employee, with edge color intensity reflecting collaboration strength (e.g., darker edges for more co-authored papers or joint courses).
- **Common Connection:** Identify shared collaborators among multiple selected employees.
- **Connectivity (Clusters and Components):** Identify collaborative clusters and their structure within the department.

Attribute-based Tasks

- **Nodes Attributes:** Filter or identify employees based on academic rank, research interest, or sub-department.
- **Links Attributes:** Distinguish collaboration types (research vs. teaching); identify strongest or weakest collaborative ties.

Browsing Tasks

- **Follow Path:** Explore indirect collaboration paths within the department.
- **Revisit:** Return to previously explored collaborators to examine additional connections.
- **Scan:** Quickly scan the network to identify unusual or prominent collaboration patterns.

Overview Tasks

- Visualize overall collaboration patterns within the department.
- Identify sub-departments or groups with higher collaborative activity.

3.1.6 Potential Future Analytical Tasks

These tasks are not currently supported due to the limited scope of the dataset, but could be implemented in future work if broader data sources (e.g., RicGraph) are integrated.

Topology-based Tasks

- **Accessibility (Indirect Connection):** Explore indirect collaboration paths that span across departments, faculties, or external institutions.

Attribute-based Tasks

- Apply filters based on university-level metadata, such as inter-faculty course contributions, spin-off involvement, or affiliations with industry partners.

Browsing Tasks

- Browse and follow cross-department or cross-faculty collaboration paths at the university level.

Overview Tasks

- Generate university-wide collaboration trend visualizations or heatmaps.
- Visualize broader societal or industrial collaboration networks beyond the department.

3.2 Mapping User Requirements to Analytical Tasks

The user requirements defined in Section 3.1 provide the core functionalities that enable users to carry out the analytical tasks described in this section. This mapping clarifies how each system feature supports specific user goals, ensuring alignment between system design and analytical utility.

Table 3.2: Mapping Between User Requirements, Analytical Tasks, and User Group

ID	**Functionality Description**	**Supported Analytical Tasks**	**User Group**
R1	Integration of research and teaching collaboration data	All tasks (data foundation)	Academic Staff, Education Coordinators, Department Leadership, Students
R2	Dual-layer representation: research and teaching	Attribute-based filtering; Link attributes; Layer-based scanning	Academic Staff, Education Coordinators
R3	Exploration of collaboration profiles	Topology-based tasks (Adjacency, Common Connection, Connectivity)	Academic Staff, Students
R4	Conditions filtering of collaborations	Attribute-based filtering; Overview trend analysis; Time-based cluster detection	Academic Staff, Department Leadership
R5	Keyword-based search and filtering	Attribute-based tasks (Node attributes, Link attributes); Browsing tasks (Scan)	Academic Staff, Education Coordinators, Department Leadership, Students
R6	Hierarchical and network views	Overview tasks; Browsing (Follow Path); Topology-based cluster analysis	Department Leadership, Education Coordinators
R7	Web-based interface	All tasks (enables access and usability)	Academic Staff, Education Coordinators, Department Leadership, Students
R8	User-friendly design	All tasks (reduces cognitive load)	All
R9	Exporting visualizations (optional)	Reporting and presentation of results	Academic Staff, Education Coordinators, Department Leadership

The mapping between user requirements and analytical tasks provides a bridge between system design and the analytical goals of end users. It ensures that the system offers functionality that directly enables the tasks identified in Section 3.1.4, based on the needs of all the major stakeholders

Chapter 4

Dataset Description

In Chapter 3.1.1, we identified the collaboration analysis functions that the system must support, and noted the available data sources: teaching data exported as an internal Excel file by the program coordinator of the Department of Information and Computing Sciences (which differs from the public data on Utrecht University's Osiris), and research data retrieved in JSON format via a RESTful API from Utrecht University's PURE system, containing detailed records of each researcher's work history and publications.

This chapter focuses on the intrinsic characteristics of these two data streams to inform subsequent modeling and integration. We first describe data sources and scope, then analyze hierarchical structure and attribute dimensions, and finally discuss data quality and preprocessing strategies.

4.1 Data Sources and Scope

The system relies on two primary data streams:

- **Research Collaboration Data**: Retrieved from PURE, including records of co-authorship and project collaborations among faculty in Utrecht University.
- **Teaching Collaboration Data**: Provided as an internal Excel file by the department's program coordinator, which logs co-teaching assignments; this dataset differs from the publicly available Osiris data.

4.2 Hierarchical Structure and Attribute Dimensions

4.2.1 Employee Nodes

Each employee node is characterized by:

- **Organizational Hierarchy**: department → division → research group → researcher
- **Node Attributes**: employment status (active/inactive), academic title, affiliated unit, etc.
- **Connected Nodes**: other employees
- **Edge Types**:
  1. Research collaboration (co-authorship)
  2. Teaching collaboration (co-teaching)

4.2.2 Course Nodes

Each course node includes:

- **Node Attributes**: course ID (unique identifier for courses with identical names)
- **Connected Nodes**: employees
- **Edge Type**: teaching collaboration (co-teaching)

4.2.3 Publication Nodes

Each publication node includes:

- **Node Attributes**: publication title, URL link
- **Connected Nodes**: employees
- **Edge Type**: research collaboration (co-authorship)

4.3 Data Quality and Preprocessing

To ensure data accuracy, consistency, and usability, we conducted a comprehensive data quality assessment and applied the following preprocessing steps:

4.3.1 Completeness

- Missing Fields Detection: evaluated the completeness of required fields (ID, name, timestamp) and identified records with missing course terms or publication dates.
- Missing Value Imputation: manually supplemented missing teaching term data using the academic registry; flagged or retrieved missing DOI/URL for publications via the PURE lookup service.
- Data cleaning: Removed publication records with no internal employee participating.

4.3.2 Consistency

- Naming Standardization: unified naming conventions for employee names, IDs, and timestamp formats.
- ID Alignment: cross-checked employee IDs between PURE and Excel sources; resolved discrepancies using a composite key of name and department with manual verification.

4.3.3 Accuracy

- Outlier identification: flagged extreme degree nodes (e.g., an employee associated with hundreds of publications) for manual validation of name ambiguities or data errors.

4.3.4 Timeliness

- Time Window Filtering: retained collaboration records from 2015 to 2024 to maintain relevance and reduce historical noise.

Summary Statistics:

- Total nodes: 794

  - Active: 331
  - Inactive: 463
- Total edges: 2,010 (employee–employee connections)
  - Teaching collaboration-only edges: 422
  - Research collaboration-only edges: 1,536
  - Mixed edges (both teaching and co-authorship): 52
- Total courses: 109
  - Maximum that an employee participated: 5
- Total research publications: 4,515
  - Maximum that an employee published: 302

These figures characterize the density and scope of a medium-sized computer science department's research and teaching collaboration network, providing quantitative guidance for subsequent visualization performance and layout strategy.

Chapter 5

System and Interaction Design

5.1 Color Encoding and Visual Distinction

To reduce cognitive load and enable rapid differentiation of entity types and collaboration modalities, we apply the following consistent color scheme:

- **Node Colors:**
  - Publications: *Green* nodes, indicating research outputs.
  - Courses: *Blue* nodes, representing teaching artifacts.
  - Researchers: *Gray* nodes, denoting individuals in the network.

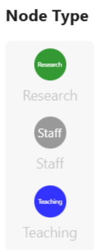


Figure 5.1: Node type legend

- **Edge Colors:**
  - Co-authorship only: *Green* lines, linking researchers via shared publications.
  - Co-teaching only: *Blue* lines, linking researchers via shared courses.
  - Mixed collaborations (both research and teaching): *Red* lines, highlighting dual-modality partnerships.

Figure 5.2: Edge type legend

This tri-color encoding (green for research, blue for teaching, red for mixed) leverages preattentive color differences to minimize user effort in distinguishing collaboration types and focusing on multi-faceted relationships.

5.2 Visualization design

5.2.1 View Decomposition

Given user requirement 3.1 R3 ("enable exploration of individual collaboration profiles and identification of the strongest collaboration links") and R6 ("offer both hierarchical overview and interactive network views"), it becomes clear that a single, undifferentiated node–link diagram cannot simultaneously satisfy both tasks. Only *researchers* participate in the institution's multi–level hierarchy (University > Department > Division > Research Group), whereas *courses* and *publications* lack a comparable nesting structure. Including all three entity types in one canvas not only obscures the underlying hierarchy, but also leads to visual clutter, making it difficult to discern which researcher–pairs collaborate most intensively. Instead, we treat courses and publications as *detail attributes* of individual researchers and split the visualization into two coordinated views. The **main view** renders only researcher nodes—laid out to reflect the hierarchical context—and draws co-authorship and co-teaching edges to reveal who collaborates with whom and by what modality. Upon selecting a researcher, a **detail view** displays that individual's specific collaborations along with associated courses and publications, thereby preserving both the clarity of the hierarchical overview and the ability to explore detailed collaboration profiles as required by R3 and R6.

5.2.2 Layout selections for main view

Evaluation Criteria

Based on data characteristics (794 researcher nodes, 2 010 researcher–researcher edges, irregular four-level hierarchy) and user requirements

R3 "Enable exploration of individual collaboration profiles and identification of the strongest collaboration links."

R6 "Offer both hierarchical overview and interactive network views."

we derive four layout criteria:

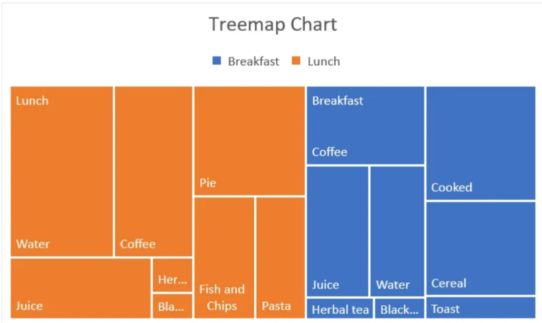
1. **Hierarchy Fidelity:** must clearly encode Department→Division→Research Group→Researcher
2. **Network Proximity:** strongly collaborating researchers should be placed close together.
3. **Edge Readability:** co-authorship and co-teaching links must be traceable without excessive crossings or long arcs.
4. **Space Efficiency:** must accommodate hundreds of nodes and edges without wasted whitespace.

Mainstream Candidate Layouts

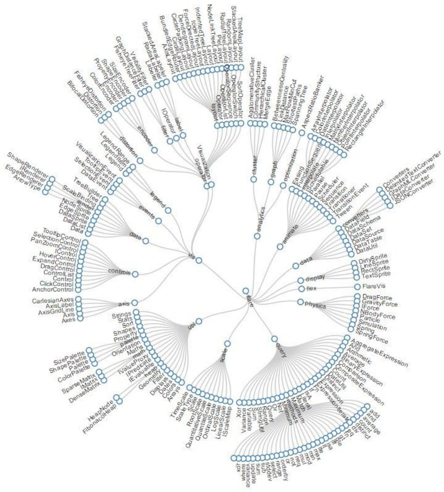
We first consider two canonical, widely-adopted hierarchical layouts:

Other (Non-Mainstream) Hierarchy Layouts

Beyond Treemap and Radial Tidy Tree, we briefly considered several alternative hierarchy visualizations. *Sunburst* extends treemaps into a circular, space-filling form with concentric rings for depth, but inner rings can be partially occluded and narrow outer wedges hinder labeling in deep or unbalanced trees [70]. *Icicle plots* provide a linear, rectangular, space-filling variant of radial trees; however, deep hierarchies can produce very long strips that exceed common viewports, inducing excessive scrolling/zooming [36]. *Circle packing* preserves containment by nesting circles inside parents, yet sacrifices adjacency cues and leads to large size variation, which complicates area comparison and makes routing researcher–researcher ties impractical [77]. 3D *Cone Trees* add a third dimension to show branching, but demand spatial navigation and suffer from occlusion and



(a) Example of Treemap



(b) Example of Radial Tidy Tree

Figure 5.3: Figures of Treemap and Radial Tidy Tree

Table 5.1: Comparison of Treemap and Radial Tidy Tree Layouts

Criterion	**Treemap** 5.3a	**Radial Tidy Tree** 5.3b
Hierarchy Fidelity	Nested rectangles handle skipped levels gracefully.	Concentric rings encode each node's depth.
Network Proximity	No native support for edges; cannot place collaborators meaningfully.	Nodes are fixed on rings, so collaborators may remain far apart.
Edge Readability	N/A (no edges).	Bundled arcs reduce crossings but remain long and do not encode strength.
Space Efficiency	Fills the entire canvas without wasted whitespace.	Uses circle sectors but leaves gaps between rings.

distortion that slow overview and degrade edge readability [61]. Finally, *Hive plots* align branches on radial axes and connect nodes with arcs; they work best for flat or shallow structures, as axis proliferation under high depth/branch counts quickly leads to visual overload [40]. Collectively, these trade-offs made them less suitable for our department-scale, mixed-layer use case focused on rapid overview, stable labeling, and readable cross-node connections.

None of these alternatives simultaneously deliver (a) clear multi-level hierarchy, (b) compact rendering of researcher–researcher edges, and (c) straightforward label legibility in deep, uneven trees. This reinforces our choice of a Treemap-inspired, constraint-based Cola.js layout as the only approach that can blend perfect nesting with network-driven clustering and maintain readability in our large, irregular academic hierarchy.

A Treemap-Inspired Constraint-Based Force Layout

Table 5.1 summarizes the strengths and weaknesses of Treemap and Radial Tidy Tree against our four evaluation criteria.

- **Hierarchy Fidelity:** Both layouts faithfully encode the four-level academic hierarchy. Treemap does so via nested rectangles that gracefully accommodate skipped levels, while Radial Tidy Tree uses concentric rings to place each researcher at the correct depth.

- **Network Proximity:** Neither layout supports clustering collaborators by tie strength. Treemap has no native edge mechanism, so collaborators cannot be co-located, and Radial Tidy Tree fixes nodes on rings, forcing even the strongest collaborators into distant angular positions.

- **Edge Readability:** Only Radial Tidy Tree can draw links (e.g. with bundling), but the resulting arcs remain long and cannot convey relative collaboration strength. Treemap provides no facility for edge rendering.

- **Space Efficiency:** Treemap maximizes canvas usage with no wasted whitespace, whereas Radial Tidy Tree leaves gaps between rings and under-utilized angular sectors.

Overall, Treemap delivers perfect nesting and full space-filling, but lacks any support for visualizing researcher–researcher ties. Radial Tidy Tree provides depth clarity and link overlay, but at the cost of rigid geometry and wasted space. These limitations motivate our hybrid Constraint-Based Layout(Cola) 5.4 approach, which preserves nested regions while enabling network-driven clustering and clear edge rendering.

Figure 5.4: Figure of A Treemap-Inspired Constraint-Based Force Layout

To blend the strengths of Treemap (perfect nesting, space efficiency) with the network proximity of force layouts, we use a constraint-based layout with rectangular "box" constraints. Concretely, we place a manual box at the division level to emulate a treemap-like partition; nodes inside each division remain free to arrange via force-directed dynamics without additional manual pinning. Collaboration edges (co-authorship and co-teaching) are mapped to springs whose stiffness and ideal lengths scale with collaboration counts, drawing tightly connected researchers into compact clusters. The layout is solved with Cola's stress-majorization engine [26], which optimizes a global stress objective while respecting declarative grouping/containment constraints, thereby balancing hierarchical separation and network proximity.

This hybrid approach preserves the "nested" regions of a Treemap while allowing node positions to reflect true collaboration intensity—overcoming the rigidity of Radial Tidy Tree and the edge absence of Treemap.

5.2.3 Layout Selection for the Side View

The side view's primary goal is to satisfy requirement R3— *"enable exploration of individual collaboration profiles, including which colleagues a researcher has worked with, the types of collaborations, and the relative collaboration intensity"*. Given the underlying data structure (each researcher has at most five courses, a moderate number of collaborator links, and potentially many publications (up to 300)), we require a layout that:

1. **Clearly separates entity roles** (courses, collaborators, publications) into distinct regions;
2. **Highlights collaboration counts** (edge thickness or proximity) without obscuring nominal relationships;

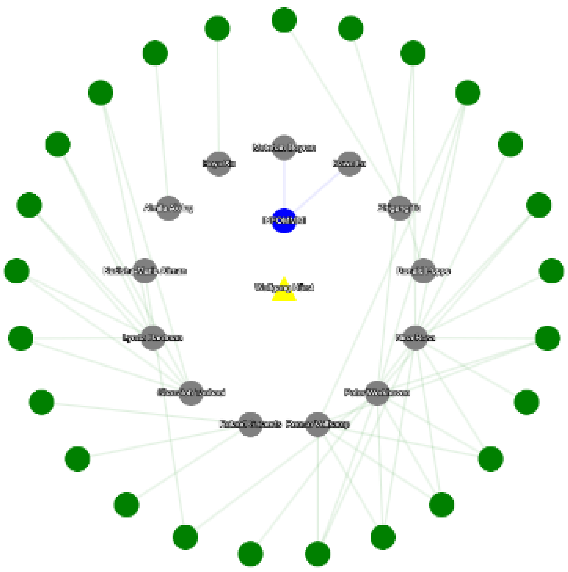


Figure 5.5: Figure of the concentric Layout for side view

Rationale for Concentric Layout in the Side View The concentric layout 5.5 directly addresses the requirements for detailed exploration of a selected researcher's collaboration profile (R3), offering:

- **Role Segmentation:** Entities are organized on discrete rings by type—courses occupy the innermost ring (at most five, reflecting the smallest entity set), collaborators the intermediate ring (a moderate number of peers), and publications the outer ring (potentially many, placed furthest to avoid clutter). This ordering aligns with the underlying data distribution and provides immediate visual separation of heterogeneous node types.
- **Intuitive Collaboration Tracing:** Edges radiate either inward (from publications and courses toward the focal node) or laterally (among collaborator nodes), enabling users to follow each link unambiguously and to assess collaboration intensity via edge thickness or color.

