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What is the State of the Art on UX Data Visualization? A Systematic Mapping of the Literature

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Abstract: From a Human-Computer Interaction perspective, data visualizations are visual representations of data that improve users' cognitive capabilities during a task. In particular, UX data visibility can raise a team's engagement with the UX design and better inform product decisions. However, researchers and professionals lack a foundation to build new UX data visualizations. In this context, this paper describes a Systematic Mapping of the Literature that aims to consolidate the state of the art on UX data visualizations. To guide the open coding of the findings, we defined ten questions that span the Visual Information Seeking Mantra and the four levels of Munzner's analysis framework. We identified 28 well-known and seven custom chart formats, with the node-link diagram arising as the most popular. Most of the visualized data comes from software logs, and there is a lack of exploration of UX metrics, acoustic data, and demographic data as data sources. Regarding the Visual Information Seeking Mantra, visualizations had a zoom and filter function and a details on demand function for most chart formats. However, most chart formats lacked overview functions. Our findings provide a broad overview of the literature that can support the creation of new UX data visualizations.

Keywords: user experience, UX, systematic literature mapping, user data, information visualization.

1 Introduction

User experience (UX - *User eXperience*) arises from the interaction between the user's internal state, the software, and the context of use [Hassenzahl and Tractinsky, 2006]. The practices associated with UX go beyond establishing a product design. They also involve an experiential perspective of the users. This perspective arises from the combination of user needs and emotions before, during, and after the interaction [Gibbons, 2020].

The literature defines data resulting from user interaction with a product as UX data [Albert and Tullis, 2022]. UX data can be quantitative or qualitative. Its sources include formal and informal collection, such as spontaneous conversations with end users [Fabijan *et al*., 2016; Rivero and Conte, 2017; Kieffer *et al*., 2019]. This data can serve various purposes, from validating initial product ideas during the predevelopment phases [Hokkanen *et al*., 2016] to assessing the overall UX post-development [Fabijan *et al*., 2016].

Data obtained during different moments of use shed light on how the UX evolves in the long term. For instance, it can help explain how the UX reflects the learning curve of users [Kujala *et al*., 2011]. Furthermore, UX data contribute to understanding the relationship between pragmatic and hedonic aspects of UX, such as usability and user needs [Moellendorff *et al*., 2006].

UX data can inform company decisions about improving a product or developing a new one. The literature advocates for more UX data visibility to engage a team with the UX design [Zaina *et al*., 2021; Kashfi *et al*., 2019]. However, UX data is rarely explored to improve and create software [Kashfi *et al*., 2019].

Data visualizations can facilitate the interpretation of UX data. Munzner [2014] defines data visualizations as visual representations of data that assist users in carrying out tasks. The author proposes a visualization analysis framework with four nested levels: domain, which refers to the context of use and the target audience; abstraction, which encompasses the data and task abstraction; idiom, which defines the visual encoding and interaction idioms; algorithm, which refers to the computational implementation.

While there are existing papers about UX data visualizations, the literature on this subject is sparse. The lack of an overview of the literature limits a precise understanding of its gaps and potential for further investigations. This paper aims to answer the research question: *What is the state of the art on UX data visualization?* The results of this investigation provide Human-Computer Interaction (HCI) researchers and practitioners with a broad overview of categories, trends, and gaps related to UX data visualizations — covering purposes, data sources, chart formats, interaction functionalities, technologies, and more. These findings may inspire further investigations into UX data visualization from various perspectives, as our review addresses multiple aspects of the literature. To the best of our knowledge, no other literature review has examined UX data visualization through as many diverse lenses as ours.

To achieve the paper's goal, we conducted a Systematic Mapping of the Literature (SML) that selected 57 papers. To support the consolidation of the findings, we derived ten guiding questions from the four nested levels of Munzner [2014]'s framework while also considering the Visual Information Seeking Mantra of Shneiderman [1996]. For the qualitative analysis of the SML, we adopted the open coding technique [Saldana, 2013]. The papers reported successful cases of visualizations that helped users analyse software from a UX point of view. The investigation revealed several chart formats as well as the data sources combined with each one of them. We also produced codes for the research methods, purposes, technologies, and interaction functions related to UX data visualizations.

This paper is structured as follows: Section 2 describes the related work; the process followed for the SML is detailed in Section 3; Section 4 presents the findings of the coding stage organized according to the ten guiding questions; the results are discussed in Section 5 and compared with the framework of Munzner [2014] in Section 6; finally, the limitations of the SML are presented in Section 7 and the conclusion in Section 8.

2 Related Work

The papers related to UX data visualization usually focus on particular points about users and propose the adoption of well-known chart formats. Considering charts for timeline visualization, Karapanos *et al.* [2012] built a line chart to show the evolution of the user's perceived experience. Alternatively, Da Silva Franco *et al.* [2019] displayed user sentiments through time in a Gantt chart and animated scatterplot. Combined with user sentiment, Da Silva Franco *et al.* [2019] also used eye-tracking data in the scatterplot and in a scanpath. On the other hand, Móro *et al.* [2014] employed tables and bar charts to display eye-tracking data.

Büschel *et al.* [2021] and Kepplinger *et al.* [2020] featured custom chart formats. Through a mixed reality toolkit, Büschel *et al.* [2021] contextualized user interaction and movement in its original environment. The authors provided scatterplots, heatmaps, and point plots in the toolkit. In addition, it contained a 3D tube format to encode the movement of devices. In the context of Games User Research, Kepplinger *et al.* [2020] developed a visualization of triangulated data. The data consisted of user sentiment, gaze information, and character movement. In this visualization, a trajectory map encoded movement, outlines of in-game objects depicted gaze information, and particle clouds represented user sentiment.

Hussain *et al.* [2018] also made use of triangulation with data from audio devices, video equipment, biometric devices, surveys, and user interaction logs. Influenced by Semiotic Engineering, Jansen Ferreira *et al.* [2017] presented an approach focused on user interaction logs to guide UX design. The approach consisted of exploring data collected at the strategic, tactical, and operational levels. To communicate the UX of a product between interdisciplinary teams, Lachner *et al.* [2016] created a radar plot that displays nine UX dimensions of a product. These dimensions measured the impact of the UX of a product in distinct areas of a company.

There are studies that investigate the literature on eye tracking data and sentiment visualization. However, these studies do not focus on visualizations derived from data sources that describe user interactions with software applications. For instance, Blascheck *et al.* [2017] classified 110 papers on eye-tracking data visualization, categorizing them based on multiple criteria about data sources and chart formats. The authors further segmented the visualizations according to their suitability for point-based or AOI-based analysis. Similarly, in a survey of 132 papers on sentiment visualization, Kucher *et al.* [2018] analyzed visualizations across several categories, including data domain, data source, analytic tasks, visualization tasks, visual encoding of variables, and chart formats. To explore the uncertainty in sentiment and stance visualizations, Ramalho *et al.* [2023] conducted a survey examining 35 papers. This study classified the visualizations based on evaluation criteria, purpose, data source, data encoding, chart format, and the representation of uncertainty. In a Systematic Literature Review focused on visualizations in opinion mining systems, Shamim *et al.* [2014] identified visualizations that encode the polarity of reviews. However, these visualizations were primarily targeted at domains such as phones, vehicles, printers, and books, rather than software applications.

Some secondary studies have explored specific scopes of the literature on UX data visualization. For example, Davila *et al.* [2023] performed a Systematic Literature Review to identify purposes, data sources, and challenges on heatmap visualizations of user interaction data captured during usability tests. In addition, Wallner and Kriglstein [2013] conducted a literature review on gameplay data visualization. They focus on visualizations for game development purposes. From their findings, the visualizations were categorized according to target audience (player or game developer), field of application (specific game or across games or genres), data sources, and chart formats.

Although papers exploring UX data visualization are present in the literature, its knowledge is still sparse. Therefore, it is difficult to form a comprehensive assessment of its gaps and potential. In this context, this paper aims to investigate and synthesize knowledge about the domain, abstraction, idiom, and algorithms of UX data visualizations in line with Munzner [2014]'s framework.

3 Methodology

Systematic Mapping of the Literature (SML) is a method for investigating primary studies that provides an overview of the literature within a research field [Kitchenham and Charters, 2007; Petersen *et al.*, 2008]. SMLs aim to offer a high-level classification scheme for a research field rather than an in-depth analysis, typical of a Systematic Literature Review (SLR) [Petersen *et al.*, 2008]. Thus, an SML is more appropriate than an SLR to establish evidence and structure research literature that is still underexplored [Kitchenham and Charters, 2007; Petersen *et al.*, 2008]. To achieve a comprehensive overview that supports researchers and practitioners in managing UX data visualizations, this paper adopts the SML process outlined by Petersen *et al.* [2008]. Figure 1 illustrates the process with the outcomes of each stage, as described in the following subsections. All authors partici-

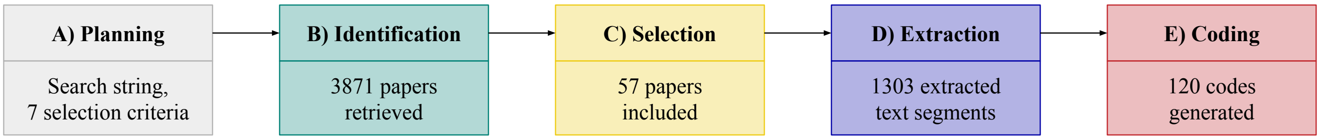

Figure 1. Stages of the SML.

pated in Stage A. Under the supervision of the second and third authors, who have experience in SMLs, the first author was responsible for Stages B to E.