5.2.4 Edge bundling

Motivation In both the Cola *main view* and the concentric *side view*, we have many nodes and long links—especially ones that jump across groups and between research and teaching. When every link is drawn separately, lines overlap and tangle, *edge readability* drops, and it's hard to tell who is connected to whom. To fix this, we use *edge bundling*: to reduces visual clutter, restores edge readability, and keeps node positions (from the Cola and concentric layouts) unchanged.

Hammer bundling Classic HCI response-time thresholds (0.1/1/10 seconds) indicate that delays beyond 1 second disrupt users' flow and require visible feedback, while very long delays (larger 10 seconds) leads losing attention [52]. Controlled experiments also suggest a tolerable waiting time of about 2 seconds for information retrieval tasks (with feedback increasing tolerance)[54]. In large-scale field data, more than 50% of mobile visits abandon pages that take more than 3 s to load.[1]

We set a practical interaction budget of $\leq$3 seconds, meaning that after any user operation (e.g., dragging, filtering, or focus changes), the system should respond within this time frame. Consequently, edge bundling computations and rendering must also adhere to this latency constraint. The $\leq$3 seconds figure is a design budget / engineering target that guides algorithm and pipeline choices for interactive use, not a user-study outcome measure.

To assess the running time of different edge bundling algorithms for interactive use, we report runtimes of two edge-bundling algorithms under **out-of-the-box default parameters**, emulating a "developer just calls the library" usage. Implementations are: **KDE/"hammer"** (Datashader's `hammer_bundle` v0.18.2) and **FDEB** (`pavlin-policar/FDEB` v0.0.2). All methods were run on the same dataset (794 nodes, 2,010 edges), and the same hardware/software environment on a MacBook Pro M1 Max. **We timed the backend bundling call only**—the wall-clock duration of the function/API that computes the bundled polylines—excluding data loading, (de)serialisation, any network transfer, and any client-side rendering. Each method was executed 30 times.

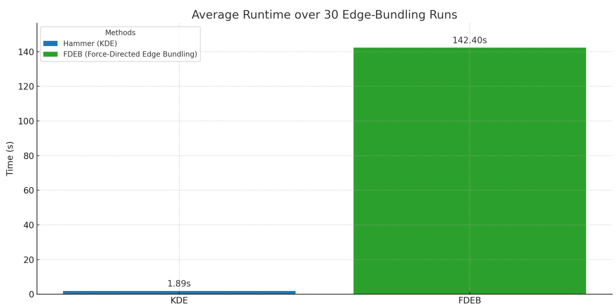
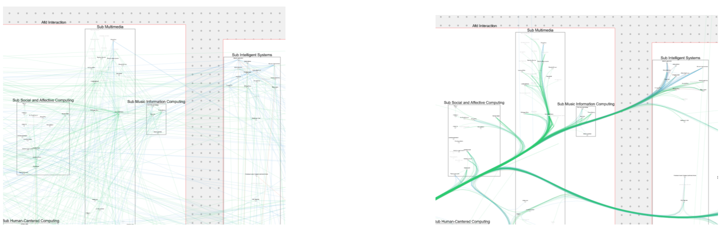


Figure 5.6: Chart of the average runtime over 30 times edge bundling runs

Based on the budget above, We therefore adopt an image-space, KDE-based bundling (Datashader's "hammer") because it delivers comparable clutter reduction at a substantially lower computational cost than force-directed approaches on large. The KDE/"hammer" method offers the shortest calculation time for interactive use, see the chart 5.6.[2]



(a) Before edge bundling (b) After edge bundling

Figure 5.7: Charts of Hammer bundling in part of the main view before and after

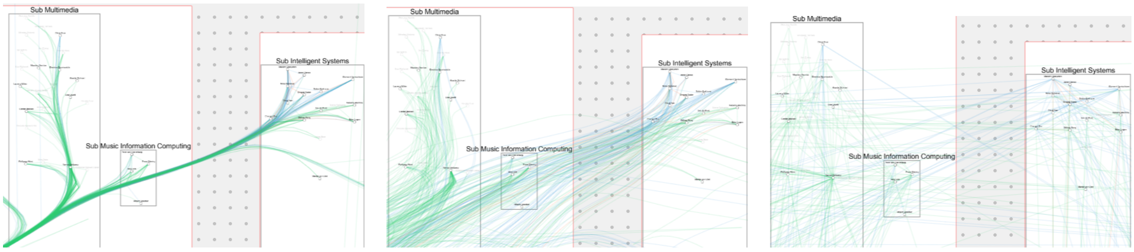
[1]See Google, *The Need for Mobile Speed* (2016), and Think with Google, *Mobile Page Speed: New Industry Benchmarks* (2018).

[2]KDEEB: density-map based bundling with efficient advection toward ridges; see Hurter et al. (EuroVis 2012). GPU bundling (CUBu) reports 50×–100× speedups over fast CPU methods but targets CUDA-based pipelines.

Bundle Strength Control

Edge bundling makes dense areas readable, but it can also *over–simplify* the picture: individual routes become hard to trace and subtle differences between links may disappear as Chart 5.7 shows. To support deeper exploration without giving up the clutter reduction, we introduce a simple, method-agnostic *relaxation* control.

The idea is to keep two shapes for each edge: its raw (unbundled) polyline a and its bundled polyline b. A single strength parameter $t \in [0, 1]$ interpolates between them, so that $t = 0$ shows the fully bundled view and $t = 1$ shows the original, unbundled view; intermediate values reveal "what's inside" the bundle.



(a) 100% bundling strength (b) 60% bundling strength (c) 0% bundling strength

Figure 5.8: Charts of main view with different bundling strength

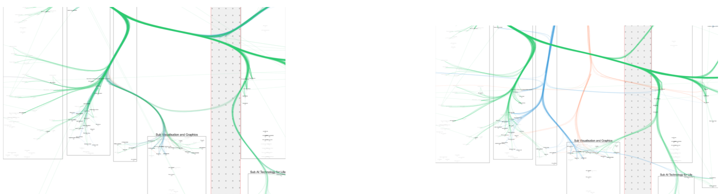
To let users look *inside* a bundle and trade clutter reduction for per-edge traceability, we interpolate between each edge's raw polyline and its bundled polyline. Let $a(s)$ be the unbundled geometry and $b(s)$ the bundled geometry of the same edge, both re-sampled to N points by arc length.[3] Given a strength parameter $t \in [0, 1]$, we render the intermediate curve

$$x_t(s_k) \;=\; t\, a(s_k) \;+\; (1-t)\, b(s_k), \qquad k = 0, \ldots, N-1,$$

so $t = 1$ shows the raw edge, $t = 0$ shows the fully bundled edge, and intermediate t values "relax" the bundle, as Chart 5.8 shows.

Layered (type-wise) edge bundling

Different link types in our data (e.g., *research*, *teaching*, and *hybrid*) carry different meanings. A single, global bundle can collapse these meanings by pulling unlike links into the same "highway." To avoid that, we offer another feature which is **layered (type-wise) bundling**: edges bundle only with *their own type*



(a) no separation (b) separated by edge type

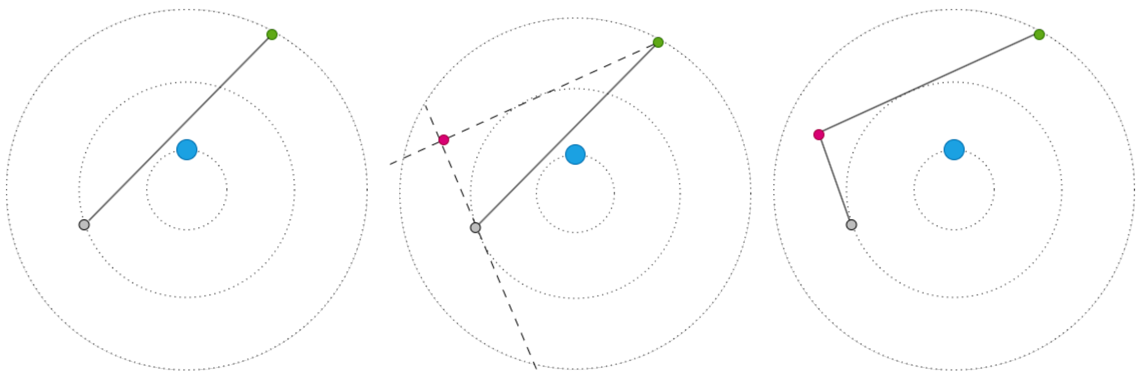
Figure 5.9: Charts of Hammer bundling with and without being separated by edge type

This keeps the multiplex semantics intact—users can still see clear corridors for each type—while we get the same clutter reduction benefits of bundling.

[3]Any bundling method can be used to obtain b; the mechanism below is method-agnostic.

Side view: layered bundling policy. In the concentric *side view*, we apply type-wise bundling with rules that differ from the main view to preserve the ring semantics:

- **Courses $\leftrightarrow$ Researchers.** The number of course nodes and links is small (typically single digits), so we keep them *unbundled and straight.* Bundling here adds little value and can over-smooth already sparse ties.
- **Publications $\leftrightarrow$ Researchers.** Publications sit on the outer ring and researchers on the inner ring. To preserve the ring semantics and avoid cut-through artefacts, we use a *data-driven threshold*: let T be the per-view edge-count threshold (after filters). If the number of publication$\leftrightarrow$researcher links is $< T$, we render them unbundled for precise tracing; if it is $\geq T$, we apply *hammer (KDE) bundling* to form a clean corridor between the rings.
- **Dummy-waypoint routing.** When the number of edges in the concentric side view is greater than the threshold T, some publication$\rightarrow$researcher links cut straight across the *researcher* ring (and occasionally the *course* ring). If we bundle such links as-is, the resulting curves pierce rings and break the intended layered semantics.



(a) edges crossing ring (b) create dummy node (c) routing the edge

Figure 5.10: Charts of steps for making the dummy nodes

For any publication–researcher link whose straight segment intersects the researcher ring (5.10a), we insert an invisible *dummy waypoint* to keep the route in the inter-ring corridor: (5.10b) at the researcher node R, take the tangent line to the researcher ring; at the publication node P, take the tangent to the same ring that is closest in angle to R on the circle; (5.10c) let D be the intersection of these two tangents (the dummy waypoint); replace the direct edge R–P with the two-segment path $R \rightarrow D \rightarrow P$. We then apply bundling to these routed segments.

As chart 5.11 shows, this method prevents “cut-through” artefacts, preserves the concentric layering (rings are only entered near endpoints), and still yields clear, type-wise corridors for long cross-ring ties.

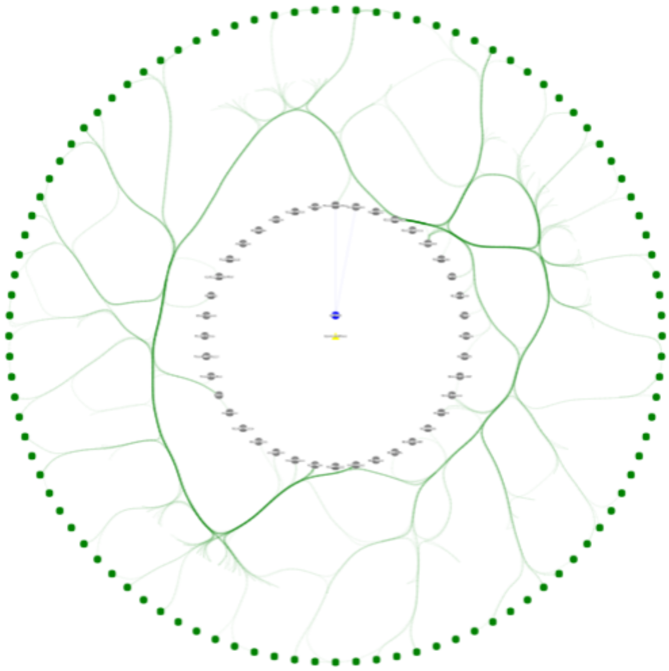


Figure 5.11: Chart of the concentric Layout after dummy-waypoint routing and edge bundling

5.3 Interactive design

This section specifies how users *act* on the visualization to answer our research questions(RQ 1.3) while meeting the user requirements (UR 3.1). We keep interactions consistent across the *main* (Cola 5.4) and *side* (concentric 5.5) views and enforce a sub–3 s feedback budget 5.2.4.

5.3.1 Goals

- **G1 (UR1, RQ1):** Keep dense areas readable while letting users trace specific ties.
- **G2 (UR2, RQ3):** Preserve multiplex semantics (research/teaching/hybrid) during interaction.
- **G3 (UR3, RQ2):** Maintain responsive updates (< 3 s) with clear progress feedback.
- **G4 (UR4, RQ1–3):** Provide on-demand detail without losing the big picture.

5.3.2 Main view interactions

The main view provides a set of direct manipulation and filtering operations designed to support the design goals G1–G4. Specifically, the following interactions are supported:

1. **Search and focus.** A search box 5.12 supports fuzzy matching on researcher names. Selecting a search result automatically centers and zooms the main view on the corresponding node. *(Supports G4)*
2. **Navigation.** The graph can be freely navigated using mouse wheel zooming and left-button panning, enabling overview-to-detail exploration of the departmental network. *(Supports G4)*
3. **Filtering.** Multiple filter 5.13 mechanisms are provided:

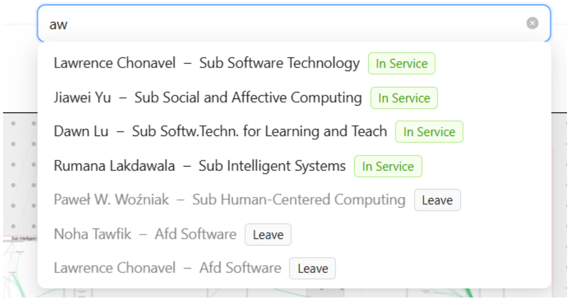


Figure 5.12: Search bar of the main view

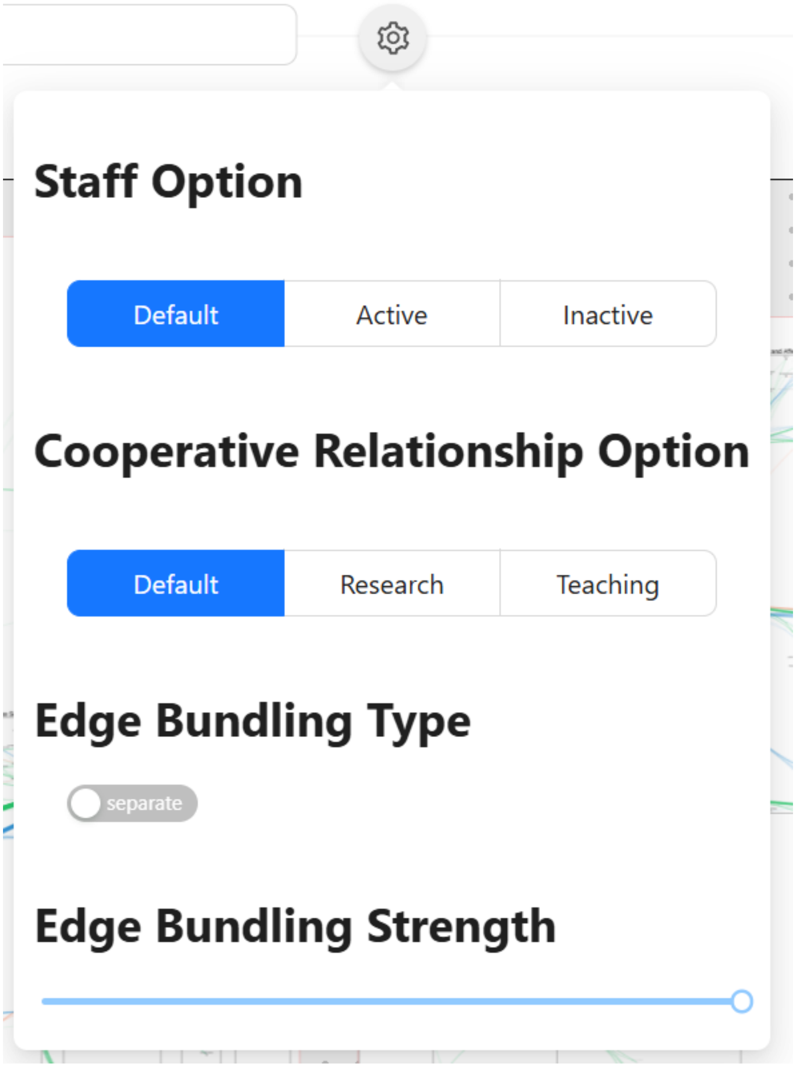
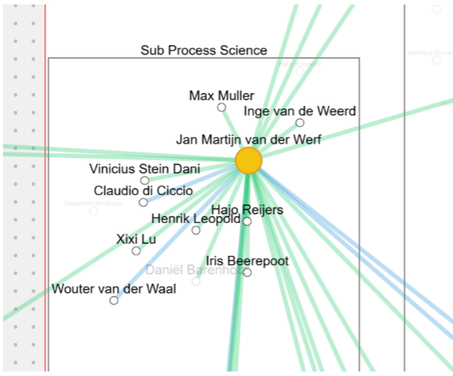


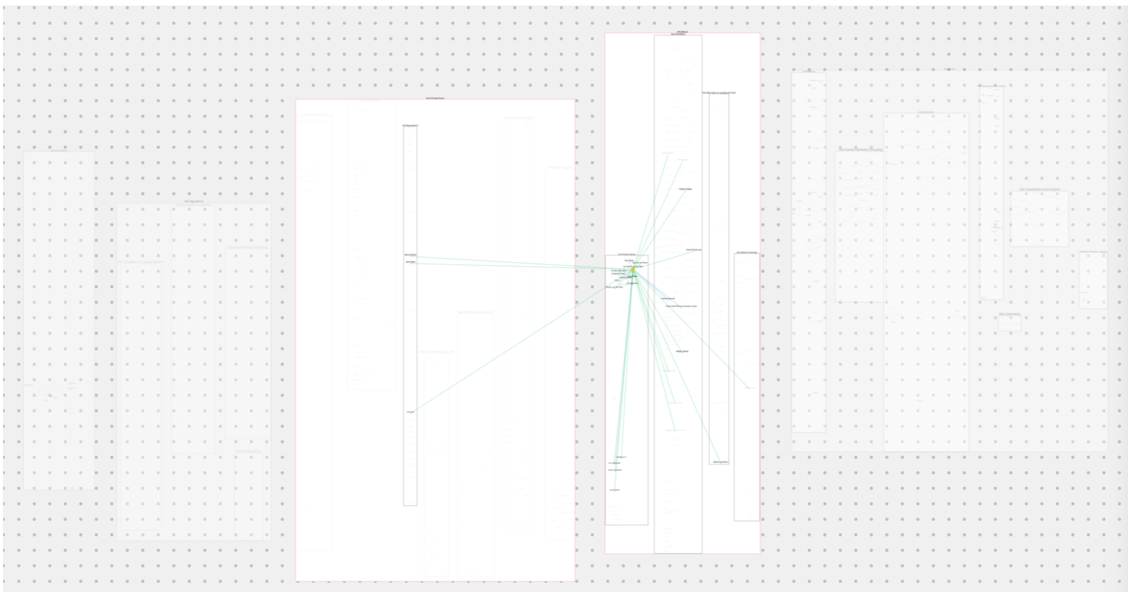
Figure 5.13: Multi-filters of the main view

- Researcher employment status filter: shows only researchers with the selected status, hiding all unrelated nodes and their incident edges. *(Supports G1, G4)*
- Edge-type filter: shows only edges of the chosen collaboration type (research, teaching, or hybrid) while keeping all nodes visible. *(Supports G2)*
- Bundling mode and slider: toggles edge bundling by the type and adjusts bundling strength to reduce visual clutter in dense regions. *(Supports G1, G3)*

4. **Drag and Clickable.** Individual researcher nodes or organizational parent nodes can be dragged:
   - Dragging a researcher highlights only their related edges and temporarily hides all unrelated ones; on release, the view restores. *(Supports G1, G4)*
   - Dragging an organizational node moves its container without altering inner structure. *(Supports G4)*



(a) Highlight the clicked node and connected elements



(b) Transparent the unrelated nodes and edges

Figure 5.14: Charts of the main view when a researcher node is clicked

Additionally, clicking a researcher node enlarges it and highlights all connected neighbors and edges as chart 5.14a shown, while unrelated nodes fade to transparency 5.14b. This action also triggers the side view, which appears on the right. Closing the side view restores the original state. *(Supports G4)*

5. **Manual bundling.** After nodes are repositioned, edge bundling does not update automatically. Users may trigger bundling explicitly by pressing ` key to trigger the edge bundling based on current layout and nodes positions. *(Supports G1, G3)*

5.3.3 Side view interactions

The side view consists of two coordinated parts: a concentric layout and a dynamic information panel. It is designed to complement the main view by providing focused exploration of an individual researcher and their direct teaching or publication ties, supporting goals G1–G4.

1. **Search and focus.** A dedicated search box 5.15 supports fuzzy matching not only on

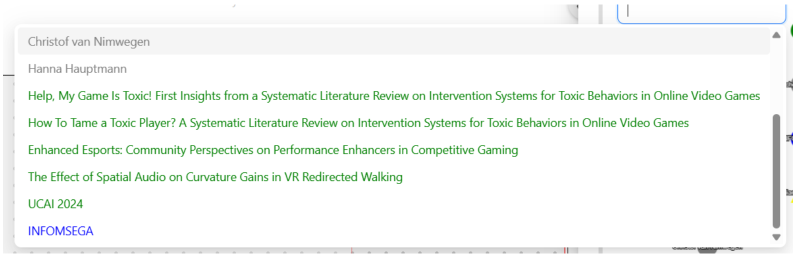


Figure 5.15: Search box in side view

researcher names, but also on course identifiers and publication titles. Selecting a search result automatically centers the concentric layout on the corresponding node. *(Supports G4)*

2. **Legend.** A color legend 5.16 is displayed in the top-right corner of the concentric view to

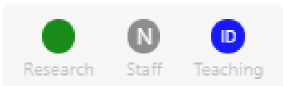


Figure 5.16: The legend in concentric layout of side view

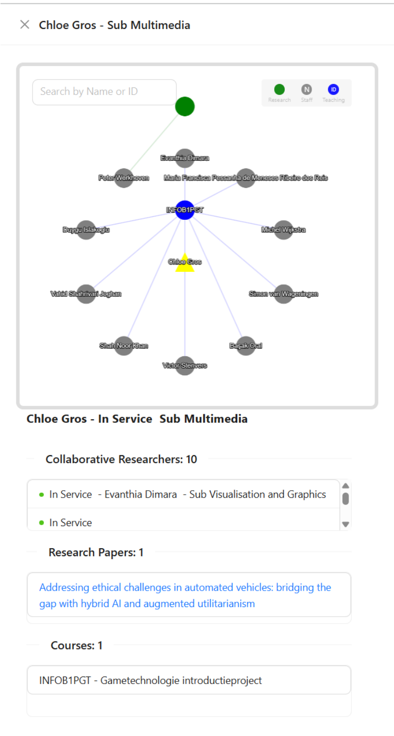
clarify the semantic mapping of node colors (e.g., researcher, course, publication). *(Supports G2, G4)*

3. **Navigation.** The concentric layout can be zoomed and panned, enabling flexible overview and inspection of rings without losing the overall structure. *(Supports G4)*

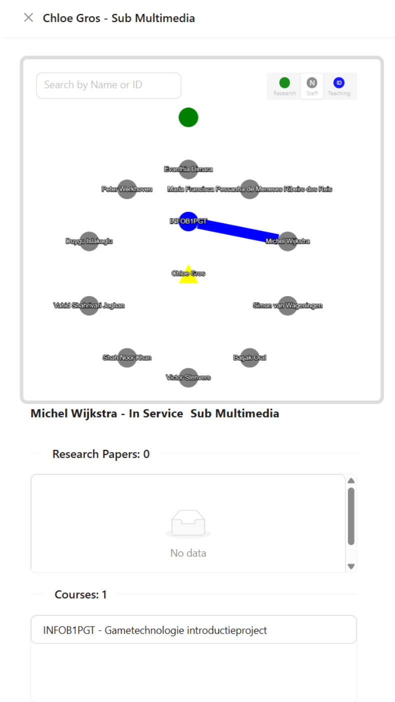
4. **Click and hover interactions.**

    - Clicking a node highlights the selected element and its incident edges in the concentric layout. The information panel below updates to show detailed metadata (e.g., course description, publication list, collaborators) as figure 5.17 shows. *(Supports G1, G4)*
    - Hovering over an item in the information panel temporarily hides unrelated elements in the concentric view, allowing focused inspection of the hovered entity. Pressing `Esc` restores the default state. *(Supports G1, G4)*

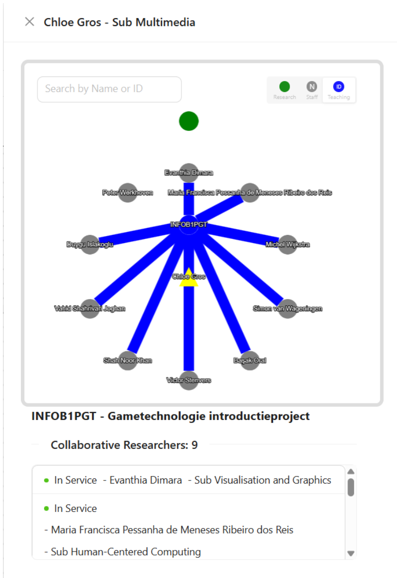
Notably, nodes in the concentric view are fixed in position and cannot be dragged, ensuring the semantic stability of the ring structure. *(Supports G2, G3)*



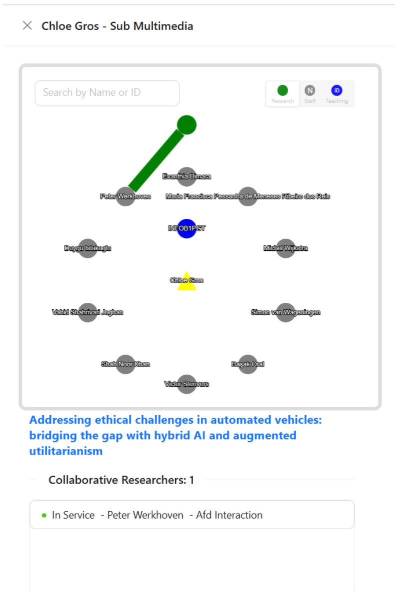
(a) Concentric view and details panel by default



(b) Concentric View and Detail panel when a researcher node being clicked



(c) Concentric View and Detail panel when a course node being clicked



(d) Concentric View and Detail panel when a publication node being clicked

Figure 5.17: Side view when clicking different type of node

5.4 Technical Stack

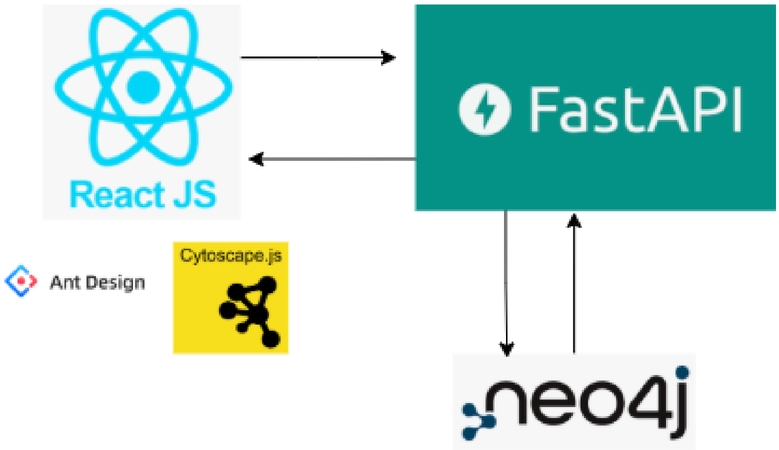


Figure 5.18: Architecture of the application

Frontend: React + Ant Design We build the client as a React single–page application. React's component model fits our modular views (main/side), stateful controls, and rapid iteration. Ant Design (antd) is used as the UI component library to provide consistent, accessible widgets (search, sliders, drawers, legends) and reduce styling/interaction boilerplate.

Graph rendering: Cytoscape.js (Canvas/WebGL) Both network views are rendered with Cytoscape.js. We use its Canvas/WebGL backends instead of SVG to avoid DOM overhead and sustain smooth pan/zoom/hover on thousands of elements. Cytoscape also provides the *cola* and *concentric* layouts we adopt, along with a stylesheet-like API and event model for interactive styling.

Backend: Python (FastAPI) Server-side edge bundling computation is implemented in Python; the service is built with FastAPI.

Data layer: Neo4j Neo4j stores researchers, organizational units, courses, publications, and typed relations (research/teaching/hybrid). A native graph store suits traversal-heavy queries (ego-nets, typed filters, year/status constraints). Cypher queries and indexes on names, course codes, and years keep interactive query latency predictable.

Chapter 6

Methodology

6.1 Study Design

This chapter details our *formative*, task-based expert evaluation of a unified research–teaching network visualisation platform. Our goal is to examine whether integrating co-authorship and co-teaching supports *interpretable* and *auditable* analysis at the department scale, addressing **RQ** and **SQ1**–**SQ5**. We adopt a protocol combining (i) *task-level* ratings using Wall et al.'s value-driven framework (ICE–T) [76], (ii) a *system-level* System Usability Scale (SUS) [10], and (iii) a short *semi-structured interview* [37] focused on workflow fit and design implications.

For each expert participant, we followed a fixed procedure. Participants completed the full task set on the prototype; immediately after *each* task they provided ICE–T ratings (Insight, Confidence, Essence, Time; 1–7). Once all tasks were finished, they completed the SUS (0–100). Finally, we conducted a brief semi-structured interview to capture workflow fit, the value and limits of unifying layers, hierarchy choices, perceived strengths/limitations, and desired improvements. Quantitatively, we report task-level ICE–T summaries and overall SUS. Qualitatively, we thematically code interview notes [24]. We then interpret quantitative patterns alongside the corresponding qualitative evidence to derive system-level conclusions and design implications.

6.2 Participants

Eight employees (**E1**–**E8**) from Utrecht University participated under informed consent. Roles were: *education coordination* (2 participants), *academic staff* working on computer science and visual computing (4 participants), and *research IT/engineering* (2 participants). No names, job titles, or unique identifiers were collected; quotes are attributed only as "E#". All participants self-reported no colour-vision deficiency.

We report qualitative statements in anonymised, paraphrased form and tag them with *(E#, role/focus, mode)* to indicate who is who while preserving privacy; no names or unique identifiers were collected. The role, focus area and the evaluation mode are described as Table 6.1.

Table 6.1: Participant overview (anonymised). Minimal fields used to link paraphrases to user roles.

ID	Role	Focus	evaluation mode
E1	Coordinator/Researcher	[Research/Admin]	[In person]
E2	IT Officer	[Admin]	[In person]
E3	Phd Student	[Research]	[Online]
E4	Coordinator	[Admin]	[Online]
E5	Lecturer	[Research / Teaching]	[Online]
E6	Professor	[Research / Teaching]	[In person]
E7	Research IT / Engineering	[Admin/IT]	[In person]
E8	Lecturer	[Research/Teaching]	[In person]

6.3 Evaluation Process

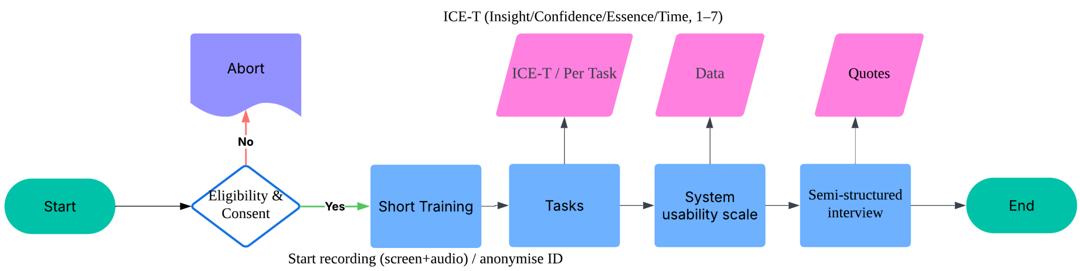


Figure 6.1: The process figure of Task-based usability evaluation protocol

Figure 6.1 illustrates the protocol followed in the formative expert evaluation. The study sessions were conducted either *in person* or *online*. In the in-person setting, the participant interacted with the system on a 13-inch Apple MacBook Pro (M1, 2020), provided by the researcher. For the online setting, participants used their own computers to access the system via a browser. Two participants had the evaluation online via teams, the rest went in-person. Each session followed the same procedure.

Protocol (step–by–step)

1. **Eligibility & consent.** We verified eligibility, obtained written consent, and assigned an anonymous participant ID. Recording (screen+audio) started at this point. Participants had previously self-reported no color-vision deficiency (see Section 6.2).

2. **Short training (7–10 min).** We demonstrated the core interactions: *Search*, *Active* toggle, *Type* filter (research/teaching/mixed), *Separate vs. Union by type*, and the (optional) *edge-bundling strength*. We emphasized that **all counts and type judgments must be read from the details panel**; bundling is for readability only.

3. **Tasks (presented one-by-one).** Participants completed 9 tasks(full text in Appendix D). After each task, they immediately filled the **ICE–T** (see the questionnaire in Appendix C).

4. **SUS.** After all tasks, participants filled the 10-item SUS (5-point), later scored to 0–100.(full questionnaire in Appendix E)

5. **Semi-structured interview (15–20 min).** We asked about workflow fit, the value/limits of the unified layers, hierarchy choice, strengths/limitations, and desired improvements (guide in Appendix F). We captured verbatim quotes where relevant.

6. **Debrief and end.** Optional comments; recording stopped.

Data captured

- Per task: ICE–T (1–7).
- Post-session: SUS (0–100) and interview audio/screen recordings.
- **Recordings (with consent)**: audio of the interview and optional screen recordings, used solely for transcription and qualitative coding; recordings are anonymised and not analysed for time-on-task.

Typical timeline

Table 6.2: Typical session timing (total ≈ 60–90 minutes).

Phase	Duration
Eligibility & consent	2–3 min
Short training	7–10 min
Tasks (one-by-one; ICE–T after each)	25–40 min
System Usability Scale (SUS)	2–3 min
Semi-structured interview	15–20 min
Debrief	1–2 min

6.4 Tasks (Overview)

Tasks were designed directly from the stated user requirements; each task operationalises one or more required system functions, consistent with human-centred, requirements-driven evaluation practice [1, 53].During sessions, prompts were instantiated with pre-selected entities from the dataset for coverage and answerability;In this thesis, we present *anonymised* versions of the same prompts. Tables 6.3 and 6.4 summarise the task battery used in the expert study. Table 6.3 lists the anonymized questions and expected answer formats; Table 6.4 maps each task to the analytical leveland rationale.

Task ordering rationale

We ordered tasks from *simple to complex* so that participants could progressively master the interaction concepts while we ensured coverage of all views and controls (Search, Active, Type, Separate vs. Union, optional bundling, details panel). Given that this is a *formative* expert study and our outcome measures are *subjective* (ICE–T, SUS, interviews), such pedagogical ordering reduces cognitive overload without compromising the goal of assessing *to what extent* the unified view supports multi-level exploration.