3.1 Stage A - Planning

As a first step, we elaborated the search string. Through an iterative process, three researchers refined the search string by including, excluding, and testing different combinations of keywords. For each test, the three researchers independently analyzed the metadata of distinct random samples of retrieved papers. Based on words found in seminal works of the UX data visualization literature [Dittrich *et al.*, 2019; Büschel *et al.*, 2021; Lachner *et al.*, 2016; Kepplinger *et al.*, 2020], the first tested string was ("information visualization" OR "information visualisation" OR "infovis") AND ("user experience" OR "UX" OR "UX data" OR "UX-data" OR "UX data driven" OR "UX data-driven"). Due to the limited number of retrieved papers, the researchers tested the inclusion of three new keywords separately: "emotion", "sentiment", and "sentiment analysis". The metadata analysis revealed that the new keywords retrieved no additional relevant papers. Subsequently, by excluding the keywords "information visualisation", "UX-data", and "UX data driven", the researchers discovered that these terms did not influence the relevance of the search results. Following this insight, the researchers modified the original search string by excluding these three keywords and testing the inclusion of "graph" and "UX measure". They found that "UX measure" improved the relevance of the retrieved papers while "graph" significantly increased the number of papers unrelated to UX data visualization.

After these refinements, we defined the SML's search string as ***("user experience" OR "UX" OR "UX data" OR "UX measure") AND ("information visualization" OR "InfoVis")***. This string combines the terms "UX" and "user experience" from the User Experience field [Hassenzahl, 2010] with the terms "information visualization" and "InfoVis" from the Information Visualization field [Munzner, 2014]. Furthermore, we included the terms "UX data" and "UX measure". The term "UX data" denotes the data generated during the user interaction with a software application [Albert and Tullis, 2022], and "UX measure" refers to the measured characteristics of the interaction [Hartson and Pyla, 2018]. Except for "InfoVis", these terms were drawn from seminal works of the UX data visualization literature [Dittrich *et al.*, 2019; Büschel *et al.*, 2021; Lachner *et al.*, 2016; Kepplinger *et al.*, 2020]. Despite this, the term "InfoVis" was kept as the abbreviation of "information visualization".

Drawing from the digital libraries recommended by Buchinger *et al.* [2014] for scientific research, we applied the search string in four digital libraries of relevance to Software Engineering [Kitchenham and Charters, 2007]: *ACM Digital Library*, *IEEE Digital Library*, *ScienceDirect*, and *Scopus*. From the search results, we selected papers that addressed all inclusion criteria and did not match any exclusion criteria. The exclusion criteria were: (CE1) not published in a journal or conference proceedings, (CE2) have up to four pages, (CE3) be a secondary study, (CE4) be a duplicate paper, and (CE5) be unavailable in English. As described by their motivations, we adopted the following inclusion criteria:

- (CI1) acts on the user interaction with a software application through data visualization.
  - Motivation: to ensure that the visualization presented contributes to improving the user interaction with a software application. This contribution may arise from users analyzing their own interaction or a development team analyzing the user interaction.
- (CI2) focuses on visualizing data related to user interaction with a software application.
  - Motivation: to ensure that the paper presents a visualization with data about UX as its source. For instance, the selection should exclude papers proposing business data or software codebase visualization.

3.2 Stage B - Identification

In January 2023, we applied the search string across all fields in each digital library. Table 1 shows the number of papers returned from each digital library. In total, we retrieved 3871 papers. Instead of using the search string builder provided by each database, we applied the same search string across all databases using the simple search function available in each. Furthermore, we did not use automatic filters from the digital libraries to reduce the sample of papers.

	Returned	CE1 to CE5	Accepted (CI1 and CI2)
ACM Digital Library	1017	612	11
IEEE Digital Library	41	18	1
ScienceDirect	466	307	2
Scopus	2347	1829	42
Total	**3871**	**2766**	**57**[1]

Table 1. Number of papers returned and accepted per search base after applying the selection criteria.

[1]The search did not return the seminal work of Lachner *et al.* [2016], but we included it in the SML as justified in Section 3.3.

Extraction A:

"By visualizing the time on task as violin plots, two main insights can be generated. [...] On the other hand, displaying the violin plots next to each other allows a visual comparison of the individual flows."

- Question Q05
  - **source:** fifth extraction from P56 for Q05
  - **code:** performance metric
- Question Q06
  - **source:** fourth extraction from P56 for Q06
  - **code:** violin

Extraction B:

"It [(the visualization)] provides clutter reduction to highlight general patterns in the data, by using techniques such as interactive lenses (Tominski et al., 2017) and edge bundling (Zhou et al., 2013)."

- Question Q07
  - **source:** first extraction from P51 for Q07
  - **code 1:** focus plus context
  - **code 2:** data aggregation
- Question Q09
  - **source:** second extraction from P51 for Q09
  - **code:** focus plus context

Figure 2. Extraction examples with correlated codes.

3.3 Stage C - Selection

First, we applied the exclusion criteria based on the papers' metadata made available by the digital libraries. After that, we considered the inclusion criteria based on their titles and abstracts. Finally, we revised the selection after reading the remaining papers. Table 1 details the number of selected papers in each step.

The seminal work of Lachner *et al*. [2016] describes its proposed visualization as a UX tool and focuses on presenting the characteristics of the displayed data rather than the developed visualization. Thus, the paper does not mention terms that characterize the Information Visualization field, such as "information visualization" or "InfoVis". As a consequence, the execution of the search string did not return it. However, we included it in the SML as it fits the selection criteria. As a result, we accepted 57 papers. Appendix A identifies the selected papers from P01 to P57.

3.4 Stage D - Extraction

To form a comprehensive overview of the literature, we derived ten questions from the analysis framework of Munzner [2014] to guide Stages D and E (see Figure 1). The framework divides visualization analysis into four nested levels: domain, abstraction, idiom, and algorithm. These questions cover the four levels of the framework, as discerned in Table 2. For each selected paper, we extracted text segments relevant to the guiding questions and linked each segment to its corresponding source and questions. All extractions are centralized on an electronic spreadsheet page.

Considering the idiom level questions, questions Q7 to Q9 refer to the Visual Information Seeking Mantra: "Overview first, zoom and filter, then details on demand" [Shneiderman, 1996]. The mantra structures the user navigation flow and guides design decisions concerning visualization interaction functions. According to the mantra, the user should initially receive an overview of the data. Then, the visualization should progressively reveal details in response to user interactions. According to Wall *et al*. [2019] and Stasko [2014], the value of a visualization is based on its ability to reveal the essence of the data through an overview. The usability benefits of combining the overview and focused views outweigh their costs, for example, by increasing the user task completion rate [Cockburn *et al*., 2009]. In addition, overviews reduce the cognitive effort for interpretation and aid user navigation through the data space [Hornbæk and Hertzum, 2011]. The Human-Data Interaction Design Guidelines of Victorelli and Reis [2020] recommend reducing the information density and gradually revealing the data.

Level	ID	Question
Domain	Q1	What are the described objectives of the papers?
	Q2	What research methods were used, and how many participants were included?
	Q3	What were the achieved results in evaluations?
Abstraction	Q4	What are the purposes of use of the visualizations?
	Q5	What data sources were explored by the visualizations?
Idiom	Q6	What chart formats were used?
	Q7	How was the function of "having an overview of the data" included in the visualizations?
	Q8	How was the function of "applying zoom and filters to the displayed data" included in the visualizations?
	Q9	How was the function of "viewing the data at the most detailed level" included in the visualizations?
Algorithm	Q10	What technologies were used to develop the visualizations?

Table 2. Guiding questions of the SML's extraction and coding stages, divided according to the analysis framework of Munzner [2014].

3.5 Stage E - Coding

To consolidate the findings, we used the open coding technique [Saldana, 2013]. We examined and compared the extracted text segments from Stage D (see Figure 1) to find patterns within the data. Based on the identified similarities and differences, we grouped the text segments and assigned a code to each group. Each code encapsulated the essence and meaning behind each group. As the analysis progressed, the codes were refined and merged.

We documented the coding for each guiding question in a separate electronic spreadsheet page. Each page contains the corresponding codes generated and the associations between extractions and codes. Figure 2 shows two examples of extractions with their sources and codes.

4 Results

Figures 3 and 5 show the number of selected papers by source and author, respectively. Meanwhile, Figure 4 displays the cumulative number of papers over the years. Considering the SML's selection, the first publication on UX data visualization was in 2006. Since 2013, the number of publications has quintupled. The papers are distributed across 39 sources, including conferences, journals, and symposiums, with the Conference on Human Factors in Computing Systems (CHI) having the highest number of papers. Among 177 authors, 18 have published more than two papers. In the following subsections, we organized the results of the SML in response to the predefined questions and highlighted the generated codes in *italics*.

4.1 What are the described objectives of the papers?

Most (32) of the papers aim to *assist in the UX evaluation of a software application*. Some of these papers focused on displaying attitudinal data, such as user feedback [P06, P19, P24, P54], user sentiment [P24, P25, P50], results of card-sorting sessions [P09], and answers to questionnaires and surveys [P04, P31, P42, P43]. Others focused on the analysis of behavioral data, such as eye tracking [P28, P44, P51, P55], user trajectory [P08, P16, P35, P48, P49, P53, P56], and user actions and software events [P01, P02, P10, P17, P20, P21, P26, P36, P52, P57]. In particular, one paper focused on elaborating collaborative discussion and analysis features for UX evaluators [P17]. A quarter (16) of the papers aimed to facilitate the analysis of player behavior. Their visualizations either aim to *inform the player* about their performance [P30, P34, P38] or *assist in the PX evaluation of a game* (PX — Player eXperience) [P03, P05, P07, P11, P13, P15, P18, P22, P23, P29, P38, P40, P45, P47]. Four papers about UX and PX evaluation also intended to create visualizations accessible to multidisciplinary development teams [P18, P20, P31, P42].

Some papers aim to *raise user awareness* about the interaction with the software. With visualizations of their sentiments, users assessed how the interaction influenced their emotional state [P25, P37]. Through visualizations of web navigation [P27, P39, P41] and music playback histories [P32], users analysed their behavior and preferences. Two papers intended to *guide exploratory searches in text collections* [P33, P46]. Other papers aim to *facilitate the communication of data discoveries* [P12, P14, P42]. For instance, a paper included a visual narrative creation feature on a visualization to enhance the communication of steps preceding a discovery [P14]. In another scenario, a paper proposed a visualization to communicate a product's UX among interdisciplinary development teams [P42].