Operational definitions (fixed for all tasks).

- **Collaboration existence** means a *one-hop* tie between two researchers.
- **Types** are *research* (co-authorship), *teaching* (co-teaching), and *mixed*.

Table 6.3: Generic task descriptions used in the evaluation (no personal or organizational identifiers).

Task ID	Generic prompt (anonymized)
T1	Select all research groups that belong to a given *division*.
T2.a	Given *Researcher X*, check whether they are *Active* or *Inactive*.
T2.b	Given *Researcher Y*, check whether they have *any collaborations*.
T2.c	Given *Researcher Z*, choose the *type(s)* of collaboration they have.
T3	Given *Researcher X*, determine their *major* collaboration type.
T4.a	Given *Researcher X*, check whether they collaborated with anyone from *Division P*.
T4.b	Given *Researcher X* and *Researcher Y*, check whether they have ever collaborated.
T5	Given *Researcher X*, report: (i) # *collaborators*; (ii) # *publications*; (iii) # *courses participated*.
T6	Given *Researcher X*, find their *top collaborator* and the *number of collaborations* (research + teaching).
T7	Given *Researcher X* and *Researcher Y*, determine their *main collaboration type*.
T8	Given *Researcher X* and one of their *publications/courses*, report # *participants* and how many are *Active* now.
T9	(Open) Choose one *research group* (from 3 provided). (i) Name a member with the *most in-group collaborators* (and how many). (ii) State the group's *dominant collaboration type*.

- **Counts** use a single rule: *papers + teaching terms*, de-duplicated by item and time window. The *major* type is the one with the highest count; ties are broken by total events, then recency.
- **Active** indicates current employment at the time of the snapshot.
- **Group "most collaborators"** in the open task refers to the number of distinct *within-group* collaborators.
- **Source of truth.** Edge bundling and type-wise separation improve overview readability only; all numeric judgments and examples must be read from the *details* panel (items and counts).

Table 6.4: Mapping between tasks, analytical level and Rationale.

Task ID	**Analytical level**	**Rationale**
T1	Division → Group	Validates hierarchy recognition and navigation—an entry point for multi-layer exploration within a single interface.
T2.a	Researcher	Confirms the basic locate→inspect flow for researcher status, a prerequisite for researcher network exploration.
T2.b	Researcher	Checks one-hop existence clarity in the unified model, showing that research and teaching layers can be read as one network.
T2.c	Researcher	Tests whether collaboration *types* (research/teaching/mixed) remain interpretable after unification.
T3	Researcher	Elevates from existence to a *dominant type* summary, indicating that the unified view supports concise researcher profiles.
T4.a	Researcher → Division	Exercises cross-division filtering to verify ties across organizational boundaries—key for university-wide navigation.
T4.b	Pair (dyad)	Demonstrates pair-level verification in the unified interface, explaining why two researchers are connected.
T5	Researcher (+ artifacts)	Audits people–artifact linkage (collaborators, publications, courses) in one place—evidence of effective multi-layer integration.
T6	Researcher	Validates unified *ranking + counting* workflows and their auditability within the single visualisation.
T7	Pair (dyad)	Assesses whether pair-level *type* can be determined reliably in the unified model.
T8	Artifact → People	Tests backtracking from an item (publication/course) to participants and current status—supporting cross-layer exploration.
T9 (Open)	Group	Free exploration of a group's hubs and dominant type; synthesises multiple operations to demonstrate real-world researcher network exploration in the unified view.

6.5 Measures

Task-level (per task)

We adopt the ICE–T framework (Insight, Confidence, Essence, Time), each rated on a 7-point Likert scale. Construct meanings: *Insight* (new/useful understanding), *Confidence* (answer certainty), *Essence* (captures/communicates the gist), *Time* (perceived efficiency/acceptability).

System-level (post-session)

We administer the **System Usability Scale (SUS)** once (10 items, 5-point), scored to 0–100.

Qualitative

We then conduct a *semi-structured interview* covering five themes: workflow fit, value of unified layers, hierarchy choice, strengths/limits, and desired improvements (the protocol followed can be found in Appendix F).

6.6 Analysis Plan

6.6.1 Quantitative

Formative criteria Following prior ICE–T practice, we treat **4 as neutral** and—by inspiration from Chen's study—use $\geq$**5** as *above-neutral* (good/acceptable) for interpretation [13]. A task is labelled as *passed* only if the medians of all four ICE–T dimensions are $\geq 5/7$; otherwise it is *not passed*. Following Bangor et al.'s adjective-and-percentile mapping of SUS scores, we treat a total SUS score of 68 as the *average* benchmark (approximately the 50th percentile); accordingly, in this study we interpret scores > 68 as *above average* [5].

Per-task ICE–T analysis. For each task t and each ICE–T dimension d, we summarise participant scores with the *median* (reported to one decimal) and the *interquartile range (IQR; Q_1–Q_3)*. Each task is visualised with a *boxplot with jittered points*: the box spans Q_1 to Q_3, the central line marks the median, whiskers extend to the most extreme observations within $1.5 \times$ IQR of the quartiles, and points beyond are plotted as outliers; a horizontal reference at 5/7 indicates the above-neutral threshold defined in §*Measures*. Textual results describe the distributional shape (e.g., tails/outliers) and state whether the per-dimension medians pass (median ≥ 5) or not. All plots share the same y-axis (1–7) and annotation style;

ICE–T heatmap (overview). To enable at-a-glance comparison across tasks and dimensions, we also plot a *task*$\times$*dimension* heatmap whose cell values are the per-task medians for *Insight*, *Confidence*, *Essence*, and *Time*. Rows are ordered T1–T9 and columns are fixed as I/C/E/T; each cell is *annotated* with the median (one decimal), and a shared colorbar spans the full 1–7 response range to ensure comparability across cells.

SUS analysis. Each participant's SUS total was computed with standard scoring (odd items: add $Q-1$; even items: add $5-Q$; sum $\times 2.5$ to obtain 0–100). We summarise totals with mean $\pm$ SD and median + IQR and visualise them with a strip+box plot;

We also report the two subscales on a 0–100 scale—*Usability* (Q1, Q2, Q3, Q5, Q6, Q7, Q8, Q9) and *Learnability* (Q4, Q10)—following the two-factor structure identified by Lewis and Sauro [45], with even-numbered items reverse-coded and scores linearly rescaled to 0–100 using the standard SUS scoring procedure [10].

Finally, we provide per-item descriptive summaries on the reverse-coded 1–5 scale (higher=better): item means, SDs, and top-two-box proportions (responses in $\{4,5\}$), and comment on distributional features (e.g., low-score tails, ceiling/floor effects, large SDs) in relation to observed task workflows.

6.6.2 Qualitative

We analysed the interviews using the *Framework Method* [24]. First, we familiarised ourselves with the Teams recordings and our notes. Next, we coded the material mainly according to the topics in our interview guide (details in Appendix F), while adding inductive codes for unexpected issues. We iteratively refined a simple coding framework and summarised evidence—with traceable quotes—into a participant-by-theme matrix to support trustworthiness and auditability [55, 47].

6.7 Ethics and Data Management

Participation was voluntary; consent was obtained prior to recording. Screen/audio recordings and raw form responses were stored on institutional drives accessible only to the research team. Reports include anonymised aggregates and paraphrased quotes labelled by participant ID (E#). No sensitive information is retained.

Chapter 7

Result

7.1 Quantitative Analysis

7.1.1 ICE-T

ICE-T Integrated results

Across the nine expert tasks, **8/9** pass the formative benchmark (all four medians ≥ 5), with **T9 not passing** due to sub-threshold *Confidence* and *Time* (C=4.0, T=4.5; Table 7.1, Fig. 7.1). At a glance, T2–T5 and T7–T8 form a high-performing cluster with most medians in the 6–7 range; T1 and T4 pass but are borderline on *Time* (both = 5.0); and T6 is uniformly borderline across items (medians at or near 5.0).

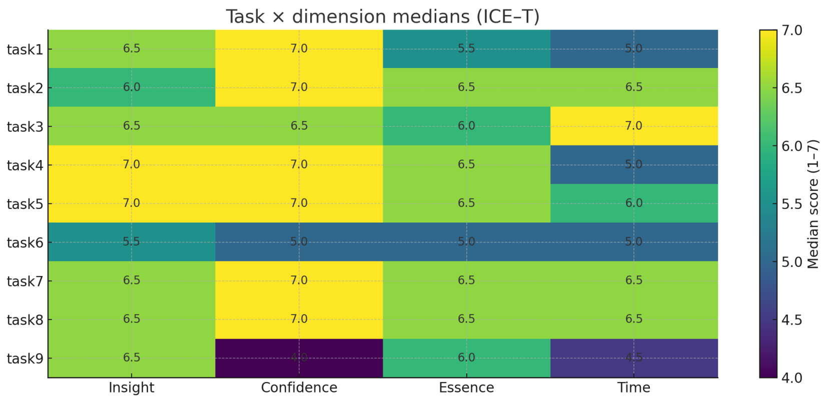
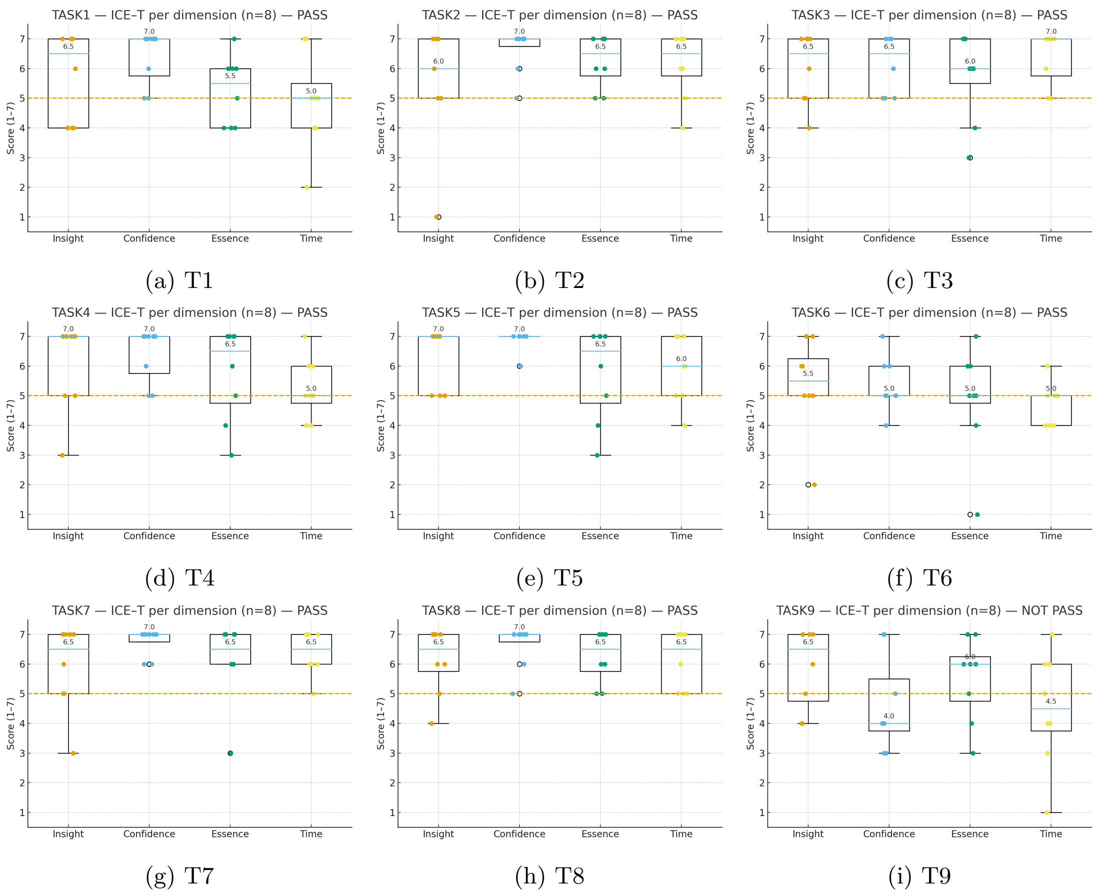


Figure 7.1: The figure of task × dimension medians

By dimension, *Insight* is consistently adequate across all tasks (range 5.5–7.0; 8/9 tasks ≥ 6.0); *Confidence* is high for 7 tasks (≥ 6.0), borderline once (T6) and failing once (T9); *Essence* is adequate for 7 tasks (≥ 6.0) with a slight dip in T1 (5.5) and a threshold case in T6 (5.0); and *Time* is the weakest dimension overall, with 5 tasks ≥ 6.0, three at the threshold (T1, T4, T6), and one sub-threshold (T9). The heatmap in Fig. 7.1 summarises these medians, and the 3×3 overview plus individual boxplots with jittered points (reference line at 5/7) provide full per-task distributions.

Per-Task ICE–T

T1 (Fig. 7.2a,Large Fig D.10). All four items meet the benchmark. *Insight* has a high median of 6.5 with a long box (IQR=3.0; Q1=4.0, Q3=7.0) and whiskers spanning 4–7, indicating



(a) T1 (b) T2 (c) T3

(d) T4 (e) T5 (f) T6

(g) T7 (h) T8 (i) T9

Figure 7.2: Per-task ICE–T distributions (boxplot + jittered points; horizontal reference at 5/7).

Table 7.1: Formative benchmark per task (✓ if median ≥ 5 in that dimension; Pass = all ✓).

Task	Insight	Confidence	Essence	Time	Pass
T1	✓	✓	✓	✓	✓
T2	✓	✓	✓	✓	✓
T3	✓	✓	✓	✓	✓
T4	✓	✓	✓	✓	✓
T5	✓	✓	✓	✓	✓
T6	✓	✓	✓	✓	✓
T7	✓	✓	✓	✓	✓
T8	✓	✓	✓	✓	✓
T9	✓		✓		

responses concentrated at the top but with a lower-mode cluster at 4.0. *Confidence* is strong and tight (median=7.0; IQR=1.5 with Q1=5.5, Q3=7.0; min–max 5–7). *Essence* sits just above neutral (median=5.5; IQR=2.0 with Q1=4.0, Q3=6.0; min–max 4–7). *Time* is borderline with the median exactly 5.0; the box spans Q1=4.0 to Q3=6.0 (IQR=2.0) and whiskers extend 2–7, showing the widest variability for this task on perceived efficiency.

T2 (Fig. 7.2b,Large Fig D.11). This task passes with compact, high distributions. *Insight* centres at 6.0 (IQR=2.0; 5.0–7.0) with a single low minimum at 1.0; *Confidence* is near-ceiling (median=7.0; IQR=1.0 with Q1=6.0, Q3=7.0; min–max 5–7). *Essence* is high and tight (median=6.5; IQR=1.0 with Q1=6.0, Q3=7.0; min–max 5–7). *Time* is also high (median=6.5; IQR=1.5 with Q1=5.5, Q3=7.0; min–max 4–7).

T3 (Fig. 7.2c,Large Fig D.12). All items pass with a particularly strong *Time* distribution (median=7.0; IQR=1.5 with Q1=5.5, Q3=7.0; min–max 5–7). *Insight* and *Confidence* have medians of 6.5 (both IQR=2.0; 5.0–7.0 for the box; mins at 4 and 5 respectively; max=7). *Essence* is adequate (median=6.0; IQR=2.0 with Q1=5.0, Q3=7.0; min–max 3–7), showing the widest spread among the four items for this task due to a low-end tail.

T4 (Fig. 7.2d,Large Fig D.13). This task passes with near-ceiling central tendency on *Insight* and *Confidence* (both median=7.0). *Insight* shows a box from Q1=5.0 to Q3=7.0 (IQR=2.0; min–max 3–7); *Confidence* is tighter (IQR=1.0; Q1=6.0, Q3=7.0; min–max 5–7). *Essence* centres at 6.5 with the widest dispersion in this task (IQR=2.5; Q1=5.0, Q3=7.0; min–max 3–7). *Time* is borderline (median=5.0; IQR=1.5 with Q1=4.5, Q3=6.0; min–max 4–7).

T5 (Fig. 7.2e,Large Fig D.14). All items pass with high central tendencies. *Insight* and *Confidence* are both at the top end (median=7.0; Insight IQR=2.0 with Q1=5.0, Q3=7.0; Confidence IQR=1.5 with Q1=6.0, Q3=7.0; mins 5–6, max 7 for both). *Essence* is high but more dispersed (median=6.5; IQR=2.5 with Q1=5.0, Q3=7.5† approximated to 7.0 in the figure; min–max 3–7). *Time* centres at 6.0 with a moderate box (IQR=2.0; Q1=5.0, Q3=7.0; min–max 4–7).

T6 (Fig. 7.2f,Large Fig D.15). T6 passes but is uniformly borderline across items, with medians at 5.5 (*Insight*) and 5.0 for *Confidence*, *Essence*, and *Time*. *Insight* has IQR=1.5 (Q1=5.0, Q3=6.5) and whiskers 2–7; *Confidence* IQR=2.0 (Q1=5.0, Q3=7.0) with min–max 4–7; *Essence* IQR=1.5 (Q1=5.0, Q3=6.5) with min–max 1–7 (the lowest minimum of this task); *Time* is the tightest (IQR=1.0; Q1=4.0, Q3=5.0; min–max 4–6), sitting exactly at the threshold.

T7 (Fig. 7.2g,Large Fig D.16). This task passes with a compact, high profile. *Insight* median=6.5 (IQR=2.0; 5.0–7.0; min–max 3–7); *Confidence* is near ceiling (median=7.0; IQR=1.0

with Q1=6.0, Q3=7.0; min–max 6–7). *Essence* is high (median=6.5; IQR=1.0 with Q1=6.0, Q3=7.0; min–max 3–7), showing one isolated low observation; *Time* median=6.5 with the tightest spread in this task (IQR=1.0; Q1=6.0, Q3=7.0; min–max 5–7).

T8 (Fig. 7.2h,Large Fig D.17). T8 passes and mirrors T7 in shape. *Insight* has median=6.5 (IQR=1.5; Q1=5.5, Q3=7.0; min–max 4–7); *Confidence* is again near ceiling (median=7.0; IQR=1.0; Q1=6.0, Q3=7.0; min–max 6–7). *Essence* median=6.5 (IQR=1.5; 5.0–6.5–7.0; min–max 5–7) and *Time* median=6.5 (IQR=2.0; Q1=5.0, Q3=7.0; min–max 5–7), both with most points clustered in the 6–7 band.

T9 (Fig. 7.2i,Large Fig D.18). T9 is the only task that does not pass; *Insight* and *Essence* are adequate, but *Confidence* and *Time* are sub-threshold. *Insight* median=6.5 with an IQR of 2.5 (Q1=4.5, Q3=7.0; min–max 4–7), showing a high top cluster and a lower quartile at 4.5. *Confidence* has the lowest central tendency among all tasks (median=4.0; IQR=2.0 with Q1=3.0, Q3=5.0; min–max 3–7), indicating a broad mid–low distribution. *Essence* remains adequate (median=6.0; IQR=2.0; Q1=4.5, Q3=6.5; min–max 3–7). *Time* is the weakest here (median=4.5; IQR=2.5 with Q1=3.5, Q3=6.0; min–max 1–7), with the lowest minimum across all tasks and a long lower tail.

7.1.2 System Usability Scale

SUS distribution

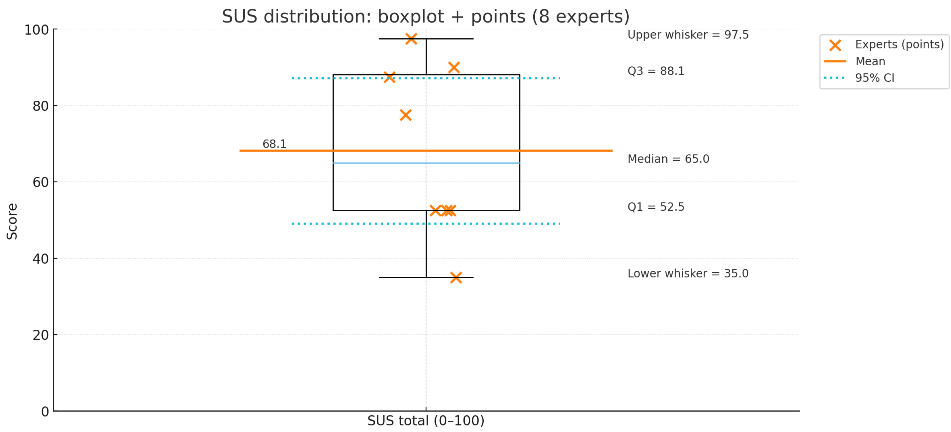


Figure 7.3: The figure of the distribution of SUS

With $n = 8$, the **median 65.0** says a *typical* expert currently sits just below the accepted benchmark (68), so usability is *borderline* for an average user; the **mean 68.1** sits on the benchmark but is propped up by polarization (two very high scores $\geq$90 offset a very low 35), so the average masks inconsistency; the **IQR [52.5, 88.1]** shows that half of the experts range from "barely OK" to "very good," i.e., the system works well in many contexts but not reliably across contexts; the **whiskers 35–97.5** expose the failure and champion cases—there *is* a low-end failure mode (35) that must be designed out while preserving the excellent experiences (97.5); the **95% CI 49.1–87.2** around the mean is wide with n=8, so we cannot claim the true mean is safely above 68 yet—this flags uncertainty rather than success.

SUS subscales.

Figure 7.4 splits the SUS into two summed subscales on a 0–100 metric (even-numbered items reverse-coded first so that higher is always better): *Usability* on the left (Q1, Q2, Q3, Q5, Q6,

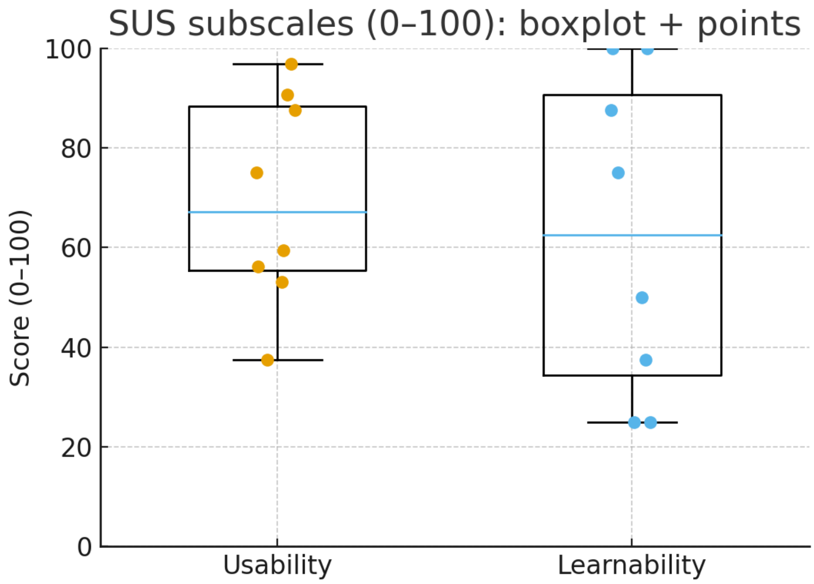


Figure 7.4: SUS per item (reverse-coded 1–5): bars show mean±SD; line shows top-two-box ({4,5}).

Q7, Q8, Q9) and *Learnability* on the right (Q4, Q10). Each dot is one participant (n=8); the box spans the middle 50% of scores (from the first quartile, Q1, to the third quartile, Q3); The horizontal line in the box is the median; the whiskers extend to the most extreme points within 1.5×IQR.

Quantitatively, **Usability** centres in the mid–high region with **Median=67.2**, **Q1=55.4**, **Q3=88.3** (**IQR=32.9**), **Mean=69.5±21.1**, and a range of **37.5–96.9**. In plain terms, half of the participants fall between roughly 55 and 88, with most dots clustering around the median and only a few reaching the very top end, so perceived day-to-day *usability* is generally positive and fairly consistent across people. **Learnability**, by contrast, shows a wider spread: **Median=62.5**, **Q1=34.4**, **Q3=90.6** (**IQR=56.2**), **Mean=62.5±32.0**, range **25.0–100.0**. Here the box is taller and the dots are more scattered, which means experiences about "how much you need to learn to get going" and "how quickly it clicks" vary a lot: some participants are near the top of the scale while others are much lower. Reading the two boxes side by side, the left box (Usability) is tighter and sits solidly above the middle of the scale, whereas the right box (Learnability) spans much more of the vertical axis, indicating more disagreement between participants.

SUS per-item

Figure 7.5 unpacks SUS by question. Each bar (Q1–Q10) is the average score on a reverse-coded 1–5 scale (even-numbered items flipped so higher is always better); the thin line atop each bar is the standard deviation (longer = more disagreement); the green line (right axis) is the Top-2-Box percentage, the share of responses in {4,5}.

Read left to right: Q1 ("I think that I would like to use this system frequently.") sits in the mid-to-high band (mean = 3.88, median = 4.0, IQR = 1.25, range 3–5), indicating most participants would use it often; Q2 ("I found the system unnecessarily complex."; reverse-coded = higher means less complex) is mid-scale but widely spread (mean = 3.62, median = 3.5, IQR = 2.00, SD = 1.41, Top-2-Box = 50%, range 1–5), showing mixed views on complexity; Q3 ("I thought the system was easy to use.") is similar (mean = 3.50, median = 3.5, IQR = 1.25, SD = 1.31, min = 1), broadly positive with a small low-end tail; Q4 ("I think that I would need the support of a technical person to be able to use this system."; reverse-coded = less support

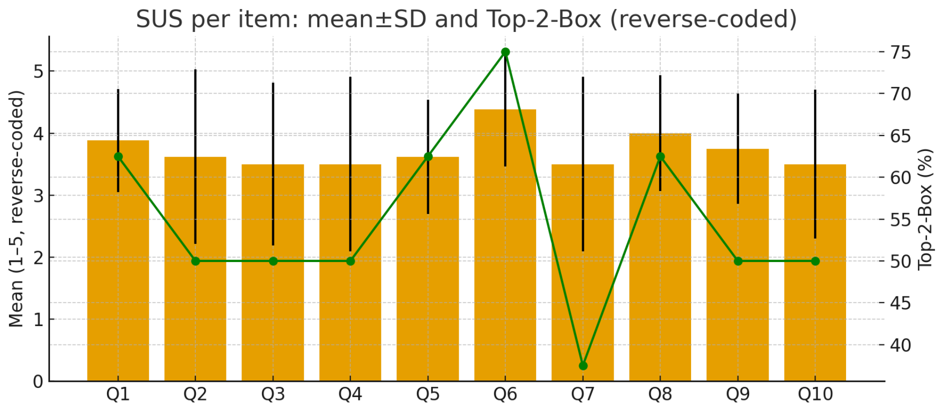


Figure 7.5: SUS per item (reverse-coded 1–5): bars show mean±SD; line shows top-two-box ({4,5}).

needed) has the widest spread (mean = 3.50, median = 3.5, IQR = 3.00, SD = 1.41, range 2–5), indicating strong disagreement about the need for support; Q5 ("I found the various functions in this system were well integrated.") is stably positive (mean = 3.62, median = 4.0, IQR = 1.00, range 2–5) with relatively tight dispersion; Q6 ("I thought there was too much inconsistency in this system."; reverse-coded = more consistent) is the strongest and most agreed-upon item (mean = 4.38, median = 5.0, IQR = 1.25, SD = 0.92, Top-2-Box = 75%, range 3–5), pointing to clear perceived consistency; Q7 ("I would imagine that most people would learn to use this system very quickly.") is mid-scale but contested (mean = 3.50, median = 3.0, IQR = 2.00, SD = 1.41, Top-2-Box = 37.5%, range 1–5), suggesting varied beliefs about how quickly others would learn; Q8 ("I found the system very cumbersome to use."; reverse-coded = not cumbersome) is solidly positive (mean = 4.00, median = 4.0, IQR = 2.00, SD = 0.93, Top-2-Box = 62.5%, range 3–5); Q9 ("I felt very confident using the system.") is mid-high with compact spread (mean = 3.75, median = 3.5, IQR = 1.25, range 3–5), indicating generally good confidence; and Q10 ("I needed to learn a lot of things before I could get going with this system."; reverse-coded = did not need to learn a lot) is mid-to-high with moderate spread (mean = 3.50, median = 3.5, IQR = 1.50, SD = 1.20, range 2–5).

Taken together, the tall bars and high green points on Q6 and Q8 mark the clearest strengths (consistency and non-cumbersomeness), while the longer error bars and lower green points on Q2, Q4, and Q7 show where opinions diverge most (complexity, need for support, and expected learning speed).

7.2 Qualitative Analysis

Approach. We applied the *Framework Method* (Analysis Plan 6.6.2): after familiarisation and deductive+inductive coding, we populated a participant–by–theme(Interview Themes F) matrix and report anonymised, paraphrased summaries with prevalence counts ([X/8]). Verbatim quotes are not reproduced in *Results*. To preserve anonymity while making clear who is who, we tag statements with *(id, role/focus)* as Table 6.1 described.

Theme 1 — Workflow fit. Claim. The overview–side-panel workflow fits expert practice by preserving context while enabling quick verification; this underpins higher *Confidence/Essence* on top-ranked tasks (Fig. 7.1). **Paraphrased evidence.** Participants reported that keeping the side panel open allowed them to check labels and counts without losing the main canvas, reducing back-and-forth steps **[6/8]** (e.g., E6, Professor—Research/Teaching, in person; E5, Lecturer—Research/Teaching, online; E3, PhD Student—Research, online; E7, Research IT/Engineering—Admin/IT, in person). A smaller group noted detours on multi-step lookups requiring switches between overview and detail **[2/8]** (E1, Coordinator/Researcher—Research/Admin, in person; E4, Coordinator—Admin, online). **Interpretation.** A stable detail panel plus clear type encoding reduce cross-check operations, consistent with short IQRs and high medians for **T2/T3/T5/T7/T8** and the positive end of the SUS spread.

Theme 2 — Value of unified layers. Claim. Unifying co-authorship and co-teaching within one environment adds discovery value beyond single-layer tools, reflected in uniformly high *Insight* (Fig. 7.1). **Paraphrased evidence.** Participants said that seeing teaching and research side-by-side surfaced connections they usually miss in siloed tools and helped them notice potential collaborators **[5/8]** (E5, Lecturer—Research/Teaching, online; E6, Professor—Research/Teaching, in person; E3, PhD Student—Research, online; E8, Lecturer—Research/Teaching, in person; E1, Coordinator/Researcher—Research/Admin, in person), with explicit mentions of using the joint view to spot candidates **[3/8]** (E6; E5; E3). **Interpretation.** Cross-layer juxtaposition highlights bridges, outliers, and near-misses—why certain people connect—supporting researcher-network exploration and explaining the high-*Insight* cluster (**T2/T5/T7/T8**).

Theme 3 — Hierarchy choice. Claim. The affiliation/hierarchy view is useful as a secondary lens but introduces navigation overhead and can bias attention away from cross-unit ties; this maps to *Time* dips and longer IQRs (Fig. 7.1). **Paraphrased evidence.** About half described zoom/pan loops to locate groups and then return to the focal node **[4/8]** (E1, Coordinator/Researcher—Research/Admin, in person; E4, Coordinator—Admin, online; E7, Research IT/Engineering—Admin/IT, in person; E3, PhD Student—Research, online), whereas others found defaults adequate when filters were applied first **[4/8]** (E2, IT Officer—Admin, in person; E5, Lecturer—Research/Teaching, online; E6, Professor—Research/Teaching, in person; E8, Lecturer—Research/Teaching, in person). **Interpretation.** Experts value the concentric overview for the “gist” and prefer to invoke hierarchy on demand; the pattern matches **T1**’s lower *Time* and variability (borderline rather than failure).

Theme 4 — Strengths and limits of current controls. Claim. Edge bundling and type-separated encodings improve readability and support verification; however, when *ranking* collaborators or comparing near-ties, users still resort to *indirect checks* even with a bundling-strength slider. Some *high-level* queries are not directly expressed in the main view. **Paraphrased evidence.** Participants commonly described that consistent encodings and reduced clutter made checking easier **[6/8]** (E6, Professor—Research/Teaching, in person; E5, Lecturer—Research/Teaching, online; E7, Research IT/Engineering—Admin/IT, in person; E2, IT Officer—Admin, in person; E3, PhD Student—Research, online; E8, Lecturer—Research/Teaching, in person). Several **[4/8]** reported that identifying the “top collaborator” required adjusting bundling, selecting candidates, and comparing counts one-by-one (E6; E5; E3; E7). A few added that high-level prompts such as “who has the most connections in this group?” are not directly supported in a single view **[3/8]** (E1; E7; E2). **Interpretation.** Bundling and type-separated encodings reduced visible clutter and supported checking, yet they did not directly reveal a “top collaborator”; near-ties remained visually indistinguishable, prompting compare-one-by-one workflows. This co-occurred with borderline/low medians and wider IQRs on ranking-oriented tasks (**T6/T9**) and with greater dispersion in related SUS items.

Theme 5 — Desired improvements. Claim. Experts converged on small but impactful refinements targeting first-use load, navigation overhead, and high-level summarisation. **Paraphrased evidence.** Reported needs included a clearer display of the *current selection / active filters* **[5/8]** (E7, Research IT/Engineering—Admin/IT, in person; E2, IT Officer—Admin, in person; E5, Lecturer—Research/Teaching, online), a faster way to *compare two candidates side-by-side* without context loss **[4/8]** (E6, Professor—Research/Teaching, in person; E5, Lecturer—Research/Teaching, online), and remembering last-used parameters via *task-tuned pre-*

sets **[3/8]** (E8, Lecturer—Research/Teaching, in person; E5, Lecturer—Research/Teaching, online), together with minor layout tweaks to reduce panning/zooming **[3/8]** (E1, Coordinator-/Researcher—Research/Admin, in person; E4, Coordinator—Admin, online). **Interpretation.** Reported needs concentrated on status visibility (current selection / active filters), faster side-by-side comparison, remembering last-used parameters, and small layout tweaks to reduce navigation. These needs align with tasks showing borderline *Time* or dispersion in efficiency-related items; design responses are discussed in the Discussion section.

Chapter 8

Discussion

We structure the discussion as requested: first the *high-level features*—what worked and what did not—then the *low-level components and interactions*, and finally the *design implications*. We refer back to the Results for figures and statistics rather than repeating numbers here.

8.1 High-level features

At the high level, two aspects worked especially well. A single-canvas, context-preserving workflow—overview plus side panel—enabled experts to formulate and verify answers without losing their place, which is consistent with the stronger *Confidence* and *Essence* patterns on the best-performing tasks and the SUS signals for consistency and non-cumbersomeness. Equally, the cross-layer juxtaposition of teaching and research made connections visible that siloed tools tend to hide, helping participants recognise candidates worth exploring and matching the uniformly strong *Insight* results. Alongside these wins, two high-level challenges were evident. Hierarchy-first workflows introduced zoom/pan loops and nudged attention toward within-unit relations; efficiency dropped when goals were explicitly cross-unit. In addition, tasks that required ranking (e.g., "who collaborates most with X?") were not directly expressed in the current views; participants had to shortlist and verify candidates one by one, which depressed perceived *Time* and, in the hardest cases, *Confidence*. Variability on learnability-related SUS items reinforces this picture: once understood, the system works smoothly, but the slope of first use differs across users.