4.2 What research methods were used, and how many participants were included?

Some authors employed research methods to explore the visualizations' domain, such as the domain's users, tasks, and tools. Examples of these research methods are: *field studies* [P52], semi-structured *interviews* with experts [P17, P19, P20, P34, P42] and other interview types [P06], *questionnaires* with users [P34], *literature reviews* [P36, P42], and *contextual inquiries* with experts [P19]. During design, *concept tests* were applied [P20]. In some cases, the prototyping stage included continuous user [P05, P18] and expert feedback [P12].

For these methods, when specified, the number of involved participants was less than 9 in three papers [P05, P17, P20], between 10 and 30 in two [P19, P42], and above 100 in one [P34]. The participants included designers [P19], UX professionals [P05, P17, P20, P42], software and game developers [P05, P18], data analysts and scientists [P05, P12, P52], and product and customer success managers [P20]. In addition, some participants were students and professionals from other areas [P06, P34].

The prototyping stage also incorporated multiple research methods. *Usability tests* were conducted according to different experimental formats. These formats involved: a group of participants to test a prototype [P01, P07, P14, P17, P20, P23, P32, P36, P37, P45, P55, P56], a group to test and compare multiple tools, such as the proposed visualization and its variants [P19, P22, P31, P33, P39, P41, P43, P44, P48, P49], and a group for each tool to be tested [P08, P12, P25, P33, P34, P46].

In parallel to usability tests, users [P01, P12, P14, P17, P19, P20, P22, P23, P31, P32, P34, P37, P39, P41, P43, P57] and experts [P01, P07, P14, P19, P20, P34, P44, P45, P56] participated on *interviews*. These interviews were unstructured [P32], semi-structured [P07, P12, P17, P22, P23, P31, P34, P41] or structured by the repertoire grid technique [P43]. Similarly, usability tests were complemented by *questionnaires*, such as NASA-TLX [P22, P23, P48, P49], USE [P37], UEQ [P34], INTUI [P31], SUS (System Usability Scale) [P33, P48, P49], ResQue framework's questionnaire [P33], and adaptations of TAM (Technology Acceptance Model) and TAM2 [P14][2]. Authors also adopted custom questionnaires [P01, P07, P12, P17, P19, P20, P22, P23, P25, P32]. For instance, some of these custom questionnaires aim to evaluate user engagement [P12] and satisfaction [P32] and measure quality metrics of the visualization, such as clarity, ease of use, and informativeness [P07, P17, P22].

In some cases, custom questionnaires [P13, P51] and user [P51] and expert [P13] interviews validated the prototype independently of usability tests. In addition, validations were also conducted with *unmoderated remote tests* [P38, P46], *algorithmic performance analyses* [P35], *expert inspections* [P48], and analyses of *eye tracking* [P31] and *customer feedback* data [P42].

Among the research methods adopted during validation, when mentioned, the number of participants was less than 7 in eleven papers [P14, P20, P32, P34, P36, P39, P45, P48,

[2]The glossary of Appendix B describes some questionnaires.

Figure 3. Number of papers by source.

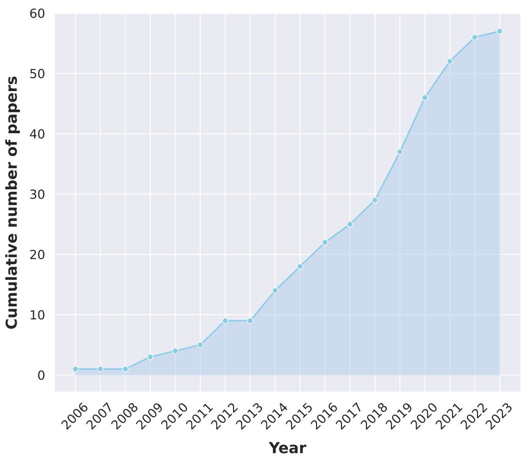

Figure 4. Cumulative number of papers by year.

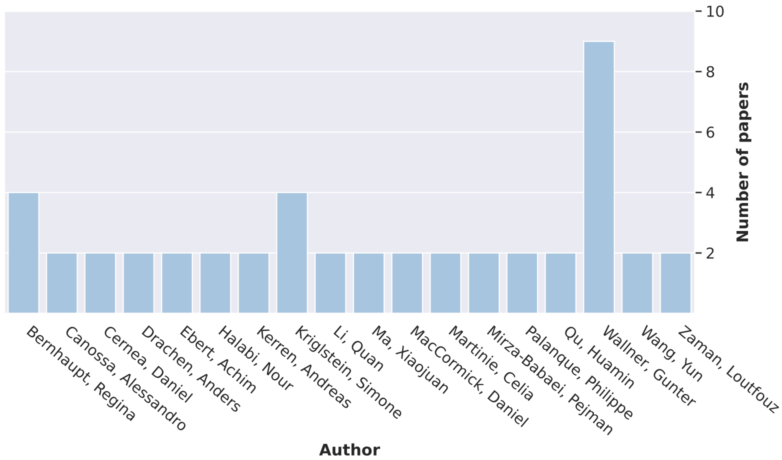

Figure 5. Number of papers by author with at least two papers.

P55, P56, P57], ranged from 9 to 16 in fifteen [P07, P12, P13, P17, P22, P25, P31, P32, P34, P37, P41, P43, P48, P49, P51] and between 20 and 50 in seven [P01, P08, P19, P23, P33, P43, P44], and was at least 100 in two [P38, P46]. The participants were designers [P19, P43], visualization experts [P36], UX professionals [P17, P20, P56], HCI experts [P36, P48], software and game developers [P07, P13, P14, P18, P22, P23, P31, P32, P45], data analysts and scientists [P41, P49], and product and customer success managers [P20]. Furthermore, some participants were students and professionals from other areas [P01, P08, P12, P25, P31, P32, P33, P34, P37, P38, P39, P43, P46, P48, P51, P55, P57].

4.3 What were the achieved results in evaluations?

Results of the evaluations indicate that *papers accomplished their described objectives*. Their visualizations reduced the workload and improved the analysis capacity of the participants during UX [P14, P17, P19, P36, P42, P43, P46, P51, P52, P56] and PX evaluations [P05, P22, P45]. In addition, some visualizations promoted emotional [P25, P37] and behavioral awareness as intended [P32, P39, P41].

Participants appreciated the presence of *complementary data*, such as contextual data [P36] and data about the software of the interaction [P44]. When these data were absent, the participants demanded more data sources and details [P20, P22, P34, P41, P42, P45]. On the other hand, *uncommon data* for domain tasks decreased the visualization's clarity [P17, P44, P45]. The same consequence arose from *ambiguous data* with an uncertain collection method [P13, P45]. Meanwhile, participants felt displeased and discouraged by *ambiguous or negative labels*, such as "miscellaneous cluster" [P39] and "negative user sentiment" [P19]. Participants also raised questions about user interaction *data privacy and ownership* [P25]. In addition, participants recognized how *data value depends on the analysis context*, such as the role of the analyst [P20] and the analysis timing (before, during, or after the interaction) [P34].

The *obstruction* of visualizations' items resulted from the high quantity, large size, and low transparency of items [P01, P07, P13, P23, P45, P48]. The *use of VR/AR headsets* limited the field of vision and induced participant fatigue [P36]. Violin [P56], stream [P39], and 3D bubble [P01] charts were *unfamiliar chart formats* for some participants. Consequentially, some participants had difficulty interpreting the encoding [P39, P56] and using the interaction idiom [P01]. Furthermore, participants mentioned *confusing and enlightening chart formats* across different data sources. Participants appreciated analysing user trajectories through Sankey and node-link diagrams [P48]. On the other hand, node-link tree diagrams posed challenges in this regard due to their limitations on representing cycles without repeating nodes [P48]. In another case, tables aided inexperienced evaluators in structuring their analysis [P19]. Meanwhile, heatmaps highlighted regions displaying atypical behavior [P13].

Regarding the interaction idiom, participants appreciated interactions promoted by the Visual Information Seeking Mantra [Shneiderman, 1996]. The following were *valued functionalities* by the participants divided according to the functions of the mantra:

(1) Overview of the data: small multiples [P51] and data aggregation [P07, P51].
(2) Zoom and filters: spatial filters [P51] and filters by user [P31], keyword [P46], category [P23], and user sentiment [P46].
(3) Details on demand: revelation of aggregated data [P52] and control of the visualization's temporal state [P22, P23, P41], camera view [P22, P23], and spatial arrangement of items [P52].

Participants also noted some *issues with the functionalities*. Data aggregation overlooked subtle or unusual user behavior patterns [P45]. Participants disregarded pre-established views of the visualizations [P22]. Furthermore, the lack of a time indicator for lengthy data filtering operations confused participants [P52].

4.4 What are the purposes of use of the visualizations?

Analyse user behavior is a common objective among the visualizations [P01, P03, P05, P07, P08, P10, P11, P12, P13, P14, P16, P17, P18, P20, P22, P23, P26, P27, P29, P31, P32, P35, P36, P38, P39, P40, P41, P42, P44, P45, P46, P47, P48, P49, P51, P52, P53, P55, P56, P57]. Some focus on visually comparing user behavior based on usage trajectory [P47] and performance metrics [P30]. Others aim to categorize users by task outcome (e.g., success or failure) to observe commonly followed trajectories [P35, P48].