8.2 Low-level components and interactions

At the component level, the strongest contributors to throughput were *search and general navigation*, together with *explicit collaborator counts* and *type-separated colour encodings*. In practice, being able to locate a target quickly and then confirm "how many" at a glance made verification immediate and reduced back-and-forth, which is consistent with the higher *Confidence* and faster perceived *Time* on the better-performing tasks (cf. Fig. 7.1; Themes 1/4). By contrast, several details introduced friction: some task flows still required extra operations before an answer could be confirmed; the search facility did not support *hierarchy-aware* lookups (it indexed researchers but not division/group nodes), which lengthened steps in affiliation-centric tasks (Theme 3); and while the *edge-bundling* control exposed otherwise hidden structure in dense views, it demanded stronger affordances or guidance to help participants know *when* and *how far* to adjust it (Theme 4/5). Together these low-level patterns explain why confidence and speed were robust in common cases yet more variable when tasks depended on hierarchical wayfinding or fine control of bundling, a variability also reflected in dispersion on learnability-related SUS items.

8.3 Design implications

We frame the implications to preserve what already works at a high level (context-preserving overview+side panel; cross-layer juxtaposition) while addressing the specific low-level bottlenecks surfaced in Results and §7.2. Each item states the change, why it is warranted (with evidence links), the expected user-visible effect, and a concrete follow-up metric for a formative re-test.

D1. Click-to-defocus to reduce focus-switch friction. *What.* Clicking on empty canvas exits the current focus state (no need to press `Esc` or find a small hit target). *Why.* Participants reported extra steps when moving between focal items and views (Theme 1/3); small but frequent switches compounded into navigation overhead, especially in hierarchy-dependent tasks. *Expected effect.* Faster attention shifts with fewer incidental clicks; more stable throughput on tasks that interleave overview and detail. *Success criterion.* Median Time for hierarchy-heavy tasks (e.g., Time_{T1}) increases by ≥ 0.5 and IQR narrows (cf. Fig. 7.1, Fig. 7.2).

D2. Hierarchy-aware search (division/group as first-class targets). *What.* Extend search to index *division* and *research-group* nodes; a hit recentres and highlights the aggregate, with a breadcrumb to the focal researcher if needed. *Why.* Search currently covers researchers only; affiliation-centric tasks therefore require zoom/pan loops (Theme 3). *Expected effect.* Shorter paths to group-level answers and fewer navigation loops; smoother starts for first-time users who think in organisational terms. *Success criterion.* Time_{T1} and Time_{T4} medians move above 5.5 with reduced IQR; SUS per-item means improve on Q3 (easy to use) and Q8 (not cumbersome).

D3. Side-by-side comparison in the side panel. *What.* Allow pinning two candidates to a persistent compare card in the side panel (shared fields, per-layer counts, deltas), without losing the main-view context. *Why.* Ranking near-ties currently requires "adjust–select–compare–toggle" loops (Theme 4); context loss and toggling depress *Time* and sometimes *Confidence*. *Expected effect.* Direct, low-friction comparisons; fewer one-by-one toggles; clearer confirmation of the "top collaborator." *Success criterion.* For ranking-oriented tasks, medians for Time and Confidence on **T6/T9** rise to ≥ 5 and IQR no longer crosses 4; SUS per-item means increase on Q9 (confidence) and Q8 (not cumbersome).

D4. Clickable aggregates with a compact leaderboard summary. *What.* Make division/group aggregates clickable to open a concise leaderboard: top-k collaborators overall and per layer, with sorting and quick highlight actions. *Why.* High-level prompts like "who in this group collaborates most?" are cumbersome in the main canvas and trigger indirect checks (Theme 4). *Expected effect.* High-level answers become first-class; users can move from group to apex without manual shortlisting. *Success criterion.* $\text{Confidence}_{\text{T6/T9}}$ and $\text{Time}_{\text{T6/T9}}$ medians ≥ 5; reduced dispersion on these dimensions relative to baseline.

D5. Compact canvas mode (fit-to-content with better label reveal). *What.* Provide a denser layout preset: reduced margins, density-aware spacing, automatic fit-to-content, and earlier label reveal at the same zoom. *Why.* Default spacing sometimes felt sparse, increasing panning to see labels (Theme 5); this added travel without adding insight. *Expected effect.* Faster orientation, fewer pans/zooms, and better at-a-glance reading of neighbourhoods. *Success criterion.* Time medians in navigation-heavy tasks (Time_{T1}) increase by ≥ 0.5; SUS per-item means rise on Q8 (not cumbersome).

D6. Guided edge-bundling control (affordances and hints). *What.* Add lightweight guidance to the bundling slider: annotated stops (e.g., "overview," "balanced," "detail"), a transient on-canvas hint when the slider is moved, and microcopy on *when/why* to adjust. *Why.* Bundling exposes valuable structure but requires know-how; several participants needed better cues on *how far* to adjust (Theme 4/5). *Expected effect.* Quicker convergence on useful settings; reduced trial-and-error before verification; lower perceived complexity for newcomers. *Success criterion.* Improved SUS per-item means on Q2 (not complex), Q4 (less support needed), and Q7 (most people learn quickly); narrower IQR on Time where dense views are common.

Collectively, these refinements target the precise pain points observed—extra operations during focus changes, hierarchy-only wayfinding through zoom/pan, indirect comparisons for near-ties, canvas travel to reveal labels, and uncertainty about bundling—while preserving the high-level strengths that drove strong *Insight*, *Confidence*, and *Essence* in the better-performing tasks.

8.4 Threats to validity & limitations

Internal validity. Task order and learning effects may have influenced ratings (participants became faster over time), and several tasks required parameter tuning (e.g., bundling strength, filters), which can confound perceived *Time* and *Confidence*. We mitigated by reporting medians and IQRs rather than means, keeping analyses descriptive, and triangulating numeric patterns with anonymised, paraphrased qualitative evidence organised in a participant–by–theme matrix (cf. §7.2).

Mode and instrumentation. Sessions ran in two modes: *in-person* on the experimenter's hardware and *remote* on participants' own machines. Differences in display size/DPI, pointing device, and network conditions may have affected interaction fluency and subjective ratings (ICE–T *Time*, SUS). We record the session mode per participant (Table 6.1) but did not stratify analyses by mode; future evaluations should either standardise the setup or treat mode as a factor.

Construct validity. ICE–T captures perceived *Insight, Confidence, Essence,* and *Time* on 7-point Likert items; these are subjective and context-dependent. Our interpretive threshold (4 as neutral; ≥ 5 above-neutral) follows prior practice but remains a choice that can shift pass/fail labels near the boundary. SUS provides a global, task-agnostic view and may under- or over-represent domain-specific nuances; subscales and per-item readouts were used descriptively rather than as latent trait estimates.

External validity. Data come from one institution (Utrecht University) and a single disciplinary context (computer science / visual computing and adjacent coordination/IT roles). Expectations about hierarchy, terminology, and workflows may differ in other departments or universities; generalisation beyond similar academic settings remains to be tested. Only the deployed layers (co-teaching, co-authorship) were evaluated; additional layers (e.g., grants, course teams) were out of scope.

Conclusion validity. With a small expert sample (n=8), uncertainty is large and the study is not powered for hypothesis testing. Boxplot medians and IQRs describe central tendency and dispersion but do not imply significance; where IQRs overlap heavily we refrain from rank claims. SUS totals, subscales, and item means are interpreted as descriptive signals; no inferential contrasts or correlations are asserted.

Ethical & privacy considerations. Person-level network views can surface sensitive patterns (e.g., low activity, imbalanced collaborations). Any deployment should enforce aggregation, access control, and audit trails. Interpretations such as "top collaborator" refer to *counted ties* in the available data and do not imply collaboration quality, impact, or intent.

8.5 Future work

Building on the limitations we identified (single-institution context, two-layer scope, descriptive measures), future work divides into *high-level* directions that extend the vision of the platform and *technical* steps that make those directions practical and testable at scale.

High-level directions. The first priority is to broaden the scope of the model beyond co-authorship and co-teaching so that the platform speaks to questions at the *division* and *programme* levels, not only individual researchers. Integrating institutional knowledge-graph sources such as *RicGraph* and open bibliographic graphs like *OpenAlex*, together with partnership data on industry collaboration, would let the system cover projects, grants, datasets, software, and external links in addition to publications and courses. With a richer scope, the platform can answer complex questions *directly*—for example, "who in this unit collaborates the most, and with which other units?" or "how did co-teaching and co-authorship patterns change between semesters or years?"—instead of relying on indirect, one-by-one checks. To support these questions at a glance, the interface should introduce concise, ranked summaries at the group/division level and temporal lenses that compare periods to reveal evolution. Because broader data also raise governance stakes, role-based access, provenance tracking, refresh cadence, and auditability need to be designed into the service layer from the outset to make institution-scale deployment viable and trustworthy.

Technical next steps. Translating the vision into a robust tool calls for several concrete improvements on both the interaction and the data/engineering sides. On the interaction side, *hierarchy-aware search* should index divisions and research groups so that users can jump directly to organisational aggregates; *side-by-side comparison* and a compact *leaderboard* in the side panel should surface near-tie rankings without context loss; a *compact canvas* preset should reduce panning and reveal more labels at the same zoom; *click-to-defocus* should make focus transitions effortless; and the *edge-bundling* control should provide lightweight guidance (annotated stops, transient hints) so that newcomers know when and how far to adjust. On the data side, adding lightweight topic extraction from titles/abstracts—or carefully constrained, auditable LLM-assisted tagging with transparent justifications in the side view—would expose thematic profiles and enable cross-layer "topic $\times$ course" exploration. The evaluation programme should mature alongside these changes: recruit across departments to probe generalisability, log objective time-on-task and errors, and include comparative baselines against single-layer tools or alternative layouts. Defaults that shape effort (e.g., bundling strength, separation toggles) should be A/B tested to reduce variance while preserving expert power. Institution-scale deployment then requires engineering follow-through: performance profiling on larger graphs, caching and precomputation for frequent summaries, sampling strategies for extreme density, and operational telemetry that supports reliability and governance. Together, these steps directly address the present constraints on scope, speed, and learnability, while preserving the high-level strengths—context preservation and cross-layer reasoning—that the study has shown to be effective.

Chapter 9

Conclusions

This thesis asked how to design and implement a *department-scale* visual analytics platform that unifies co-authorship and co-teaching, with visual representations and interactions that support expert exploration of researcher networks. We realised this vision as a working, single-canvas prototype that coordinates an overview with a side panel, employs type-aware encodings with controllable bundling, and operates on departmental data. The evaluation combined task-level ICE–T, a system-level SUS, and a structured qualitative analysis to judge whether the unified design supports sensemaking and where it needs reinforcement.

At an aggregate level, three conclusions stand out. *First*, a *context-preserving, cross-layer* workflow supports effective and auditable exploration: across tasks, *Insight*, *Confidence*, and *Essence* generally sat above neutral, and experts could verify answers without losing context. *Second*, the cost of reaching an answer was not uniform: perceived *Time* dipped when goals required hierarchy-first navigation or ranking near-ties via one-by-one checks, and learnability signals were more dispersed in these situations even as overall SUS centred near common benchmarks. *Third*, qualitative themes align with these patterns: the overview+side-panel pairing and cross-layer view enabled routine lookups, while dense regions and affiliation-centric moves introduced extra steps that slowed throughput. Taken together, these findings answer the Research Question positively: unifying teaching and research on a single canvas aligns day-to-day sensemaking with trustworthy, explainable answers, while clarifying the boundary conditions that matter for *speed and how easy it is to get started*.

Decomposing the RQ, we learned that expert workflows prioritise keeping context while verifying, rapid cross-layer lookups, and light-weight comparisons (SQ1); that data sources differ in granularity and refresh cadence, shaping provenance-preserving joins and defensible tie summaries (SQ2); that a hierarchical multi-layer graph with typed edges supports cross-layer queries and audit trails in one representation (SQ3); that a web stack coordinating a concentric overview with a side panel, search/filters, and adjustable bundling realises the interaction model on real departmental data (SQ4); and that the prototype is usable and interpretable in common cases, while efficiency varies when tasks hinge on hierarchy-first moves or indirect near-tie comparisons (SQ5).

In short, we designed and validated a viable foundation for department-scale researcher intelligence: a single-canvas, cross-layer model that makes common questions fast and accountable, and makes explicit the situations that slow experts down.

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Appendix A

Artifact Availability and Reproducibility

Code (private): `https://github.com/monsterlady/master_thesis_project/` Please contact Dr.Angelos for granting access.
Evaluated version: Release `v1.0-thesis` (commit `2fdbb6e on dev brench`, 2025-09-16).
Online Version: **Data availability:** Teaching data: anonymised/synthetic sample only (for demo); full dataset is internal and not shared.
Environment: Python 3.12.7, Node 20.19.4, Neo4j 5.2, FastAPI 0.116.1, Cytoscape.js 3.31.0, Ant Design 5.24.0 See `requirements.txt`, `package-lock.json`, and `Dockerfile`.
Reproduction steps: See `README.md` and the script `make reproduce` to (1) start backend, (2) run frontend, (3) access the application on web
Licensing & privacy: Source under Apache License 2.0 (code); datasets under institutional policy; personal data included in repository.

Appendix B

Semi-structured interviews for collection user requirements

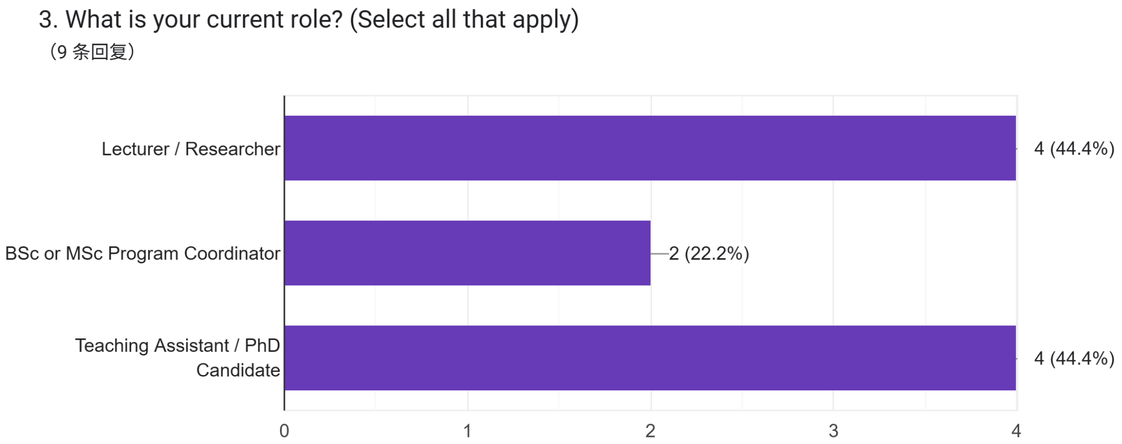


Figure B.1: Role Distribution

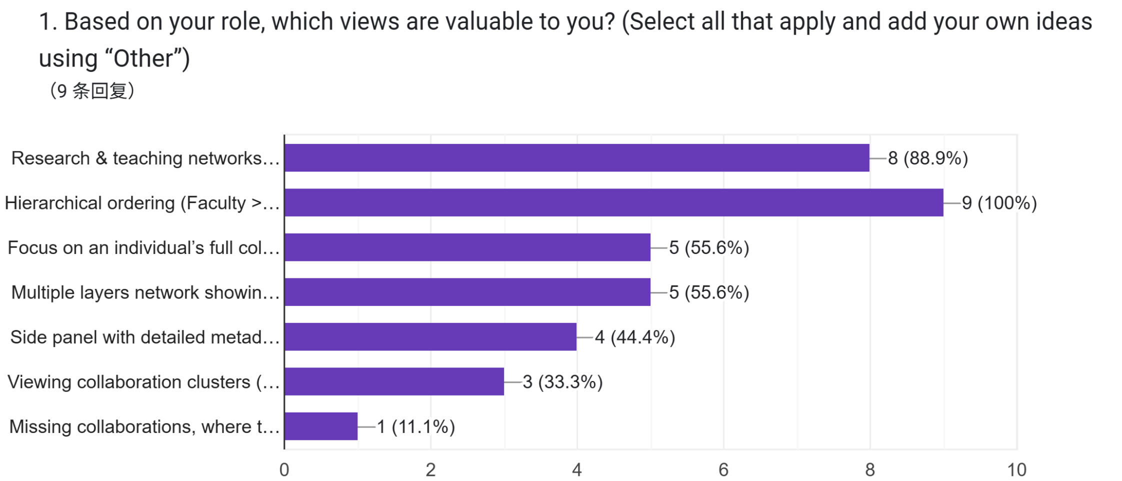


Figure B.2: Survey Q1—Which views are valuable for your role? (multiple answers allowed; $n = 9$). Top choices were *hierarchical ordering* (9/9, 100%) and *research–teaching networks* (8/9, 88.9%), followed by *individual full-collaboration view* and *multi-layer overview* (5/9 each, 55.6%), *side-panel metadata* (4/9, 44.4%), *collaboration clusters* (3/9, 33.3%), and *missing-collaboration detection* (1/9, 11.1%).