Reconstruct the interaction to *explore the perceived experience* [P02, P06, P19, P24, P31, P42, P43, P46] or *explore the internal state* of the users [P04, P09, P15, P17, P24, P25, P33, P37, P50, P54] is another described purpose. In some cases, it is possible to compare the perceived experience of a product over time or between different products [P02, P31, P42]. Furthermore, some visualizations aim to *analyse the context* of the interaction (e.g., user movement and nearby objects) [P36, P56] and *identify the user profile* based on demographic data and user behavior [P35, P53]. Finally, users are also able to produce annotations to *encode events and UX issues* [P06, P14, P16, P17, P19].

4.5 What data sources were explored by the visualizations?

It is possible to explore *demographic* data [P03, P20, P31, P35, P40] and *acoustic* data from think-aloud sessions, such as tone, volume, and speech rate [P17]. Regarding *user sentiment*, four data types emerged: excitement level (excited or calm) [P07, P13, P25], polarity (positive, negative, or neutral) [P15, P17, P19, P24, P46, P50], valence level (pleasant or unpleasant) [P25], and emotion (happy, sad, surprised, among other emotions) [P24, P37, P45, P50].

Following the use of a software application, it is possible to explore data about *user actions and software events* [P04, P05, P07, P10, P11, P12, P13, P15, P17, P18, P20, P22, P23, P26, P27, P28, P32, P35, P36, P38, P39, P40, P41, P45, P46, P47, P53, P56]. This includes an event's frequency [P12, P27, P35], intensity (e.g., scroll speed) [P17] or location on a screen [P04, P28, P36, P53]. The exploration of *navigation trajectory* through web pages [P08, P10, P27, P39, P48, P49, P52, P53] or software states is also possible [P03, P14, P16, P29, P35, P40, P56, P57]. The navigation can be associated with *eye tracking* data, such as fixation points [P28, P44, P50, P51, P55], eye movement type [P51], field of view [P44, P56], fixation duration and frequency [P28, P44, P45, P50, P51, P55], and gaze trajectory combined with the fixated regions' intensity, color, and orientation [P44].

User interaction can produce *interaction-related text*, such as user reviews [P06, P19, P24, P31, P46], transcribed comments [P07, P15, P16, P17, P36, P50], annotations [P16], metadata of visited pages [P39, P54], and words used in search fields [P33, P39] or card-sorting sessions [P09]. *UX, satisfaction, and efficiency metrics* were collected using software usability and aesthetic attractiveness questionnaires [P02, P26, P31, P42, P43]. To explore the interaction through a *performance metric*, task completion time [P04, P08, P18, P20, P26, P28, P35, P52, P53], user action frequency [P04, P27], and task success rate were considered [P18, P50, P52, P53].

4.6 What chart formats were used?

Table 3 lists *well-known chart formats* present in the papers. The visualizations also adopted custom chart formats, such as a *particle cloud system* to point out user sentiment locations [P45], a *multi-line timeline* to display concurrent user navigations [P08], and a *3D bubble* chart that compose a configurable framework [P01]. Other custom formats include a *tangible magnetic force* format [P37] and the *overlapping of points and lines* to display continuous events (lines) concomitant with discrete events (points) [P56]. Through augmented reality, a *3D tube* format depicted users' and objects' movement and dispersion of positions in their original environ-

Format	Citation	Format	Citation	Format	Citation
Adjacency Matrix	[P10, P40]	Icicle	[P02]	Scatter	[P04, P28, P36, P44, P50]
Affinity	[P06]	Line	[P05, P10, P17, P43, P56]	Sliders	[P34]
Arc	[P48]	Node-link	[P03, P09, P14, P16, P24, P26, P27, P29, P40, P48, P49, P54, P57]	Stream	[P39]
Area	[P05, P12, P39]	Plain Text	[P46]	Stripe	[P10, P17, P39]
Bar	[P02, P12, P32, P39, P46, P50, P52]	Point	[P32, P36]	Sunburst	[P41]
Box	[P02]	Radar	[P05, P30, P33, P42]	Table	[P02, P04, P14, P17, P19, P49, P53]
Bubble	[P12, P41, P51]	Sankey	[P35, P48, P56, P57]	Trajectory Map	[P05, P07, P13, P15, P40, P45]
Choropleth Map	[P07, P13, P15]	Scanpath	[P28, P50, P51]	Violin	[P56]
Gantt	[P50]			Word Cloud	[P39, P50]
Heatmap	[P11, P25, P28, P35, P36, P38, P40]				
Histogram	[P25, P34]				

Table 3. Well-known chart formats present in the literature.

ment [P36]. In addition, a *3D scene simulation* reproduced gameplay in its original virtual environment [P22, P23].

4.7 How was the function of "having an overview of the data" included in the visualizations?

Visualizations employed the *focus plus context* technique to provide details while maintaining an overview of the data [P12, P25, P26, P33, P51]. Through the *small multiples* and *superimpose* techniques, analysts could simultaneously view data of multiple users [P02, P05, P51, P56], timeframes [P26, P51], software interface regions [P51], and evaluation scenarios [P02, P26]. Chart formats that used these two techniques included the scanpath [P51], histogram [P26], table [P02], violin [P56], icicle [P02], radar [P05], and bar formats [P02, P26]. Regarding summary charts, bar [P20, P32, P39, P50] and stream charts [P39] depicted the *overall frequency and duration* of events and user sentiments by using accumulated and partitioned data over time. Numeric indicators in pop-up windows [P08] and a device color in tangible visualizations [P37] served the same objective.

To decrease the level of detail, visualizations also applied techniques to *aggregate* the data. A force-directed edge clustering algorithm aggregated data depicting gaze direction [P51]. In a trajectory map, a spatial subdivision algorithm grouped lines representing a player's character movement [P45]. In a particular case, an analyst could customize the algorithm that would aggregate the bubbles of a bubble chart [P01]. Furthermore, two node-link diagrams aggregated navigation trajectory data in multiple ways [P03, P40]. Their vertices encoded aggregations of software states resulting from customizable algorithms. Each of their edges depicted the aggregation of transitions between two states. Finally, these diagrams had symbols that represented the aggregation of users. In this case, users were aggregated based on the software state they currently were on.

4.8 How was the function of "applying zoom and filters to the displayed data" included in the visualizations?

Analysts could control the *zoom* of the visualizations [P08, P18, P24, P31, P40] and direct their view of the data through *panning* [P08, P31, P40]. Some visualizations offered the functionality of *individually hiding items on demand* [P01, P36]. Through *attribute filters*, it was possible to select which attributes to display [P08, P11, P26]. Filters based on the values of an attribute were also available but in abundance. Those filters either selected items to be displayed or highlighted. The most adopted filters were the *temporal filters* [P05, P12, P15, P17, P18, P24, P25, P27, P32, P36, P40, P41, P50, P51]. Analysts could use these temporal filters through controls [P05, P15, P32, P51], slider bars [P25], calendars [P32], and animations [P05, P12, P17, P24, P40, P41, P51].

Through *spatial filters*, analysts could pinpoint items in a region of a software interface [P51] or virtual environment [P18]. The spatial filters could also limit the data to items starting/ending in an area or around/outside a region [P51]. Assisting the analysis of movement data, *direction filters* constrained data to the movements that followed a specific direction [P51]. In node-link diagrams, *cycle and path filters* selected paths based on length [P40] and number of vertices and edges of a category [P40]. Through these filters, analysts could also pick paths that contained a vertex or edge [P24]. Furthermore, the filters could hide cycles that represented comebacks in the user navigation trajectory [P29].

Visualizations included *category filters* [P03, P05, P15, P19, P22, P23, P26, P32, P40, P51] based on, for example, categories of software events [P03, P05, P15, P32, P40]. In user review visualizations, *coverage filters* narrowed visible reviews to those unknown to the analyst [P46]. *Filters by quantitative threshold* [P03, P20, P50, P56] limited the data based on duration [P50] and frequency [P03, P56]. Furthermore, visualizations contained filters, such as *keyword filters* [P19, P39, P46], *user sentiment filters* [P15, P24, P25, P46, P50], *filters by user* [P05, P15, P29, P35, P36, P45], *filters by software* used in the interaction [P16], *annotation creator*

Code	Technologies
Algorithms and techniques	Algorithm of Andrienko and Andrienko (2011) [P07], Artificial neural networks [P15, P50], Bubble Sets [P44], CMDS [P03, P29], DBSCAN [P07, P40], Google speech recognition [P50], I-VT [P44], isomorphism check of Sun et al. (2012) [P40], K-means [P35, P39], Lexicon-based classifier [P15], LinRel [P33], algorithm of Newman (2004) [P54], QT [P03, P40], SVM [P50], and TF-IDF [P54].
APIs	Google speech recognition API [P17], and OpenGL API [P03].
Chart development software	ArcGIS [P11, P28, P47], Graphviz5 [P49], NVivo [P21], OGAMA [P28], SWISH DataLab [P49], and Universal Visualization Platform [P16].
Computer languages and associated technologies	Adobe Flash ActionScript [P08], AJAX [P18], C++ [P44], CSS [P06, P19, P32, P46], C# [P03, P28, P40], HTML [P06, P19, P30, P32, P39, P46, P50], Java [P28, P29, P32, P51, P52] (with Hadoop [P52], MDSJ [P03, P29, P40], OpenCL9 [P51], and Swing [P51]), JavaScript [P04, P06, P12, P15, P18, P19, P24, P30, P32, P35, P39, P46, P50, P55] (with D3.js [P12, P24, P35, P50, P55], jQuery [P18, P19], NodeJS [P15], Protovis [P18, P32], React [P15, P35], and RequireJS [P30]), PHP [P18, P39], Processing [P10, P51], Python [P15, P17, P19, P35, P37, P46, P50] (with Auditok [P17], Django [P19], Gensim [P46], OpenCV [P17], Praat-Parselmouth [P17], and Valence Aware Dictionary and Sentiment Reasoner [P17]), SQL [P15, P18, P19, P28, P39, P47, P55] (with MySQL [P18, P39], NoSQL MongoDB [P15], PostgreSQL [P19], RavenDB [P55], and SQLite [P28]), Swift [P31], and Typescript [P15].
Data formats	AVI [P50], CSV [P36, P50, P51], geoJSON [P28], JSON [P24, P27, P32], MOV [P50], MP3 [P50], MP4 [P50], WAV [P50], and XML [P01].
General purpose software	Box2DWeb [P12], HAMSTERS-XLE [P02], Qt5 [P44], Unity [P15, P22, P36, P45], and Webstrates [P06].
Physical devices	Arduino microcontroller [P37], Emotiv EPOC [P50], Microsoft HoloLens v2 [P36], Tobii pro X2-30 [P44], and Tobii TX300 [P28].