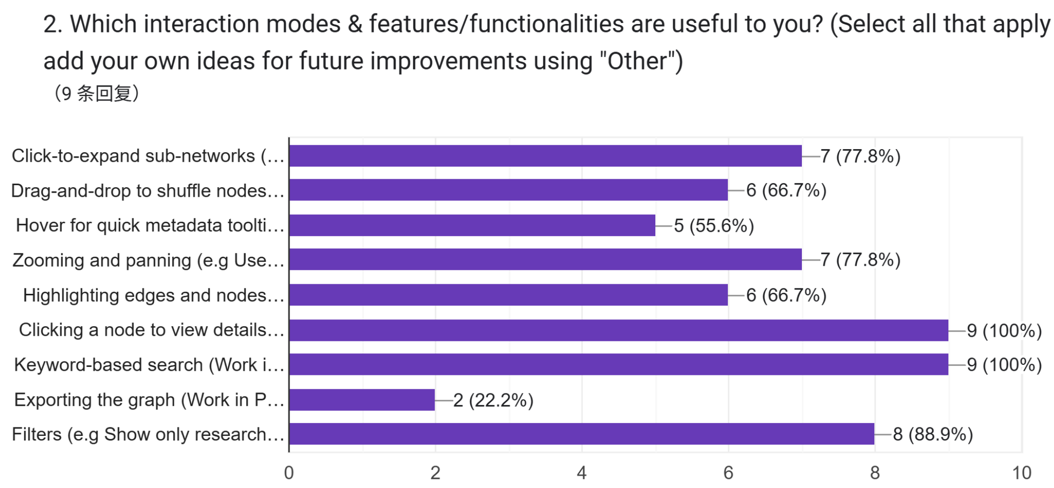
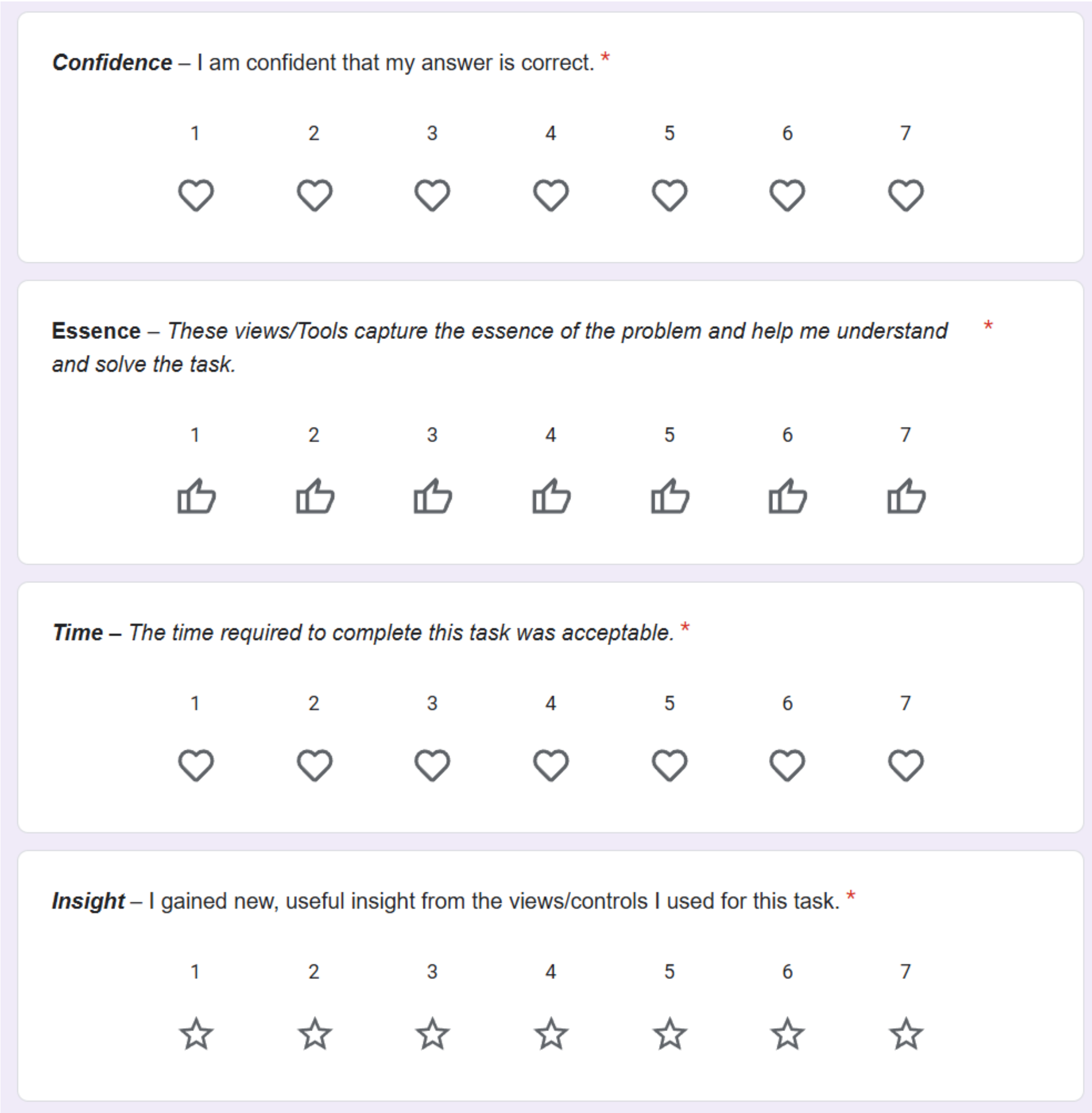


Figure B.3: Survey Q2—Which interaction modes/features are useful? (multi-select; $n = 9$). Top picks were *click node to view details* and *keyword search* (both 9/9, 100%), followed by *filters* (8/9, 88.9%), *click-to-expand sub-networks* and *zoom/pan* (7/9, 77.8%), *drag-and-drop rearrangement* and *highlighting* (6/9, 66.7%), *hover tooltips* (5/9, 55.6%), and *export graph* (2/9, 22.2%).

Appendix C

ICE-T Questionnaire

After each task finished, the participant will fill the ICE-T Questionnaire.



Confidence – I am confident that my answer is correct. *

1 2 3 4 5 6 7

Essence – *These views/Tools capture the essence of the problem and help me understand and solve the task.* *

1 2 3 4 5 6 7

Time **–** *The time required to complete this task was acceptable.* *

1 2 3 4 5 6 7

Insight – I gained new, useful insight from the views/controls I used for this task. *

1 2 3 4 5 6 7

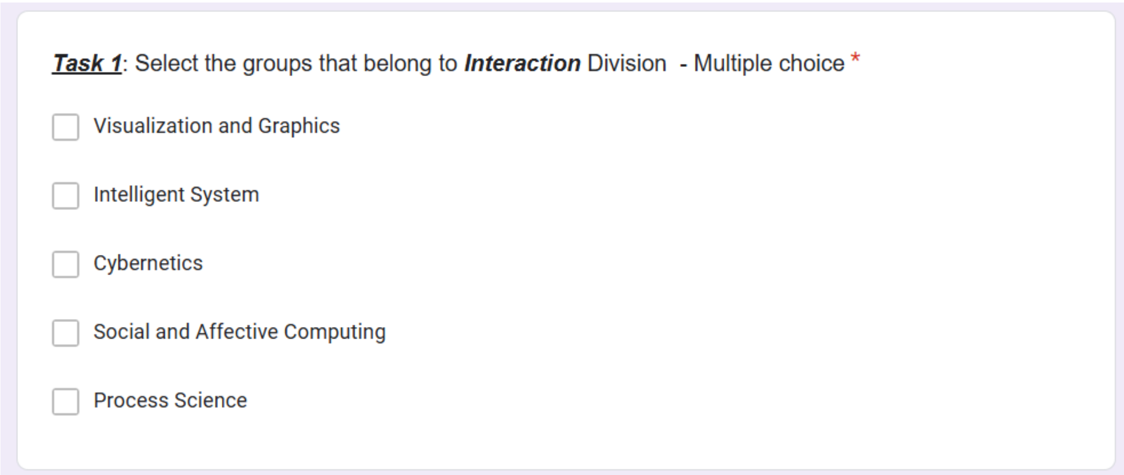
Figure C.1: ICE-T Questionnaire

Appendix D

Task Materials (Anonymised)

All personally identifiable information has been redacted.

The median value of each Dimension of ICE-T for each task.



Task 1: Select the groups that belong to ***Interaction*** Division - Multiple choice *

- [ ] Visualization and Graphics
- [ ] Intelligent System
- [ ] Cybernetics
- [ ] Social and Affective Computing
- [ ] Process Science

Figure D.1: Task 1

Task 2.a: Given a researcher: [redacted] check whether he/she is still in service or leave *

- In Service
- Leave
- Not sure

Task 2.b: Given a researcher: [redacted], check whether he has cooperative relationships *

- Yes
- None
- Not sure

Task 2.c: Given a researcher: [redacted] Choose what kind of cooperative relationships does she has *

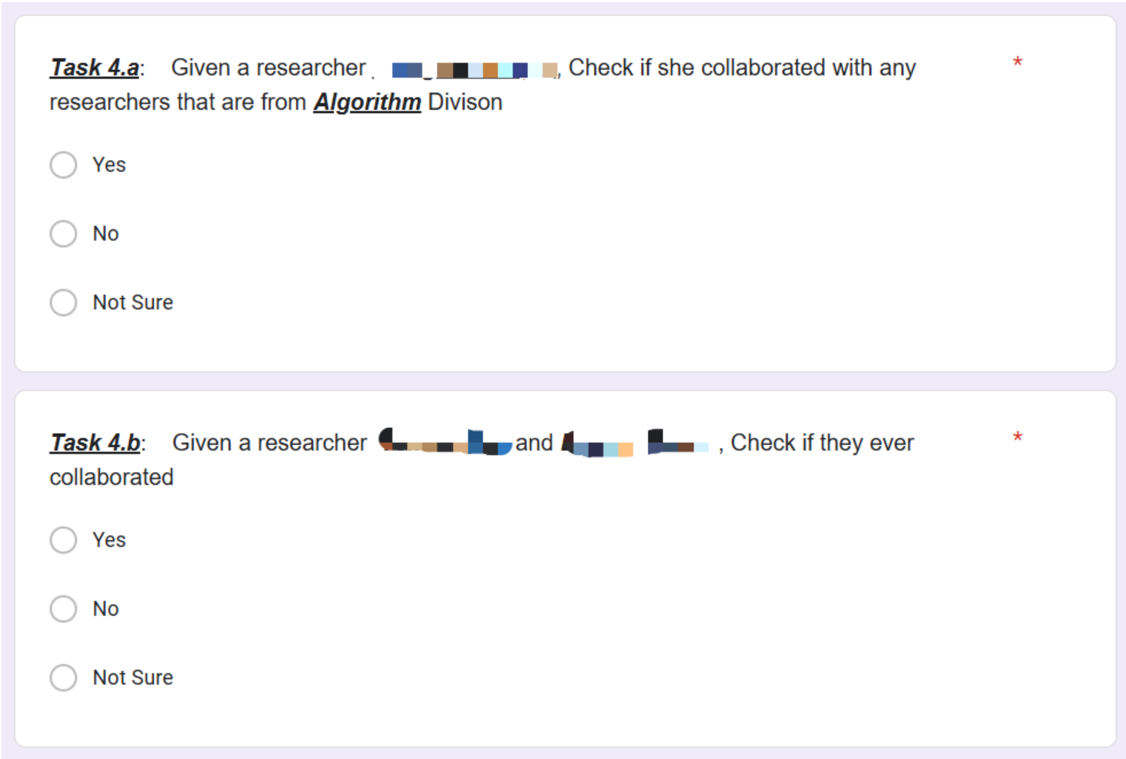
- Research Collaborations
- Teaching Collaborations
- Research & Teaching Collaborations
- None

Figure D.2: Task 2

Task 3: Given a researcher: [redacted], determine her major collaboration type *

- Teaching
- Research
- Not Sure

Figure D.3: Task 3



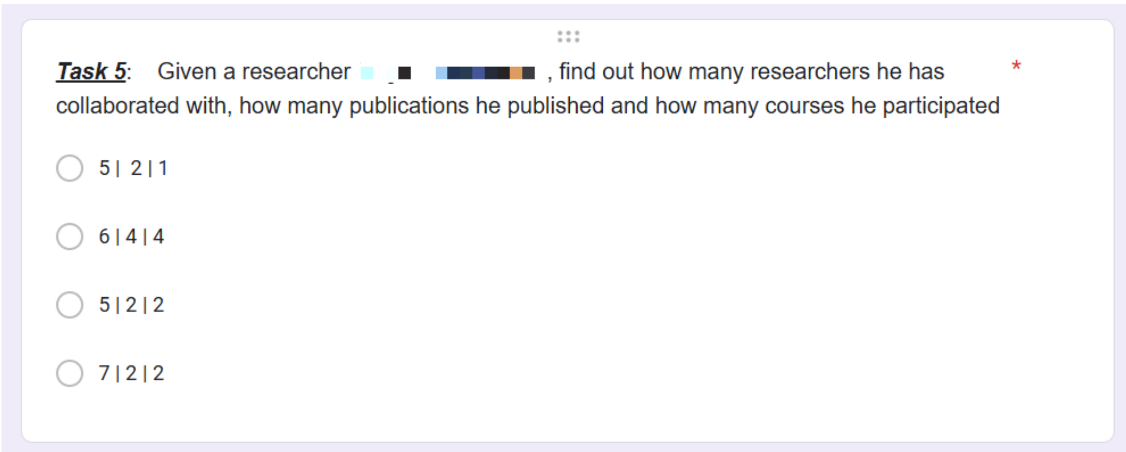
Task 4.a: Given a researcher [redacted], Check if she collaborated with any researchers that are from ***Algorithm*** Divison *

- Yes
- No
- Not Sure

Task 4.b: Given a researcher [redacted] and [redacted], Check if they ever collaborated *

- Yes
- No
- Not Sure

Figure D.4: Task 4



Task 5: Given a researcher [redacted], find out how many researchers he has collaborated with, how many publications he published and how many courses he participated *

- 5 | 2 | 1
- 6 | 4 | 4
- 5 | 2 | 2
- 7 | 2 | 2

Figure D.5: Task 5

Task 6: Given a researcher [redacted] , Find the person who has worked with him the most times, then ***calculate*** the times of the collaborations(Teaching + Research) *

- ◯ 92
- ◯ 79
- ◯ 86
- ◯ 65

Figure D.6: Task 6

Task 7: Given two researchers, [redacted] and [redacted], determine the main collaboration type between them *

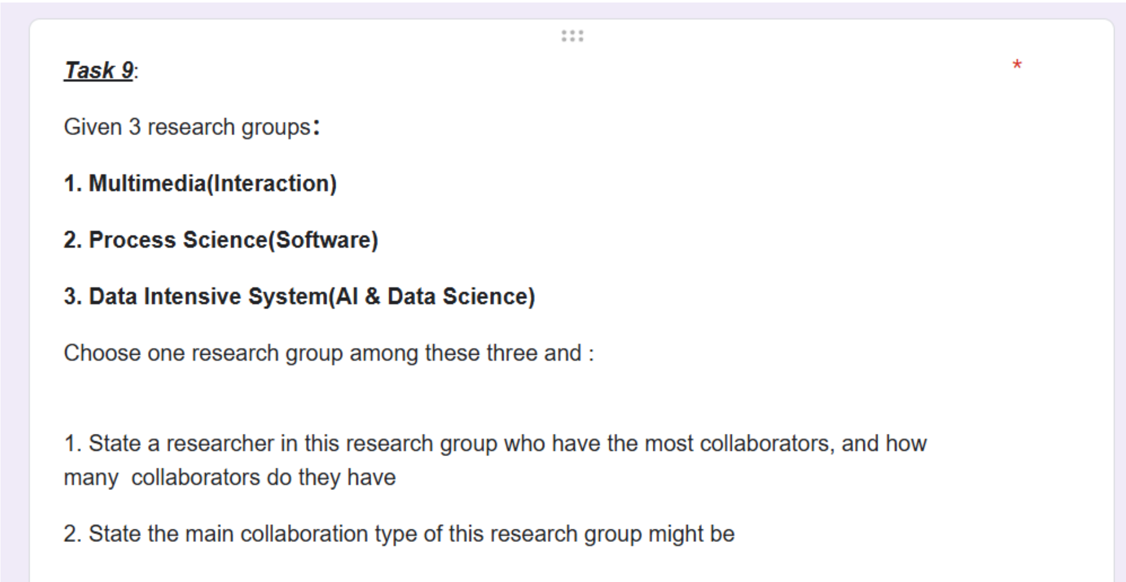
- ◯ Teaching
- ◯ Research
- ◯ Teaching & Research
- ◯ Not Sure

Figure D.7: Task 7

Task 8: Given a researcher [redacted] and one of their publications [redacted] , please find out how many researchers participated, and how many of them are in active service now *

- ◯ 10 participated | 2 in active service
- ◯ 11 participated | 3 in active service
- ◯ 12 participated | 3 in active service
- ◯ Not Sure

Figure D.8: Task 8



Task 9: *

Given 3 research groups:

1. Multimedia(Interaction)

2. Process Science(Software)

3. Data Intensive System(AI & Data Science)

Choose one research group among these three and :

1. State a researcher in this research group who have the most collaborators, and how many collaborators do they have

2. State the main collaboration type of this research group might be

Figure D.9: Task 9

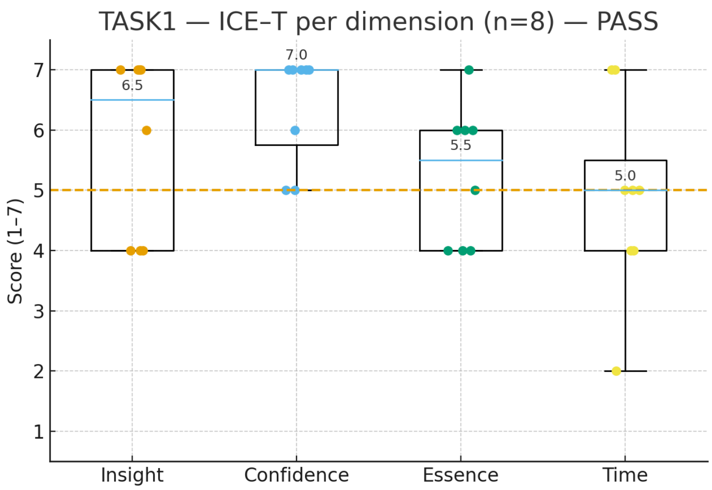


Figure D.10: Task 2 — ICE–T per-dimension distribution with median labels and pass threshold.