Table 4. Technologies used to develop the visualizations divided by generated code.

filters [P17], and *filters by session composition*, which eliminated sessions without an event of a specified type [P52].

In addition, some visualizations provided query interactions. Unlike filters, which act on the data on display, a query starts from the absence of data being visualized [Munzner, 2014]. In this regard, it was possible to select the items through a *query by keyword* [P08, P16, P46], and *query by category* [P20]. In node-link diagrams, a *query by subgraph* was also available. Through this query, an analyst could select graphs with a specified subgraph within it [P08, P40].

4.9 How was the function of "viewing the data at the most detailed level" included in the visualizations?

As mentioned in Section 4.7, the *focus plus context* technique preserved the context while revealing details of the data [P12, P25, P26, P33, P51]. Analysts had the *control of the visualization's temporal state* by interacting with a slider [P03, P22, P36, P40, P50], a button (e.g., play, pause, fast-forward) [P03, P40], and a timeline [P17, P41]. In 3D chart formats, analysts could explore details about multiple views through the *camera view control*. This control involved diverse interactions, such as movement [P01, P22, P23, P36], rotation [P01, P22, P23, P36], zoom [P22, P23], and the selection of predefined settings [P22, P23, P45], such as the user's camera view during the interaction [P22, P23].

The gradual *revelation of aggregated data* occurred as an analyst interacted with items, such as bubbles in bubble charts [P01], higher-level notes in affinity diagrams [P06], and edges in node-link diagrams [P40]. In node-link diagrams, it was possible to reveal underlying subgraphs by clicking on a vertex [P03, P40]. The press of a button expanded the lines of a table to uncover their aggregated counterparts [P19]. Furthermore, analysts could adjust the temporal (e.g., hours to days) [P32, P39, P41] and spatial granularity of the data [P45]. In particular, the spatial granularity could change according to the size of the chart's spatial mesh cells [P45].

Analysts could choose the *spatial arrangement of items* when necessary. The new arrangement could be calculated by a sorting algorithm, such as an attribute-based algorithm [P19, P40], the breadth-first search algorithm [P40], and the RCM algorithm for sorting adjacency matrices [P40]. The arrangement could also be a result of an alignment. A timeline could be centered on a chosen reference point [P26], and stacked bars could align starting from a specific event type [P52]. Finally, the analyst could overlay an item above others by pointing a mouse closer to the items' center [P08].

By selecting an item, the analyst could trigger the *highlighting of related data* by coloring [P06, P25, P39, P41] or linking [P08, P51]. For instance, clicking on items that encoded events generated links to similar events [P51]. Similarly, interacting with an item linked it to its corresponding occurrence time shown on a timeline [P08]. In addition, selecting a histogram bar highlighted regions of the software interface corresponding to the encoded events of the bar [P25].

Alternatively, selecting items also resulted in the *revelation of details* in text, audio, and image formats [P01, P02, P03, P05, P08, P14, P15, P19, P24, P26, P30, P40, P41, P45, P48, P49, P50, P56]. For instance, selecting a sector in a sunburst chart exposed the quantity represented by the sector's angle [P41]. Interaction with particle clouds revealed corresponding category and occurrence time [P45]. Clicking

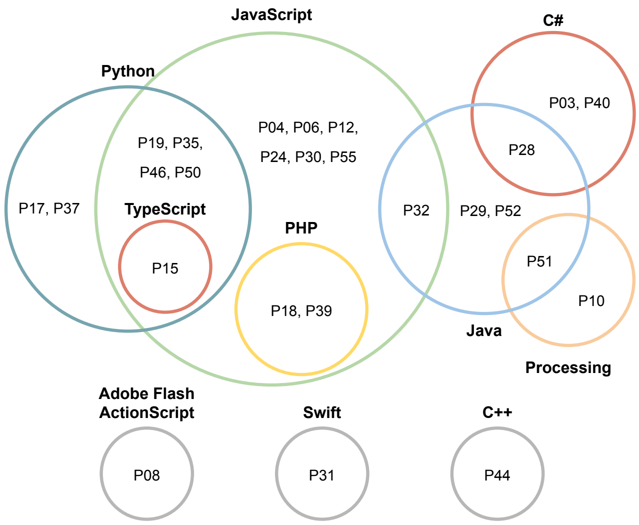

Figure 6. Intersection between programming language use (except SQL).

on symbols encoding users or feedback providers exposed attributes like demographic data [P03, P19, P40]. Additionally, Gantt chart timeline's bars were linked to audio transcriptions and image frames of the interaction recording [P50].

4.10 What technologies were used to develop the visualizations?

Table 4 details the technologies adopted during development[3]. Independently or in conjunction, papers used chart development software and computer languages to implement the interfaces and collect, process, and visualize data. The five most popular computer languages were JavaScript, HTML, Java, SQL, and Python. Figure 6 illustrates the overlap of programming language usage across the papers (SQL has been omitted to avoid overcrowding the chart, as it was used in conjunction with various programming languages). The data formats ranged from text to multimedia formats. In addition, the papers complemented the implementations with pre-existing general-purpose software, APIs, physical devices, algorithms, and techniques. Physical devices were incorporated to build tangible visualizations [P37] and collect eye tracking [P28, P36, P44] and user sentiment data [P50]. The algorithms and techniques fulfilled various purposes, including eye tracking [P44] and user sentiment classification [P15, P50], data clustering [P03, P07, P35, P39, P40, P54], and user intent modeling [P33].

5 Discussion

Figure 7 provides an overview of the codes generated through a word cloud. The size of each code is proportional to the number of papers associated with it. The word cloud highlights trends, such as the use of computer languages to develop visualizations, the purpose of analyzing user behavior, and the application of usability tests and interviews to assess the visualizations. Additionally, it reveals areas for further exploration, such as experimenting with different chart formats and data sources.

[3]The glossary of Appendix B describes some technologies.

Most papers aim to aid the UX evaluation of software applications by proposing visualizations. Some papers concentrated on developing visualizations to assist in game PX evaluation. Others focused on raising user awareness of their behavior and emotional state. Few papers prioritized creating (1) accessible visualizations for diverse audiences interested in UX data and (2) visualizations emphasizing communication rather than analysis.

The authors often applied research methods during evaluation/validation and sometimes during the conception of visualizations. Nevertheless, the SML found a diverse range of methods in both cases. Usability testing was the most prevalent, followed by questionnaires and interviews. The authors rarely used questionnaires and interviews independently of usability tests, and vice versa. Meanwhile, other methods appeared in no more than two papers.

Except for the ResQue framework questionnaire, the standardized questionnaires assessed visualizations' usability and UX. No standardized questionnaire evaluated characteristics specific to visualizations. Furthermore, the number of papers that adopted standardized questionnaires was close to the number of papers that used customized ones. During validation, UX professionals, developers, data analysts, and product managers, among others, interacted with prototypes.

The papers stated that the visualizations reduced the participants' workload and enhanced their analysis capacity during different UX data analysis tasks. Participants frequently requested additional data on the visualizations. However, issues with obstructions resulting from high information density were equally prevalent. Visualizations primarily derived data from automatically captured logs of user actions and software events. Eye tracking data and user comments, sentiments, and reviews were used to a lesser extent. On the other hand, exploration of demographic data, acoustic data, and metrics of UX, satisfaction, and efficiency remained limited.

The papers adopted a variety of chart formats. Through a Sankey diagram, Figure 8 displays the combinations of chart formats and data sources that emerged from the SML. The label of each node of the Sankey diagram is composed of a code name and the number of incident links. Each link represents, through its thickness, the number of times a chart format was combined with a data source. The most widely adopted format was the node-link diagram, often with a navigation trajectory as a data source. On the other hand, tables were the format used with the most distinct data sources. Only thirteen (40%) of the formats were combined with multiple data sources. In addition, sixteen (45%) occurred only once in the papers.

In Figure 9, a bar chart shows how many times each chart format contained each function of the Visual Information Seeking Mantra [Shneiderman, 1996]. Specifically, the size and color of each bar encode the number of distinct combinations between a chart format's code and the codes belonging to a function. For reference, Figure 9 also specifies the number of codes generated for each function as the maximum possible frequency. Among the chart formats, the node-link diagram also had the most distinct applications of the functions. In general, each format contained a few different applications of each function. The incorporation of the overview function

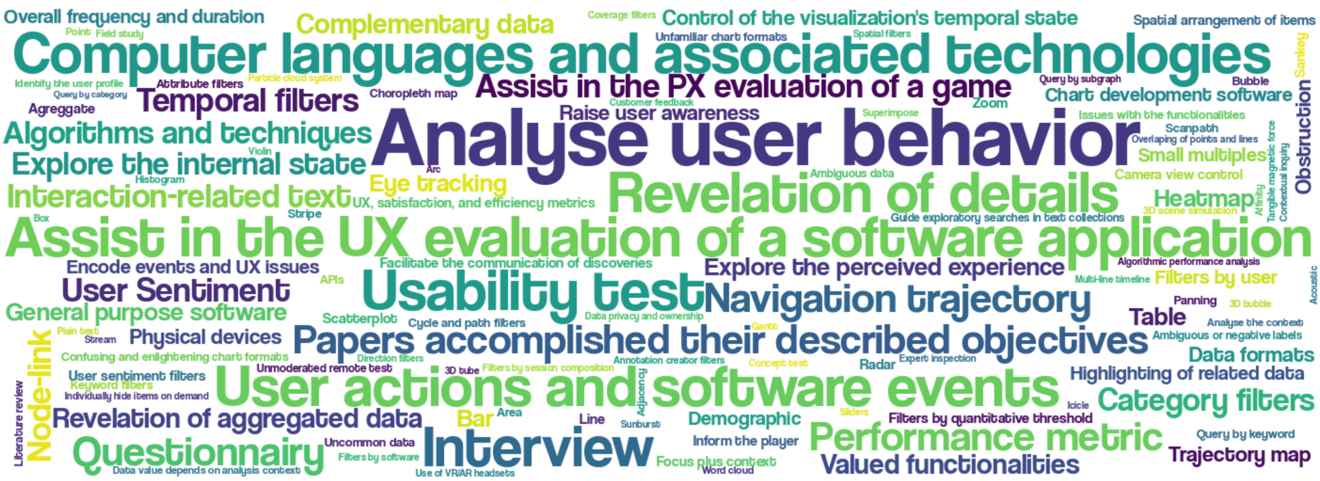

Figure 7. Word cloud of codes with size proportional to number of associated papers.

was the least mentioned in the papers. Only the node-link diagram format was combined with more than half of the possible applications of one of the functions. In addition, only 23% (8) of the formats had at least one distinct application of each function.