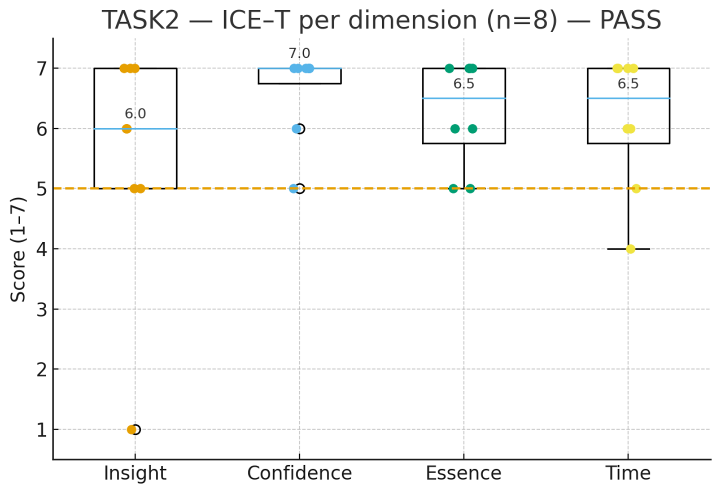


Figure D.11: Task 2 — ICE–T per-dimension distribution with median labels and pass threshold.

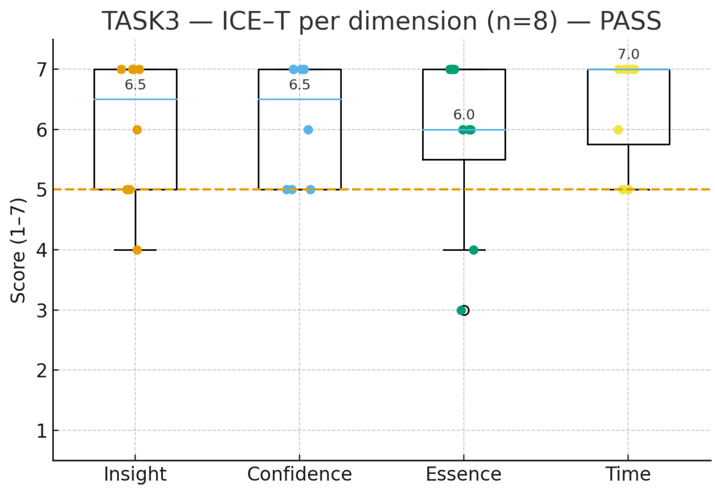


Figure D.12: Task 3 — ICE–T per-dimension distribution with median labels and pass threshold.

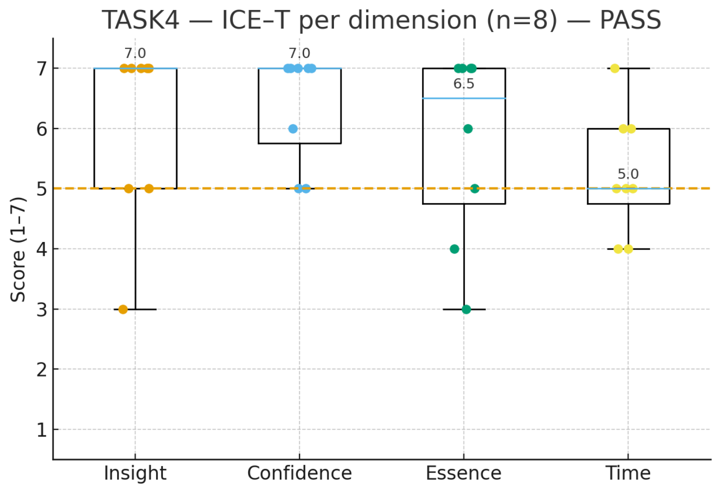


Figure D.13: Task 4 — ICE–T per-dimension distribution with median labels and pass threshold.

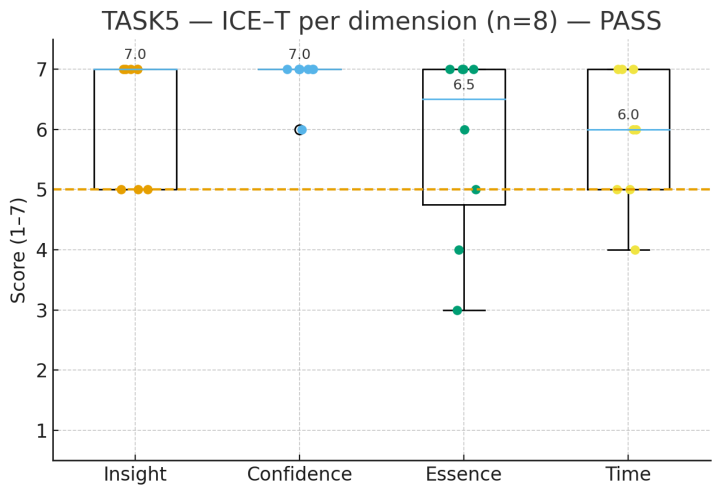


Figure D.14: Task 5 — ICE–T per-dimension distribution with median labels and pass threshold.

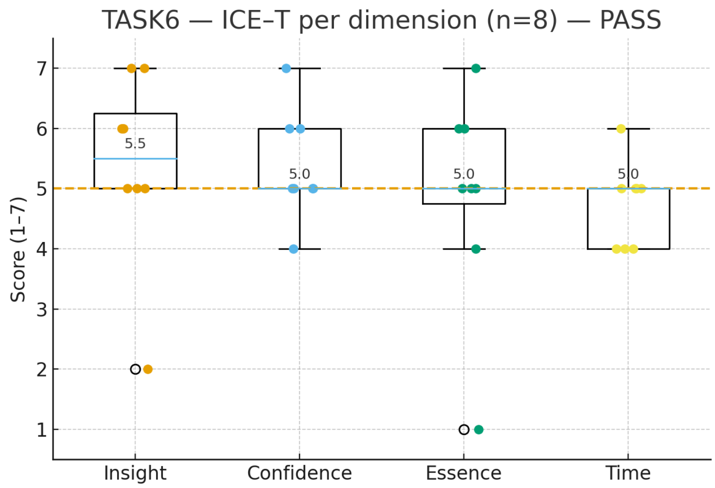


Figure D.15: Task 6 — ICE–T per-dimension distribution with median labels and pass threshold.

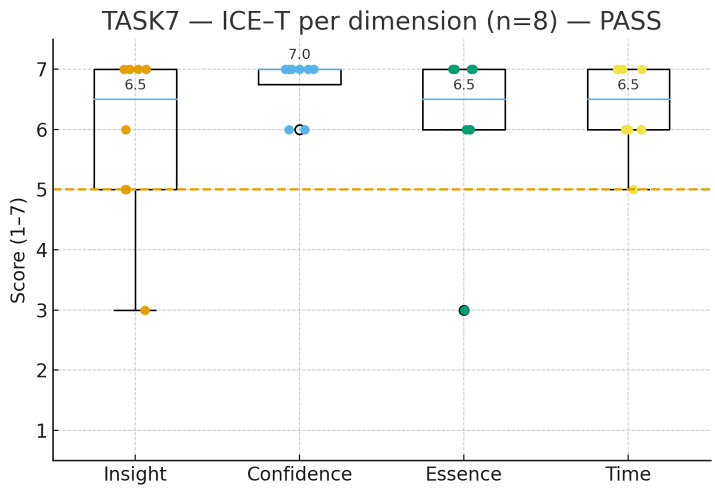


Figure D.16: Task 7 — ICE–T per-dimension distribution with median labels and pass threshold.

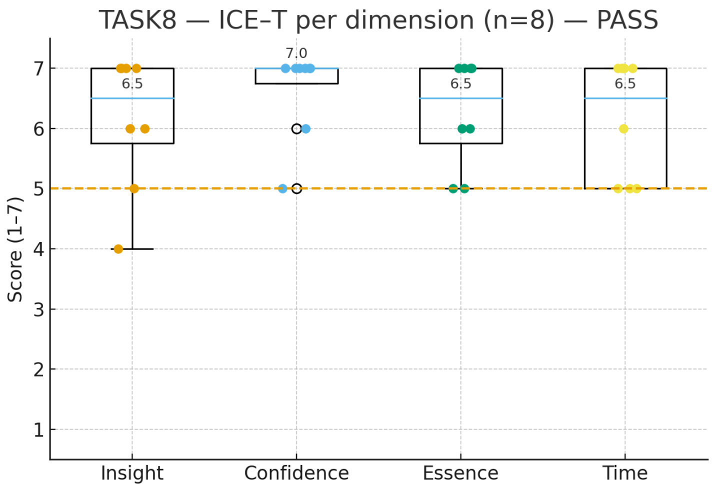


Figure D.17: Task 8 — ICE–T per-dimension distribution with median labels and pass threshold.

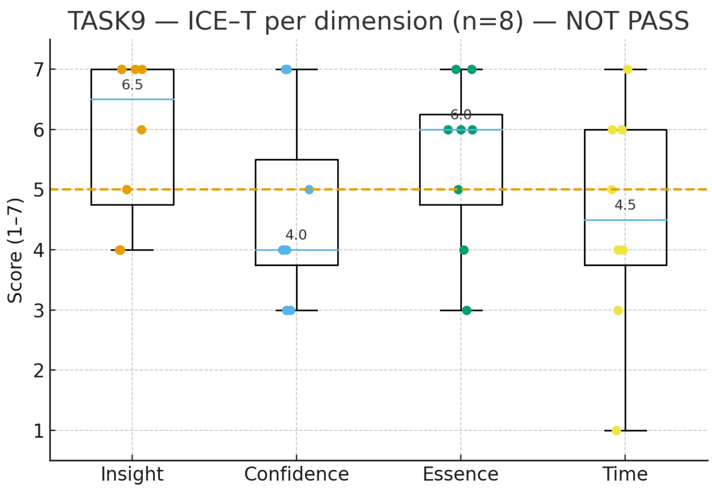


Figure D.18: Task 9 — ICE–T per-dimension distribution with median labels and pass threshold.

Appendix E

System Usability scale

I think that I would like to use this system frequently. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

I found the system unnecessarily complex. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

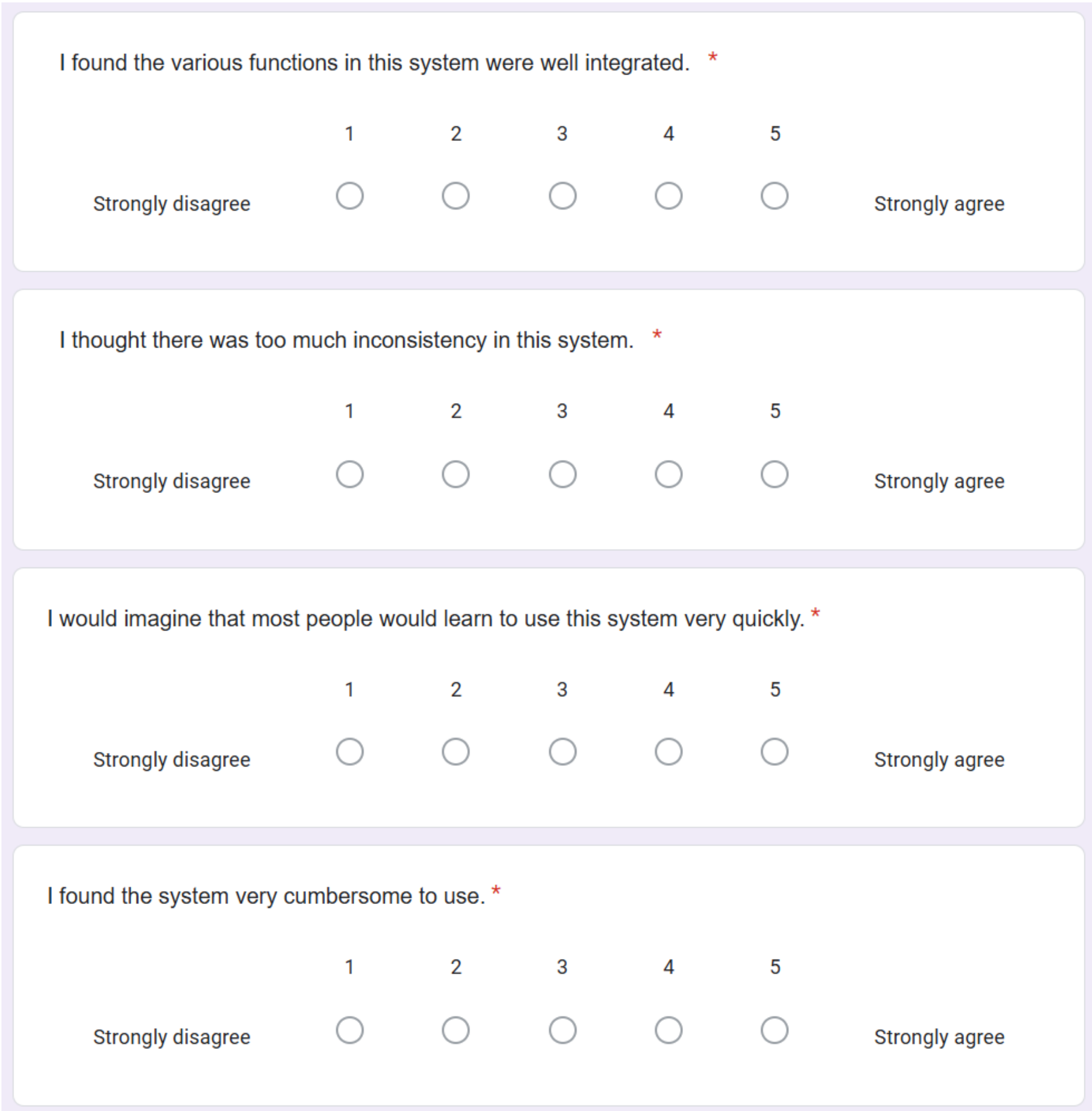
I thought the system was easy to use. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

I think that I would need the support of a technical person to be able to use this system. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

Figure E.1: System Usability Scale Questions 1 - 4



I found the various functions in this system were well integrated. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

I thought there was too much inconsistency in this system. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

I would imagine that most people would learn to use this system very quickly. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

I found the system very cumbersome to use. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Figure E.2: System Usability Scale Questions 5 - 8

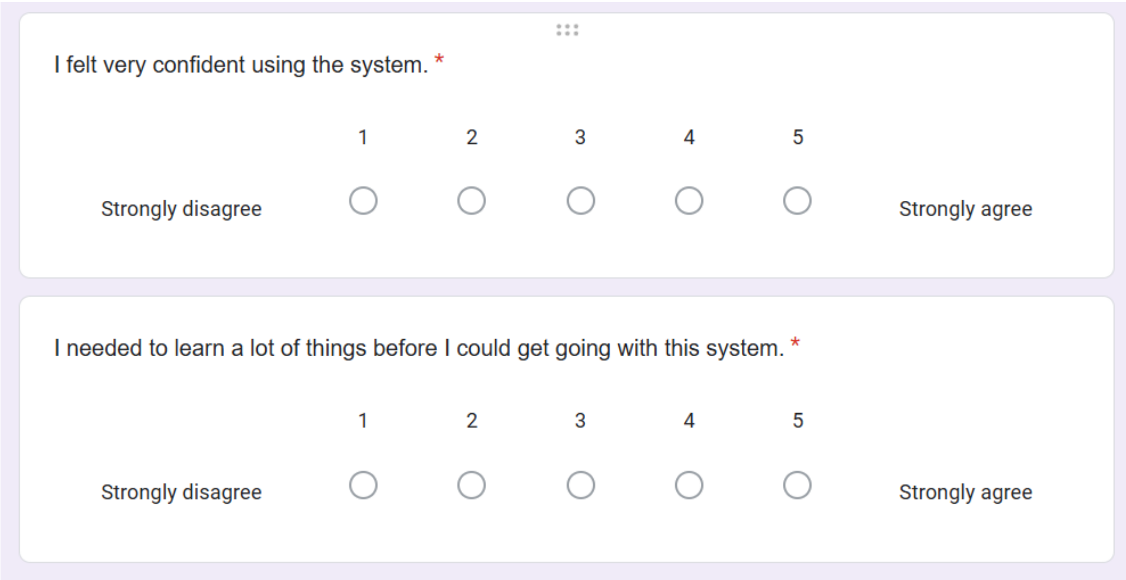


Figure E.3: System Usability Scale Questions 9 - 10

Appendix F

Semi-Structured Interview Guide

This guide was used after the task and system usability scale phase.

Workflow fit

Walk me through how you would normally investigate collaboration patterns. Where did this tool fit or break your flow?

Which interactions felt natural, and which required extra effort or workarounds?

Value of unified layers

Did seeing research and teaching together surface insights you would miss otherwise?

In which cases would you prefer separate views instead?

Hierarchy choice

Did the chosen hierarchy (researcher $\rightarrow$ research group $\rightarrow$ division) align with how you think about the organisation?

Where did levels or rollups feel too coarse or too fine?

Strengths / limits

What felt most reliable or powerful? What gave you pause (ambiguity, clutter, latency)?

Any moments where the visual encoding misled you? What's your favorite interaction/components? And Why?

Desired improvements

What is the one feature/change that would most improve your workflow?

What data or views are missing for your real tasks?