Most visualizations were created using computer languages. In some cases, chart development software was used, such as ArcGIS on three occasions. During data collection, physical devices were adopted to capture only eye-tracking data and user sentiment. Furthermore, the visualizations incorporated multiple algorithms and techniques involving artificial intelligence, such as classifiers and clustering algorithms.

6 Comparison with Munzner

As specified in Section 3.4, the SML's guiding questions are divided according to the analysis framework of Munzner [2014]. This framework facilitates visualization analysis by separating concerns about visualizations into four levels: domain situation, task and data abstraction, visual encoding and interaction idiom, and algorithm. It structures the comparison of visualizations and enables a systematic synthesis of the knowledge about design choices that pertain to a domain. In addition to its levels, the framework also incorporates the "what-why-how" questions. They are the essential questions of the framework: (1) *what* data is presented? (2) *why* use the visualization? (3) *how* is the idiom constructed? The abstraction level of the framework addresses the "what" through data abstraction and the "why" through the task abstraction. Finally, the idiom level is responsible for the choices related to "how". Next, we analyse the SML results using the analysis framework of Munzner [2014].

Domain. The primary target users of the UX data visualizations were software and game development teams. Most papers aim to facilitate the UX evaluation of a software application and the PX evaluation of a game for these users. Visualizations also focused on helping end users of the applications. Some of these papers aim to raise user awareness about their behavior and emotional state. Others intended to guide users in the exploration of an application. Regarding the application of research methods, the articles involved participants with diverse roles beyond UX professionals. Only eleven (19.2%) papers described research methods used during visualization conception. However, more than half of the papers evaluated their visualizations. Through evaluations, it was possible to identify visualizations that reduced development teams' workload and improved their analysis capacity.

Abstraction. Most (94.7%) visualizations aim to analyse user behavior, perceived experience, and user's internal state. For this purpose, they display data sourced from, for example, software logs (e.g., user actions, software events, and navigation trajectory data), external devices (e.g., user sentiments and eye tracking data), and questionnaires (e.g., UX, satisfaction, and efficiency metrics).

Idiom. The visualizations employed 28 well-known chart formats and seven custom ones. By number of citations, the formats that stood out were the bar chart (7), heatmap (7), line chart (5), node-link diagram (13), radar plot (4), Sankey diagram (4), scatterplot (5), table (7), and trajectory map (6). Visualizations also adopted different interaction idioms, such as aggregation, superimpose, panning, filtering, and selection for revealing details. The most employed among them were the manipulation of data based on its time of occurrence and the selection to reveal details. Among the SML's codes regarding the interaction idiom, fourteen (40%) referred to filters. Furthermore, three interaction idioms stood out for being more involved with a particular domain or data source: software filters, user sentiment filters, and user filters.

Algorithm. A quarter of the papers (14) used JavaScript to implement the visualization. JavaScript was usually paired with Protovis and D3.js. In contrast, only six (10.5%) papers used chart development software. Other languages have also been adopted, such as HTML, SQL, Java, and Python. Most algorithms and techniques incorporated into the visualizations stem from artificial intelligence, such as classifiers and clustering algorithms.

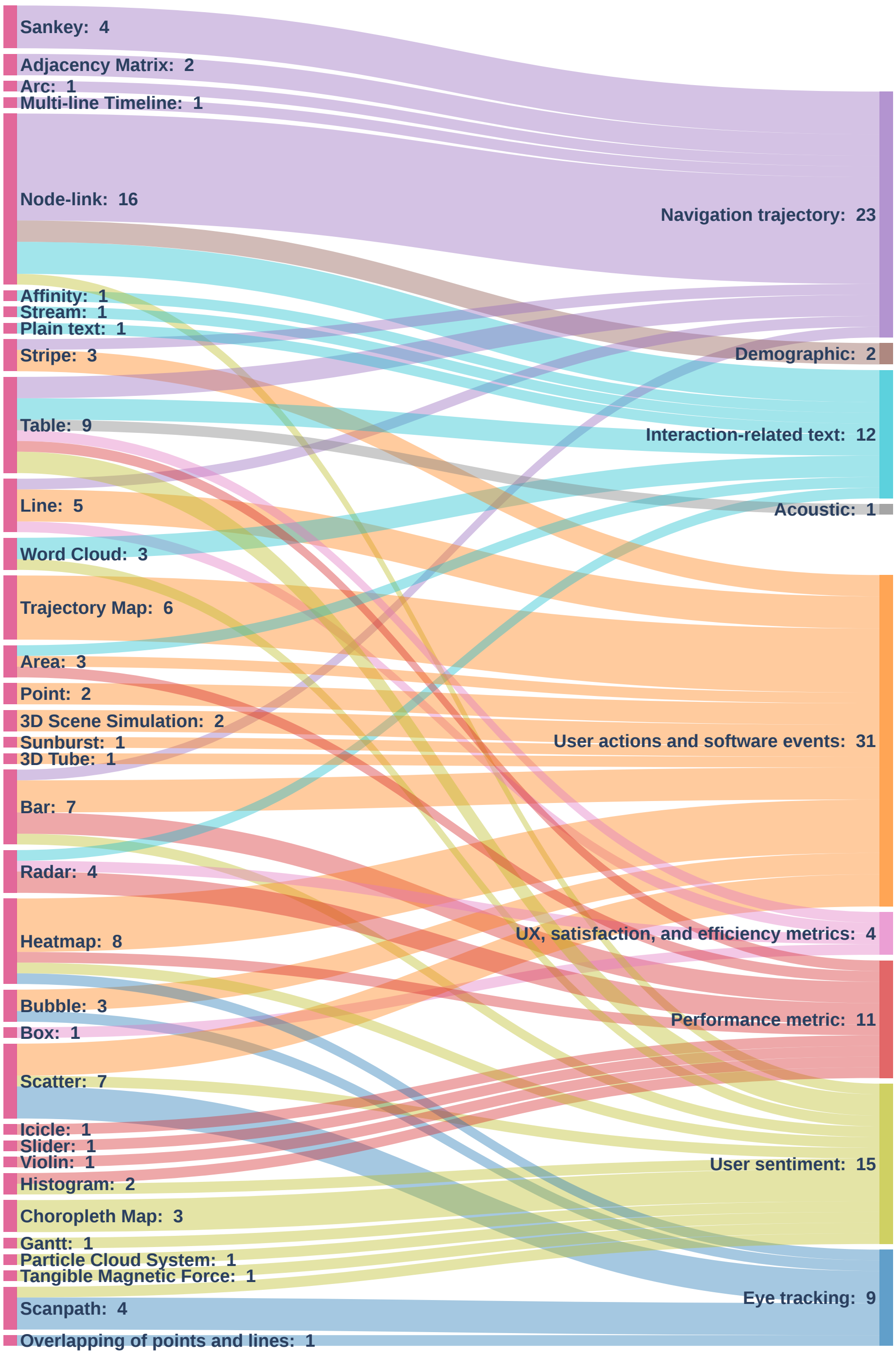

Figure 8. Combinations of data sources and chart formats that emerged from the SML.

7 Limitations and threats to validity

The papers retrieved by the search string depend on both the specific string used and the digital libraries searched. One of the limitations of this study concerns the search string applied. Although we followed best practices for string construction and tested different search strings, we recognize that the selection of terms may not have been exhaustive enough to delimit the sample of results from each scientific database. We used keywords from seminal works. However, the literature related to data visualization has a diversity of synonyms and terminological variations that this work may not have covered. In addition, the way in which the string was applied in different databases may have resulted in variations in document retrieval, either due to Boolean logic or the different functionalities and indexing of each repository. Consequently, there is a risk that we excluded potentially relevant articles or, to a lesser extent, included studies outside the intended scope. We recognize that future investigations may benefit from a broader review of search terms and additional sensitivity and precision tests to refine the results.

SMLs focus on a limited set of papers. Thus, the codes that emerged can evolve through time as the field of UX data visualization advances. For instance, new characteristics of UX data visualization may arise in future studies. In addition, a single researcher conducted the selection, extraction,

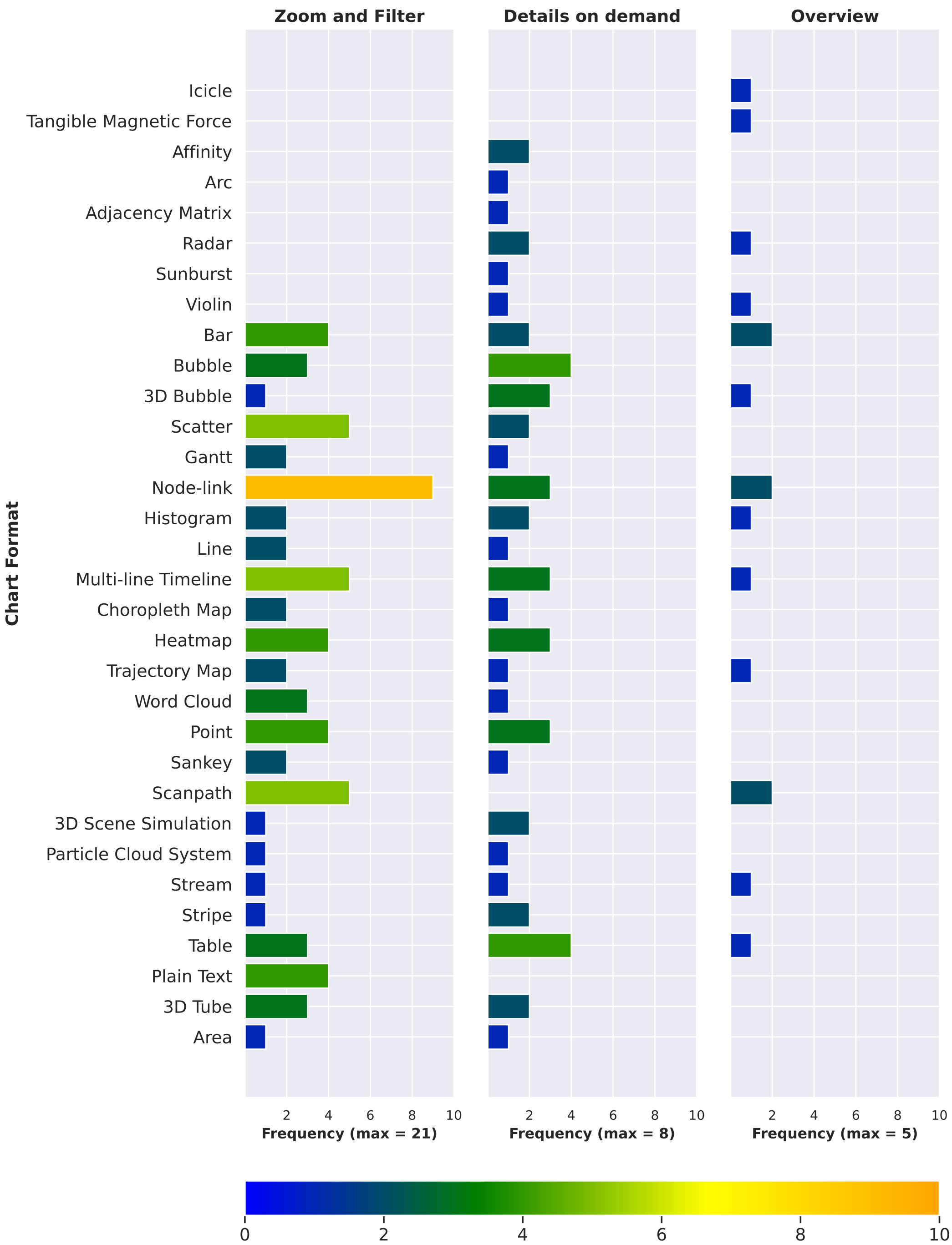

Figure 9. Relationship between the chart formats derived from coding and the functions of the Visual Information Seeking Mantra [Shneiderman, 1996].

and coding stages of the SML. Thus, the codes generated carry with them the subjective interpretations and associations of a single researcher. To decrease the potential bias of the researcher, two researchers with experience in conducting SMLs supervised the outcomes of each stage of the SML. Furthermore, the extractions and codes generated are available on an online electronic spreadsheet. It is also possible to reproduce the SML by following the stages described in Section 3.

8 Conclusions

This paper aims to support researchers and professionals building UX data visualizations by presenting the state of the art on UX data visualizations. To this end, we conducted an SML that included 57 papers that deal with visualization types and their characteristics. The open coding technique and ten guiding questions structured the analysis of the papers. The questions were based on the four levels of the analysis framework of Munzner [2014] and the Visual Information Seeking Mantra [Shneiderman, 1996].

Most of the included papers focused on helping development teams evaluate a software application's UX and a game's PX. On the other hand, developing visualizations accessible to interdisciplinary teams and visualizations that enhance the communication of findings was the primary objective of few papers. In the validation stage, only personalized questionnaires measured characteristics adjusted to the visualization evaluation. As a result of this stage, the papers reported that the visualizations contributed to user interaction analysis. Besides, the results allowed us to consolidate the advantages and pitfalls of the proposed visualizations.

The mapping between data sources and chart formats highlights the mainstream usage of user actions and software events, sometimes in the format of navigation trajectory data, as data sources. At the same time, it sheds light on the sparse experimentation of chart formats and the limited exploration of demographic, acoustic, and UX metrics data. A minority of the chart formats were combined with multiple data sources. Regarding the functions of the Visual Information Seeking Mantra, the overview function was adopted on a smaller scale. Furthermore, visualizations were rarely developed using existing tools rather than computer languages.

Our results provide a body of knowledge from which researchers and professionals can develop new visualizations. They also highlight multiple gaps for future research to explore. Furthermore, it would be valuable to investigate the practitioner perspectives on UX data visualizations through interviews or a gray literature review to, for instance, refine the codes generated or identify best practices.

Declarations

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Authors' Contributions

Lucas Katib do Amaral: Conceptualization, Methodology, Formal Analysis, Data curation, Writing (original draft, review and editing), Investigation.
Maylon Macedo: Conceptualization, Methodology, Writing (review and editing).
Luciana Zaina: Conceptualization, Methodology, Supervision, Writing (review and editing), Funding acquisition.

Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

A spreadsheet containing the extracted data and the generated codes is available at `https://docs.google.com/spreadsheets/d/e/2PACX-1vTOr9rnuQ5yJyZeEKu1mYQfOD5z54wTJPjJiCVk3-Ca4sa1hFAL1IxV3ROKX48sQqdYiVgkIcjGtKqX/pubhtml`.

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Apenddix A

See Table A.5.

Apenddix B

See Table B.6.

ID	Title
P01	A 3D visualization framework to social network monitoring and analysis [Campos Filho *et al*., 2015]
P02	A Generic Visualization Approach Supporting Task-Based Evaluation of Usability and User Experience [Bernhaupt *et al*., 2020]
P03	A spatiotemporal visualization approach for the analysis of gameplay data [Wallner and Kriglstein, 2012]
P04	A Tool to Remotely Collect and Visualize Users' Interactions with Web-Based Content [Watson and Spyridakis, 2016]
P05	A Visual Analytics Approach for Understanding Reasons behind Snowballing and Comeback in MOBA Games [Li *et al*., 2017]
P06	ADQDA: A Cross-device Affinity Diagramming Tool for Fluid and Holistic Qualitative Data Analysis [Liu and Eagan, 2021]
P07	Aggregated Visualization of Playtesting Data [Wallner *et al*., 2019]
P08	An interactive visualization for tabbed browsing behavior analysis [Cernea *et al*., 2014]
P09	Analyzing Card-Sorting Data Using Graph Visualization [Paul, 2014]
P10	Analyzing engagement in a web-based intervention platform through visualizing log-data [Morrison and Doherty, 2014]
P11	Analyzing spatial user behavior in computer games using geographic information systems [Drachen and Canossa, 2009a]
P12	Animated Narrative Visualization for Video Clickstream Data [Wang *et al*., 2016]
P13	Assessing the impact of visual design on the interpretation of aggregated playtesting data visualization [Halabi *et al*., 2019]
P14	BONNIE: Building Online Narratives from Noteworthy Interaction Events [Segura *et al*., 2018]
P15	Can you hear the player experience? A pipeline for automated sentiment analysis of player speech [Sykownik *et al*., 2019]
P16	Collecting and harnessing rich session histories [Goodell *et al*., 2006]
P17	CoUX: Collaborative Visual Analysis of Think-Aloud Usability Test Videos for Digital Interfaces [Soure *et al*., 2022]
P18	Data cracker: Developing a visual game analytic tool for analyzing online gameplay [Medler *et al*., 2011]
P19	Decipher: An Interactive Visualization Tool for Interpreting Unstructured Design Feedback from Multiple Providers [Yen *et al*., 2020]
P20	Designing a unified cloud log analytics platform [Sun *et al*., 2016]
P21	E-customized product: User-centered co-design experiences [Li and Liu, 2020]
P22	Echo: Analyzing Gameplay Sessions by Reconstructing Them from Recorded Data [MacCormick and Zaman, 2020]
P23	Echoing the Gameplay: Analyzing Gameplay Sessions across Genres by Reconstructing Them from Recorded Data [MacCormick and Zaman, 2023]
P24	EmojiText: An Information Visualization Technique for Analyzing Phrases and Sentiments [Costa *et al*., 2021]
P25	Emotion-prints: Interaction-driven emotion visualization on multi-touch interfaces [Cernea *et al*., 2015]
P26	Enriching task models with usability and user experience evaluation data [Bernhaupt *et al*., 2019]
P27	Extracting relationship between browser history items for improved client-side analytics and recommendations [Kotapalle *et al*., 2018]
P28	FeaturEyeTrack: automatic matching of eye tracking data with map features on interactive maps [Göbel *et al*., 2019]
P29	Gameplay analysis through state projection [Andersen *et al*., 2010]
P30	GameVis: Game data visualization for the web [Feitosa *et al*., 2015]
P31	InteracDiff: Visualizing and Interacting with UX-Data [Dittrich *et al*., 2019]
P32	Interactive Exploration of Music Listening Histories [Dias *et al*., 2012]
P33	Interactive Intent Modeling for Exploratory Search [Ruotsalo *et al*., 2018]
P34	Live Feedback for Training Through Real-Time Data Visualizations: A Study with League of Legends [Rijnders *et al*., 2022]
P35	Mapping User Trajectories to Examine Behavior and Outcomes in Digital Health Intervention Data [Chen *et al*., 2019]
P36	Miria: A mixed reality toolkit for the in-situ visualization and analysis of spatio-temporal interaction data [Büschel *et al*., 2021]
P37	Motiis: Fostering Parents' Awareness of Their Adolescents Emotional Experiences during Gaming [Pepping *et al*., 2020]
P38	Multivariate Visualization of Game Metrics: An Evaluation of Hexbin Maps [Wallner and Kriglstein, 2020]
P39	Personal Web Library: organizing and visualizing Web browsing history [Du *et al*., 2018]
P40	PLATO: A visual analytics system for gameplay data [Wallner and Kriglstein, 2014]
P41	PopHistory: Animated Visualization of Personal Web Browsing History [Carrasco *et al*., 2017]
P42	Quantified UX: Towards a common organizational understanding of user experience [Lachner *et al*., 2016]
P43	Reconstructing experiences with iScale [Karapanos *et al*., 2012]
P44	Saliency-based gaze visualization for eye movement analysis [Yoo *et al*., 2021]
P45	See, Feel, Move: Player Behaviour Analysis through Combined Visualization of Gaze, Emotions, and Movement [Kepplinger *et al*., 2020]
P46	Supporting Serendipitous Discovery and Balanced Analysis of Online Product Reviews with Interaction-Driven Metrics and Bias-Mitigating Suggestions [Jasim *et al*., 2022]
P47	Towards gameplay analysis via gameplay metrics [Drachen and Canossa, 2009b]
P48	Towards the detection of UX Smells: The support of visualizations [Buono *et al*., 2020]
P49	Understanding User Behavior in Digital Libraries Using the MAGUS Session Visualization Tool [Bogaard *et al*., 2020]
P50	UXmood - A Tool to Investigate the User Experience (UX) Based on Multimodal Sentiment Analysis and Information Visualization (InfoVis) [Da Silva Franco *et al*., 2019]
P51	VETA: Visual eye-tracking analytics for the exploration of gaze patterns and behaviours [Goodwin *et al*., 2022]
P52	Visual analysis of massive web session data [Shen *et al*., 2012]
P53	Visualising user–website interaction: description and evaluation of a teaching method [Więckowska and Rudnicka, 2021]
P54	Visualization of customer expectations from Web text using co-occurrence graph and auto-labeling in the service market [Saga *et al*., 2017]
P55	Visualization of gaze tracking data for UX testing on the Web [Móro *et al*., 2014]
P56	Visualizing event sequence data for user behavior evaluation of in-vehicle information systems [Ebel *et al*., 2021]
P57	Visualizing group user behaviors for social network interaction design iteration [Gu *et al*., 2015]

Table A.5. Selected papers identified.

Term	Description	Source
Andrienko and Andrienko (2011) Algorithm	Algorithm to partition a spatial region based on the clustering of points in a movement trajectory.	Andrienko, N., Andrienko. G. (2011). Spatial Generalization and Aggregation of Massive Movement Data.
ArcGIS	Geographic information system for spatial data visualization.	https://www.esri.com/en-us/arcgis/about-arcgis/overview
Artificial Neural Networks	Machine learning model based on the interconnection of units with iteratively adjusted weights to achieve an optimal non-linear function.	Rumelhart, D. E., Hinton, G. E., Williams, R. J. (1986). Learning representations by back-propagating errors.
Auditok	Python library to detect sound events in audio.	https://pypi.org/project/auditok/0.1.8/
Box2DWeb	Game engine that allows animation of symbols based on physical principles.	https://box2d.org/
Bubble Sets	Visualization technique to portray spatial and membership relationships simultaneously.	Collins, C., Penn, G., Carpendale, S. (2009). Bubble Sets: Revealing Set Relations with Isocontours over Existing Visualizations.
Classical Multidimensional Scaling (CMDS)	Algorithm to visualize items spatially based on a dissimilarity matrix.	Kruskal, J. B., Wish, M. (1978). Multidimensional Scaling.
D3.js	JavaScript library for creating data visualizations.	http://d3js.org/
Density Based Spatial Clustering of Applications with Noise (DBSCAN)	Density-based clustering algorithm.	Ester, M., Kriegel, H.-P., Sander, J., Xu, X. (1996) A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise.
Gensim	Python library with natural language processing algorithms.	Řehůřek, R., Sojka, P. (2010). Software Framework for Topic Modelling with Large Corpora.
Graphviz5	Software for visualizing graphs and networks.	https://graphviz.org/
HAMSTERS-XLE	Software environment for modeling tasks that compose an interaction.	Martinie, C., Palanque, P., Bouzekri, E., Cockburn, A., Canny, A., Barboni, E. (2019) Analysing and Demonstrating Tool-Supported Customizable Task Notations.
Hadoop	Java framework for dealing with the processing of large databases.	White, T. (2010). Hadoop: The definitive guide.
INTUI	Questionnaire to measure different dimensions of an intuitive interaction.	Ullrich, D., Diefenbach, S. (2010). INTUI. Exploring the Facets of Intuitive Interaction.
K-means	Clustering algorithm based on the minimization of intra-cluster distance.	Lloyd, S. (1982). Least squares quantization in PCM.
Linear Associative Reinforcement Learning (LinRel)	Reinforcement learning model to deal with the exploitation-exploration trade-off in decision making.	Auer, P. (2000). Using confidence bounds for exploitation-exploration trade-offs.
Multidimensional Scaling for Java (MDSJ)	Java library to apply the multidimensional scaling algorithm.	Algorithmics Group. (2009). MDSJ: Java Library for Multidimensional Scaling (Version 0.2).
NASA-Task Load Index (NASA-TLX)	Questionnaire to measure the perceived workload during a task.	Hart, S. G., Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research.
Newman (2004) Algorithm	Clustering algorithm for community detection in graphs.	Newman, M. E. J., 2004. Fast algorithm for detecting community structure in networks.
NVivo	Software for qualitative data analysis.	https://help-nv.qsrinternational.com/20/win/Content/about-nvivo/about-nvivo.htm
OGAMA	Software for analyzing eye tracking and mouse tracking data.	Voßkühler, A., Nordmeier, V., Kuchinke, L., Jacobs, A. M. (2008) OGAMA (Open Gaze and Mouse Analyzer): Open-source software designed to analyze eye and mouse movements in slideshow study designs.
OpenCV	Computer vision and machine learning library for multiple programming languages.	https://opencv.org/about/
OpenGL	Computer graphics API.	https://www.opengl.org/
Praat-Parselmouth	Python library for phonetic analysis.	Jadoul, Y., Thompson, B., & de Boer, B. (2018). Introducing Parselmouth: A Python interface to Praat.
Protovis	JavaScript library for creating data visualizations.	Bostock, M., Heer, J. (2009). Protovis: A Graphical Toolkit for Visualization.
Quality Threshold (QT)	Clustering algorithm based on the diameter of the clusters.	Heyer, L. J., Kruglyak, S., and Yooseph, S. (1999). Exploring expression data: Identification and analysis of coexpressed genes.
Recommender systems' Quality of user experience (ResQue)	User-centered evaluation framework for recommender systems.	Pu, P., Chen, L., Hu, R. (2011). A user-centric evaluation framework for recommender systems.
Repertory Grid technique	Structured interview technique based on the terms used by the participant while describing their experience.	Fransella, F., Bell, R., Bannister, D., (2003). A Manual for Repertory Grid Technique.
Reverse Cuthill–McKee (RCM)	Sorting algorithm to reduce the envelope of sparse matrices.	George, A., Liu, J. W. H. (1981). Computer solution of large sparse positive definite systems.
Sun et al. (2012) Algorithm	Algorithm to verify isomorphism between graphs.	Sun, Z., Wang, H., Wang, H., Shao, B., Li, J. (2012). Efficient subgraph matching on billion node graphs.
Support Vector Machine (SVM)	Machine learning model based on the selection of support vectors that maximize the separation margin between distinct classes.	Cortes, C., Vapnik, V. (1995) Support-vector networks.

Table B.6. Description of emerging methods, techniques, and tools from the SML (Continued on the next page).

Term	Description	Source
SWISH DataLab	Software environment for data analysis that supports the Prolog and R languages.	Bogaard, T., Wielemaker, J., Hollink, L., Van Ossenbruggen, J. (2017). SWISH Data- Lab: A web interface for data exploration and analysis.
Term frequency-inverse document frequency (TF-IDF)	Algorithm to measure the importance of a term in a document.	Salton, G., Buckley, C. (1988). Term-weighting approaches in automatic text retrieval.
User Experience Questionnaire (UEQ)	Questionnaire to measure the user experience of a product.	Laugwitz, B., Held, T., Schrepp, M. (2008). Construction and Evaluation of a User Experience Questionnaire.
Usefulness, Satisfaction, and Ease of use (USE)	Questionnaire to measure three dimensions of a product: usefulness, satisfaction, and ease of use.	Lund, A. (2001). Measuring Usability with the USE Questionnaire.
Unity	Game engine for creating 2D and 3D games and other visual content.	https://unity.com/
Universal Visualization Platform	System for creating analysis and visualization applications.	Gee, A.G., Li, H., Yu, M., Smrtic, M.B., Cvek, U., Goodell, H., Gupta, V., Lawrence, C., Zhou, J., Chiang, C.-H. and Grinstein, G.G. (2005) Universal Visualization Platform.
Valence Aware Dictionary and Sentiment Reasoner	Python library for classifying texts based on lexical analysis.	Hutto, C., Gilbert, E. (2014). VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text.
Velocity-Threshold Identification (I-VT)	Algorithm to differentiate types of gaze based on movement speed.	Salvucci, D., Goldberg, J. (2000). Identifying fixations and saccades in eye-tracking protocols.

Table B.6. Description of emerging methods, techniques, and tools from the SML (Continued).